

MNDWI-Based Flood Extent Detection for Hazard Map Evaluation

1. Introduction

Floods are among the most costly and deadly natural disasters, and a large body of evidences shows that they are becoming both more frequent and more extreme across the world due to climate change ([Aldous et al., 2011](#); [Arnell & Gosling, 2013](#); [Denchak, 2023](#); [lonno et al., 2024](#); [Smith, 2024](#)). Remote sensing techniques have wide applications for predicting, studying, and responding to flooding disasters ([Schumann, 2015](#)). In particular, they can be used to observe and measure the extent of surface water and therefore flooding, providing invaluable support for disaster response and recovery ([Popandopulo et al., 2023](#)).

Satellite technology for flood sensing developed rapidly in the past few decades but still faces many challenges, and despite a proliferation of academic studies on their usefulness, FEMA and other disaster response agencies haven't formally adopted these approaches ([Schumann & Guy, 2024](#)). This may be set to change in the coming decades, as space agencies increasingly agree that satellite data has great value for flood monitoring. Recent technological improvements in both Synthetic Aperture Radar (SAR) and high performance computing contribute to the growth of the field as well ([Schumann et al., 2009](#)). Cost is not necessarily a barrier to success: robust classifications can often be generated with free satellite data. The challenge lies in selecting the right type of data for the specific flood event and mapping goals. One of the biggest factors in this decision is temporal resolution – in order to be useful, data must be acquired at the moment of interest, and data acquired after the peak of a flood may not yield usable results ([Notti et al., 2018](#)).

Flood extent mapping can be accomplished using multiple types of remotely sensed data and countless classification models and indices. Generally, the most common approaches are to use multispectral optical imagery such as that collected by Landsat or Sentinel-2, Synthetic Aperture Radar (SAR) imagery collected by platforms such as Sentinel-1 or NASA's SNPP, or a combination of both. There is a wealth of literature outlining the comparative advantages and disadvantages of different sensors for this purpose.

Multispectral optical imagery of flood events can be classified with just a single band, often NIR, but more often multiple bands are used to create indices ([Albertini et al., 2022](#)). These typically include either the Normalized Difference Water Index (NDWI) or Modified NDWI

(MNDWI), although in some cases NDVI and MNDVI are also used. While NDWI uses the green and near infrared (NIR) bands, MNDWI makes use of the green and the longer wavelength short-wave infrared (SWIR) bands in order to more effectively filter out urban features that would otherwise resemble water (Xu, 2006). MNDWI has been shown to be more successful at identifying the extent of surface water in built-up areas, whereas NDWI performs better in areas of lots of vegetation (Che et al., 2025; Khalifeh Soltanian et al., 2019; Szabó et al., 2016). This is because surface water absorbs even more SWIR than NIR or visible bands (Li et al., 2018). Thresholds such as the Otsu threshold are typically applied to create two classes, flood/surface water and non-flood/non-surface water (Kordelas et al., 2018; Mehmood et al., 2021). The majority of studies reviewed used either Sentinel-2 or Landsat imagery. Optical analysis can still suffer from higher error rates in some cases due to partly submerged or floating vegetation and cloud cover (DeVries et al., 2017; Shastry et al., 2023). The main advantage of optical-based methods is that most multispectral platforms have much higher temporal and spatial resolutions than SAR – a crucial consideration in many contexts (Farhadi et al., 2024; Portalés-Julià et al., 2023).

SAR can be used for surface water detection in all types of weather conditions and at night, since it doesn't rely on visible light. The ability to make observations through cloud cover is especially sought after, since clouds are often present during and immediately after flood events (Zhao et al., 2024). Sentinel-1 is one of the most commonly used SAR platforms (Earth Science Data Systems, 2021). Although both can see beneath clouds, active synthetic aperture radar has a strong advantage over passive microwave sensors due to the latter's coarse spatial resolution, which usually prevents the observation of features relevant to flood response efforts (Goldberg et al., 2018). Satellites carrying SAR sensors often do not pass overhead frequently enough to capture imagery of flood events at their peak, an unacceptable downside in many cases. Although Sentinel-1 in particular is valued for its relatively short return period of 12 days, this is still long enough to often miss entire flood events or at least their peak (Farhadi et al., 2024). Classification of SAR data can also be hindered by various kinds of visual distortion and noise due to characteristics of the sensor (Portalés-Julià et al., 2023). SAR archives also do not cover nearly as long a time period as optical platforms such as Landsat, so historical studies of flood extent are bound to use optical imagery (Gumley & King, 1995; Olthof & Tolszczuk-Leclerc, 2018).

Because both approaches have benefits and drawbacks, many studies combine them. This “multimodal” approach can allow more flexibility and consistency in the temporal windows of observation, mitigating both the cloud cover and vegetation issues of optical imagery and the

return period issues of SAR sources ([Li & Demir, 2024](#)). However, the challenge then becomes creating consistent classifications from entirely different types of image data; some researchers have attempted to create models that maintain a consistent sense of what counts as “flooded” land between different sources ([Zhao et al., 2024](#)). Multiple studies use data from both Sentinel-1 (SAR) and Sentinel-2 (optical) to try to build models that agree on which pixels are water vs. non-water between the two ([Tran et al., 2022](#)).

In the United States, FEMA manages the National Flood Insurance Program (NFIP) to protect populations vulnerable to floods and to help enforce floodplain management policies ([Flood Insurance | FEMA.Gov, 2025](#)). To help determine the flood hazard of a given property or area, FEMA also provides the National Flood Hazard Layer (NFHL) geospatial database ([Flood Data Viewers and Geospatial Data | FEMA.Gov, 2025](#)). Residents and businesses in areas of high flood hazard, also known as Special Flood Hazard Areas (SFHA), are required to have flood insurance in order to be eligible for mortgages from lenders backed by the government. SFHAs are defined as “the area that will be inundated by the flood event having a 1-percent chance of being equaled or exceeded in any given year” ([Flood Zones | FEMA.Gov, 2020](#)). In other words, experts work to invent hypothetical floods of given probable frequencies, which are then represented as lines of high water on a map ([Practical Engineering, 2020](#)).

The line created by the 1%-chance flood serves as the boundary between areas subject to flood insurance regulations and those that aren't. This important line is also known as the “base flood” or, popularly, the “100-year flood.” Hydrology experts and many others, including the USGS Water Science School, are quick to point out that this latter term is misleading: it sounds like we should be able to expect exactly one of these floods every 100 years, but this is not the case. It is possible to have multiple “100-year floods” in a row, because each year has the same chance of seeing a flood of this magnitude – a 1% chance ([The 100-Year Flood | U.S. Geological Survey, 2018](#)).

Or does it? The USGS also states that statistical methods require the analysis of 10 or more years of data in order to confidently calculate this probability. As mentioned above, we know that due to climate change, floods are becoming both more frequent and more extreme. Terminology aside, could it be misleading to suggest that it's even possible to define a flood that will have the same percentage chance of happening each year? If the rates at which flood events occur have changed within the last 10 years, how can the definition of a 1%-yearly-chance flood be updated rapidly and continuously enough to protect those who live or own businesses in vulnerable areas? Risk management experts, including the director of FEMA, are increasingly pointing out that climate change has undermined the accuracy of both

the flood hazard maps themselves and the methods used to create them ([Banham, 2024](#); [Kuta, 2022](#)). Climate adaptation efforts must include more rapidly updated flood hazard maps, and new methods are needed to produce them ([Moore, 2024](#)). Beyond this, more education is needed for lay people who are increasingly realizing their life and property depend on understanding their flood risk.

Flood hazard assessment is done using many inputs, including historic and projected rainfall, soil characteristics, and slope and elevation data ([National Research Council, 2015](#); [Ayenew & Kebede, 2023](#)). However, these floods are hypothetical, and while measurements of past flood events are used in calculations, this generally doesn't include direct measurement of flood extent on specific dates. In addition to providing essential near-real-time information to disaster response agencies and local communities, remote sensing methods may offer a chance to validate existing flood hazard maps against empirical measurements of real flood events ([Masafu & Williams, 2024](#)).

This study will use MNDWI with optical imagery from Sentinel-2 and SAR data from Sentinel-1 to map the extent of flooding along the Mississippi River in Davenport, Iowa, for three flood events in Spring 2019. This classification will be compared and validated against flood maps published by the city of Davenport. The extent of these flood events will then be compared to National Flood Insurance Program hazard maps provided by FEMA. This comparison will support recommendations for the more frequent updates to flood hazard maps. By analyzing what could be considered three separate major flood events on April 8th, May 4th, and June 2nd of the same year *or* one extremely extended flood event, I hope to raise the question: How should communication about flood hazard calculation, mapping, and insurance rates change given the increase in frequency and/or duration of major flood events, and more crucially, how can these insights be used to adjust communication with the public?

A secondary purpose of this study is to test the Recommended Practices laid out in the thorough guide [Step-by-Step: Recommended Practice: Flood Mapping and Damage Assessment Using Sentinel-1 SAR Data in Google Earth Engine](#). This guide is provided by the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER), a program dedicated to ensuring international access to "space technologies" for disaster response. The Google Earth Engine script provided will be evaluated as a solution for dates when cloud free imagery is unavailable.

2. Methods

2.1 Study Area

Davenport, Iowa is of interest because it is the largest city along the Mississippi that doesn't have a permanent flood wall or levee ([Norvell, 2019](#)). While the other 3 cities in the Quad Cities built permanent flood infrastructure in the 1970s, Davenport declined, and in the decades since then its residents and government have for the most part agreed to take a different approach. To save money and preserve their natural riverfront, they use temporary flood barriers and allow a park in the floodplain to be inundated ([Powers, 2020](#)). To some degree, Davenport serves as an example of managing floods through risk reduction rather than hazard reduction: the areas that flood are non-residential, detour routes are well-established in advance, and areas of vegetation are preserved to absorb the brunt of the Mississippi's crests. However, the downtown business district is also frequently inundated and cut off from the rest of the city by floodwaters, and many business owners have been badly affected by flood events of recent years ([Schmidt, 2019](#)). As climate change leads to heavier and more frequent rainstorms, the city will have to make choices about how to continue its flood management and response strategy. This study's findings may help provide more data for this decision-making process.

A rectangular area of interest was defined encompassing the lower half of Davenport's city limits, a stretch of the Mississippi River, and a portion of Rock Island, another one of the Quad Cities. This area was chosen to highlight the area along the northern shore of the Mississippi River highlighted on FEMA's Special Flood Hazard Area maps as vulnerable to 1% and 0.02% annual chance floods. Duck Creek is also included, running laterally across Davenport to the north of downtown; this creek is bordered by more area marked as vulnerable to 1% annual chance floods, allowing us to see if the flood events of 2019 affected all urban waterways or just the Mississippi River.

Because we are primarily interested in Davenport and its flood hazard decision-making, results are first summarized for the portion of our study area that is within its city limits. However, figures are also included displaying flood extent for the entire rectangular AOI, as it's interesting to see inundation in the surrounding area as well. Further studies should compare the land cover affected by inundation in all four of the Quad Cities (Davenport, Bettendorf, Rock Island, and Moline).

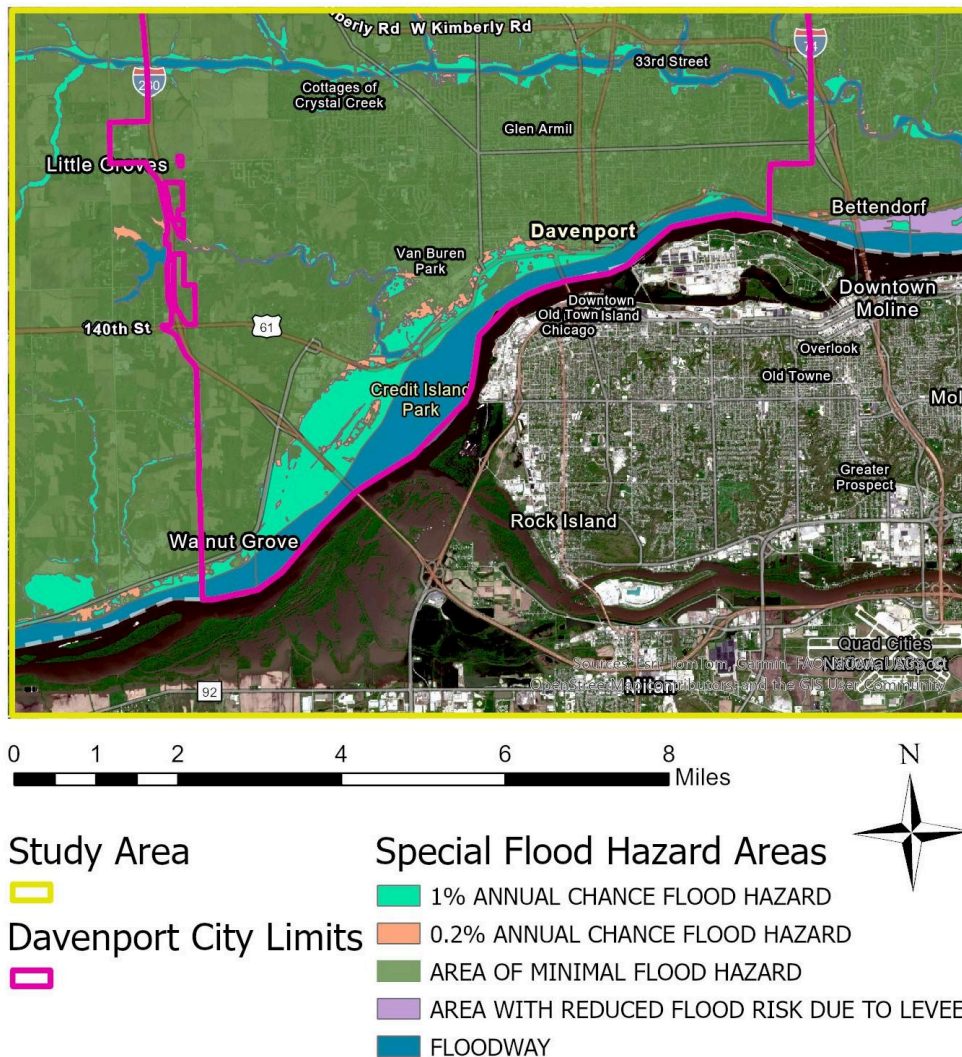


Figure 1: The study area shown with Davenport's city limits and FEMA's Special Flood Hazard Areas.

2.2 Study Date Selection and Data Acquisition

The Army Corps of Engineers at the Rock Island Lock and Dam monitor and record the water levels of the Mississippi river in the Quad Cities area (Rock Island is directly across the river from Davenport). The flood stage of the river in this location is 15 feet, and the action is 13 feet (that's the point at which officials begin flood response preparation). In the Spring and early Summer of 2019, the Mississippi river crested at the Rock Island Gage three separate times, at 20.68 feet on April 8th, 22.7 feet on May 2nd, and 21.68 feet on June 2nd. The 22.7 foot crest in May broke the record set by the flood event of 1993, which was 22.63 (NWS, 2019). By mid June, the river had been above flood stage for most of the region since the middle of March;

according to the National Weather Service, this is the longest the river had ever been in flood in a row ([NWS, 2019](#)). Davenport's downtown was flooded for 103 days of 2019 and a new record high water level was set ([Sasaki Associates, Inc., 2020](#)). On April 30th, 2019, at around 1 PM, the National Weather Service of the Quad Cities issued a warning that heavy rain and high river

levels was causing water to pool and storm drains were struggling to handle the flow. At 3:54 PM CST, a flash flood warning was issued, warning residents to seek higher ground immediately. Just minutes later, temporary flood barriers were breached and downtown Davenport was suddenly inundated, affecting many business owners ([NWS, 2019](#); [Blount, 2024](#)).

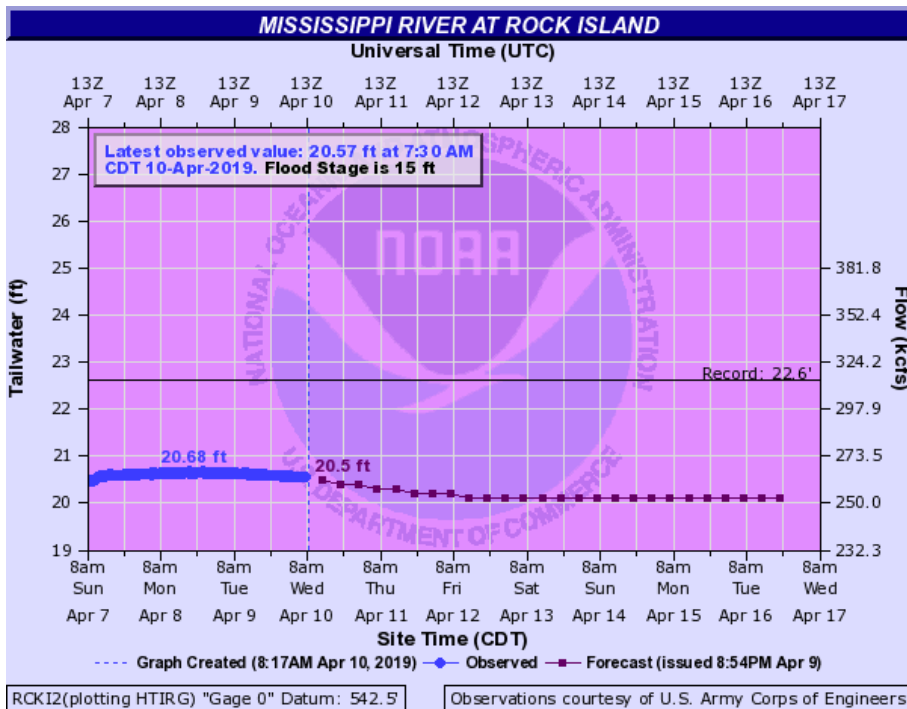


Figure 2: Hydrograph showing the river's crest at the Rock Island Gage on 4-8-2019 ([NWS, 2019](#)).

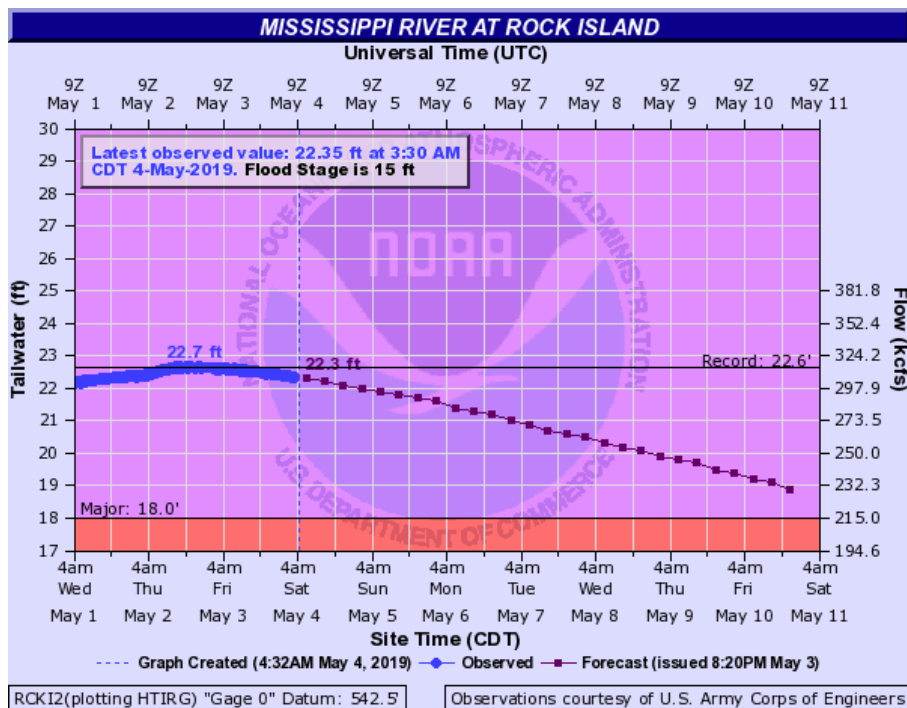


Figure 3: Hydrograph showing the river's crest at the Rock Island Gage on 5-2-2019 ([NWS, 2019](#)).

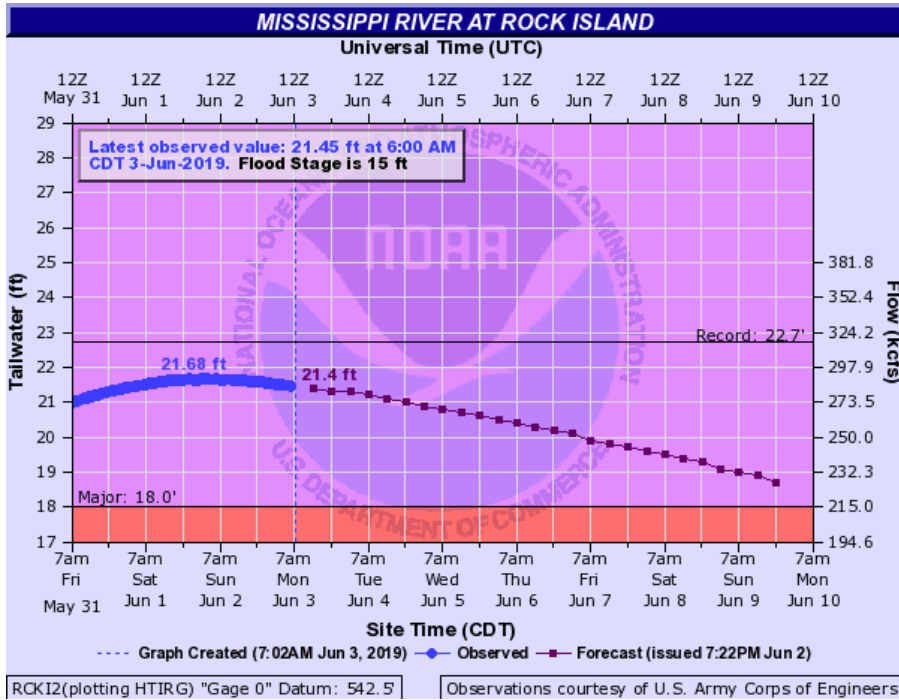


Figure 4: Hydrograph showing the river's crest at the Rock Island Gage on 6-2-2019 (NWS, 2019).

High resolution satellite imagery was acquired by Sentinel-2 on dates overlapping the peak of all three of these river crest events, highlighting one of the major advantages of optical imagery for flood extent analysis. Floodwaters are clearly visible in downtown on both May 4th and April 9th Sentinel-2 acquisitions. However, in imagery acquired on both May 29th and June



3rd, clouds almost completely obscure the view of Davenport and render it unsuitable for classification, although you can just make out floodwaters in downtown on June 3rd with close inspection (see figures 5 and 6 below). This highlights one of the major disadvantages of optical imagery for flood extent analysis.

Figure 5: Sentinel-2 imagery of downtown Davenport on June 3rd, 2019; light cloud cover mostly obscures the view, but some flood waters are visible (Copernicus Browser, 2019).



Figure 6: Sentinel-2 imagery of downtown Davenport on May 29th, 2019, entirely obscured by clouds ([Copernicus Browser, 2019](https://www.copernicus-browser.com/)).

This study therefore focuses on the April 7th-10th and historic May 1st-4th 2019 river crests. Sentinel-2 Level-2A (surface reflectance) imagery acquired on April 9th at 11:48 AM CST and May 4th at 11:49 AM CST was retrieved from browser.dataspace.copernicus.eu.

Mississippi River at Dubuque, IA
 Gage Zero - 585.47 Ft. MSL 1912
 Flood Stage - 17 Ft.
 Record High Stage - 26.81 Ft. (04/26/1965)
 River Mile - 579.9 miles above the mouth of the Ohio River
 Location of Gage -

Located in Dubuque county, IA, on the right bank at the foot of 4th Street in Dubuque adjacent to the right abutment of the Illinois Central Railroad bridge.

The National Weather Service information is also linked in the Additional Links for this station.

This gage is operated by the US Army Corps of Engineers (Rock Island District).

2018 Stage (Ft)

Day	JAN	FEB	MAR	APR	MAY	JUN	JULY	AUG	SEP	OCT	NOV	DEC
1	9.52	9.83	16.00	10.61	17.36	10.67	10.56					
2		10.08	10.24	16.57	10.69	17.05	10.30	11.93				
3		10.30	10.37	17.29	10.74	16.65	10.21	11.97				
4		10.40	10.64	18.01	10.77	16.14	9.92	12.82				
5		9.75	10.89	18.28	10.70	15.91	9.80	13.62				
6		8.82	10.89	19.24	10.69	15.57	10.11	14.19				
7		8.33	10.80	19.61	10.62	15.28	10.29	14.49				
8		8.34	10.58	19.59	10.63	14.98	9.75	14.43				
9		8.30	10.24	19.45	10.79	14.66	9.49	14.36				
10		8.17	10.18	19.28	11.22	14.33	9.35	14.22				
11		8.18	10.10	18.94	12.37	14.32	9.06	14.10				
12		8.18	10.00	18.55	12.55	14.16	8.69	14.15				
13		8.04	9.81	18.16	12.20	13.93	8.53	14.16				
14		7.83	9.76	17.81	12.08	13.75	8.62	13.98				
15		8.02	9.81	17.40	11.71	13.67	8.56	13.59				
16		8.42	10.43	16.95	11.49	13.56	8.59	12.89				
17		8.68	11.12	16.49	11.38	13.47	8.72	12.00				
18		8.90	11.40	15.97	11.16	13.23	8.84	11.15				
19		8.68	11.51	15.35	10.95	12.95	8.82	10.50				
20		8.46	11.74	14.89	11.24	13.10	8.56	10.52				
21		8.64	11.73	14.24	11.79	13.15	8.41	13.06				
22		8.76	11.67	13.68	12.42	13.17	6.80	12.93				
23		8.87	11.56	13.24	13.29	13.14	7.03	12.17				
24		9.34	11.55	12.84	13.96	13.04	8.02	11.70				
25		9.44	11.87	12.47	14.86	12.89	8.22	11.30				
26		9.51	12.16	12.04	15.86	12.53	8.59	11.51				
27		9.55	12.72	11.73	16.86	12.23	8.38	11.80				
28		9.67	13.27	11.62	17.36	11.95	8.29	11.83				
29		9.65	13.95	11.40	17.60	11.68	8.48	11.98				
30		9.78	15.02	10.88	17.54	11.35	8.89	12.05				
31		9.82		10.61		10.99	9.92					
MIN		7.83	9.76	10.61	10.61	10.99	6.80	10.50				
MAX		10.40	15.02	19.61	17.60	17.36	10.67	14.49				
MEAN		8.98	11.19	15.76	12.54	13.88	8.96	12.67				

For flood extent measurement through change detection, baseline non-flood imagery was acquired for June 3rd, 2018. A date at a similar time of year and only one year apart was selected to minimize land cover differences. June 3rd was both cloud-free and had similar phenology conditions to my study date, and the USACE Rock Island District's records show that the Mississippi was at 10.74 feet on this date, a water level well below the river's action and within the average range. While some differences in land cover may be found between this and the study dates, use of the SWIR band should minimize their impact.

Figure 7: A table showing historical data recorded by the ASACE at Rock Island in Spring and Summer 2018, used to select a flood-free control date for change detection. ([Yearly Formatted Historic Values For DBQI4. n.d.](#))

2.3 Preprocessing and Classification of Sentinel-2 Data

I retrieved Sentinel-2 imagery for both the flooded and non-flooded dates and imported bands 2 (blue), 3 (green), 4 (red), and 11 (SWIR) into ArcGIS Pro at 20m resolution and clipped them to my area of interest. I used bands 2, 3, and 4 to create true color composites for both dates. I used the raster calculator to compute the MNDWI: $(\text{Green} - \text{SWIR}) / (\text{Green} + \text{SWIR})$. This created continuous rasters with values ranging from about -0.75 to 0.7. I chose to use the Modified Normalized Difference Water Index (MNDWI) over NDWI because the use of the SWIR band makes this index better suited to urban areas than NIR, and my study is specifically concerned with the encroachment of flood waters into downtown Davenport ([Xu, 2006](#)). I visualized this index using the Percent Clip stretch method to filter out extreme outliers.

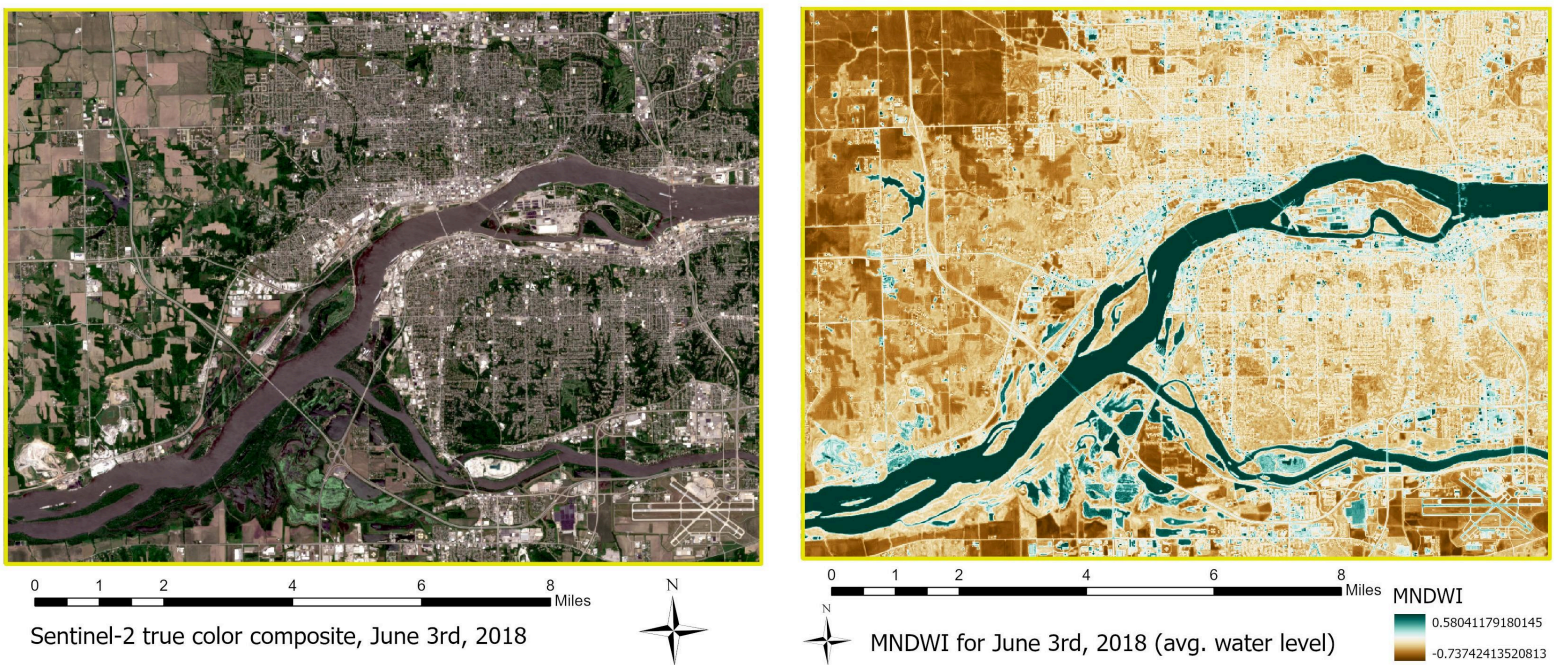
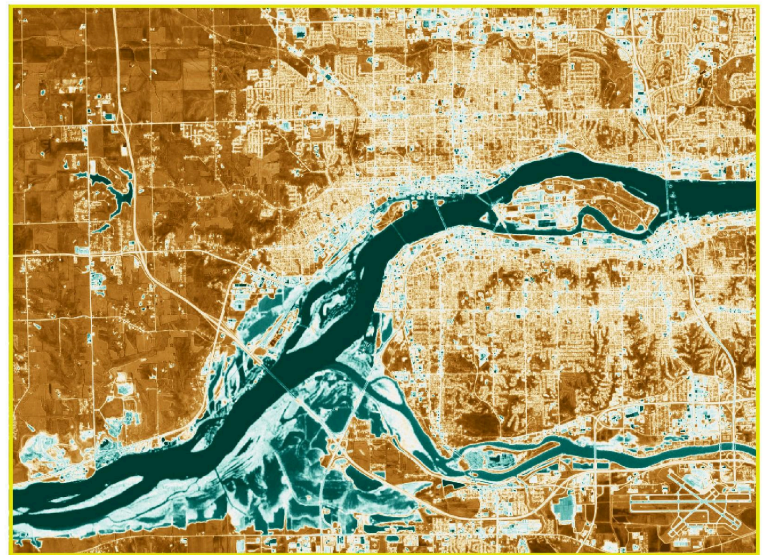


Figure 8: True color imagery and MNDWI for June 3rd of the year prior to the floods of interest. At this time, the Rock Island gage was approximately 10.7 feet – Not the lowest river water level, but well below the river's 13 foot action.

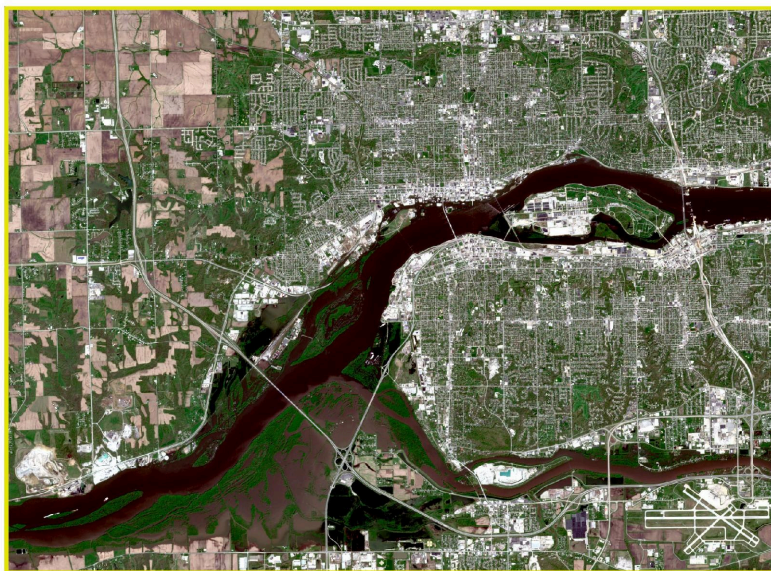


Sentinel-2 true color composite, April 9th, 2019

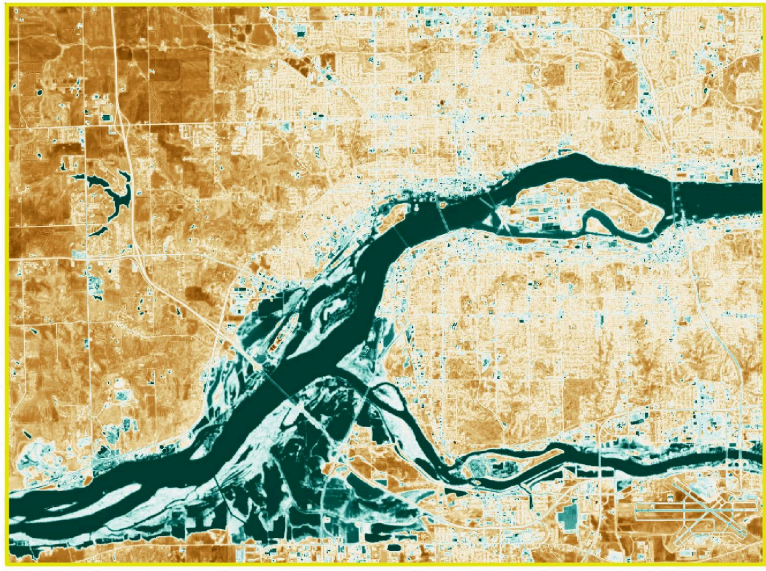


MNDWI for April 9th, 2019 (major flood stage)

Figure 9: True color and MNDWI data for April 9th 2019, the first crest of the Mississippi river at the Rock Island gage. The river reached 20.68 feet, a full 10 feet above the June 3rd 2018 baseline, 5.68 feet above minor flood stage and 2.68 feet above major flood stage. Water is clearly visible in downtown Davenport.

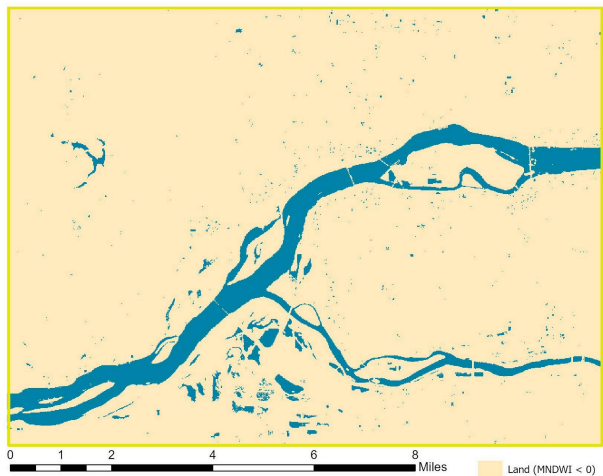


Sentinel-2 true color composite, May 4th, 2019

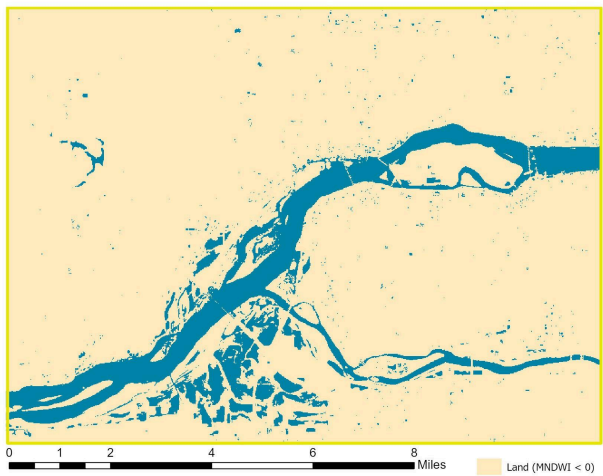


MNDWI values for May 4th, 2019

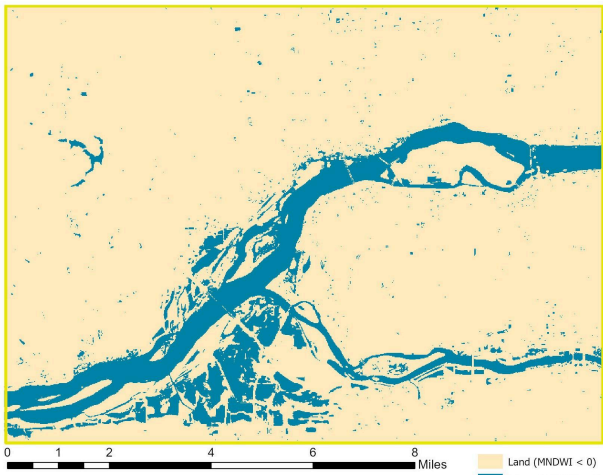
Figure 10: True color and MNDWI data for May 4th 2019. The river reached a record-setting crest of 22.7, 12 feet above our baseline, 7.7 feet above minor flood stage and 4.7 feet above major flood stage.



Thresholded MNDWI water classification, June 3rd, 2018



Thresholded MNDWI water classification, April 9th, 2019



Thresholded MNDWI water classification, May 4th, 2019

Figure 11: Maps of the surface water extent binary mask for the baseline date and the two study dates.

Next, I reclassified both rasters to create a binary surface water extent class. MNDWI values above a threshold were classified as water (value of 1) and values below it as land (value of 0). Through iterative comparison to the true color composite images made from the Sentinel-2 acquisitions of the same dates, I arrived at a threshold of 0. While a threshold of .02 filtered out slightly more noise from the built environment, I believe it also underestimated the extent of surface water. Because my purpose is to find the change between the flooded and non-flooded imagery by subtracting one raster from the other, I believe the impact of the small areas of urban noise should be negligible, as they were acquired just months apart. This urban noise is attributable to certain buildings reflectance of SWIR, and it doesn't represent a large area.

To find the extent of flooding, I subtracted the non-flood surface water extent raster from the flood extent raster, producing a difference layer. A small number of negative values were produced exclusively in areas of urban noise, so these were reclassified as land (value of 0). The count of pixels classified as water was retrieved from the difference layers attribute table for the full study area and for the portion of the city of Davenport that lay within my study area. The total area of these pixels was calculated by multiplying it by the spatial resolution, which is 20m² (400m) per pixel, and then dividing by 10,000 to convert from meters to hectares.

3. Results

3.1 Flood Extent Classification

Flood extent was estimated by summing classified water pixels at 20m spatial resolution. The total flooded area on April 9th, 2019 was about 789.28 hectares (19732 pixels) within the full rectangular study area and about 241.48 hectares (6037 pixels) within Davenport city limits. The total flooded area on May 4th, 2019 was 1,302.04 hectares (32551 pixels) within the study area and 338.16 hectares (8454 pixels) within Davenport.

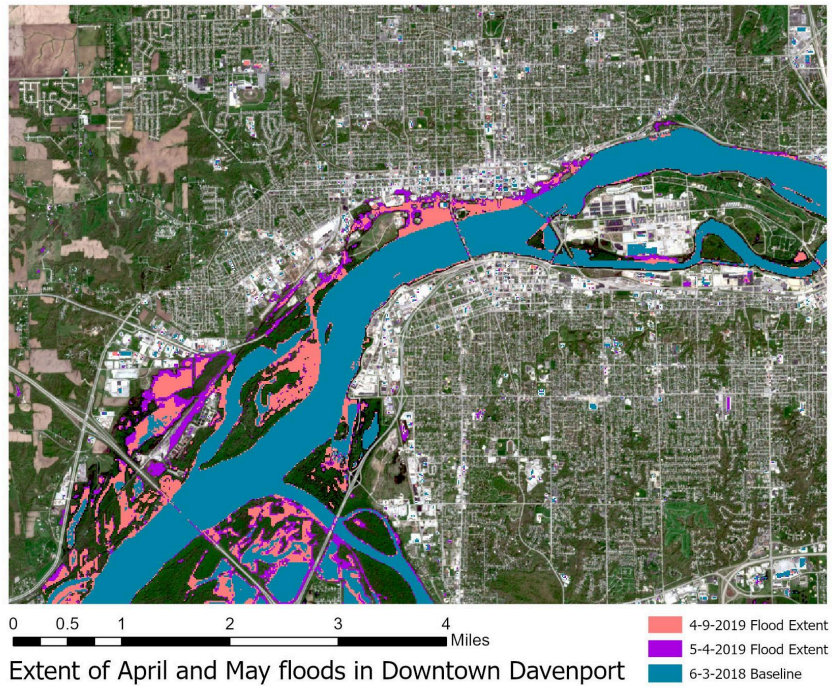


Figure 12: A close up map of downtown Davenport showing the extent of flooding on both of the two study dates and the level of the Mississippi on the baseline date.

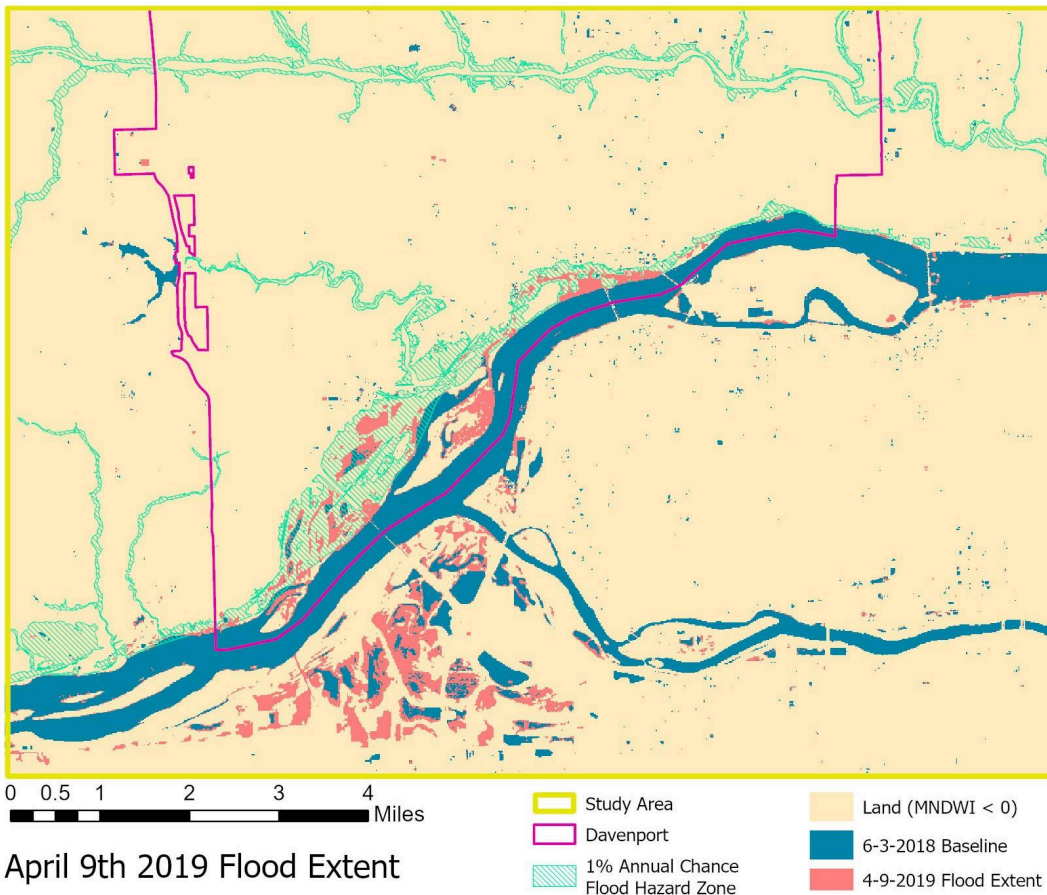
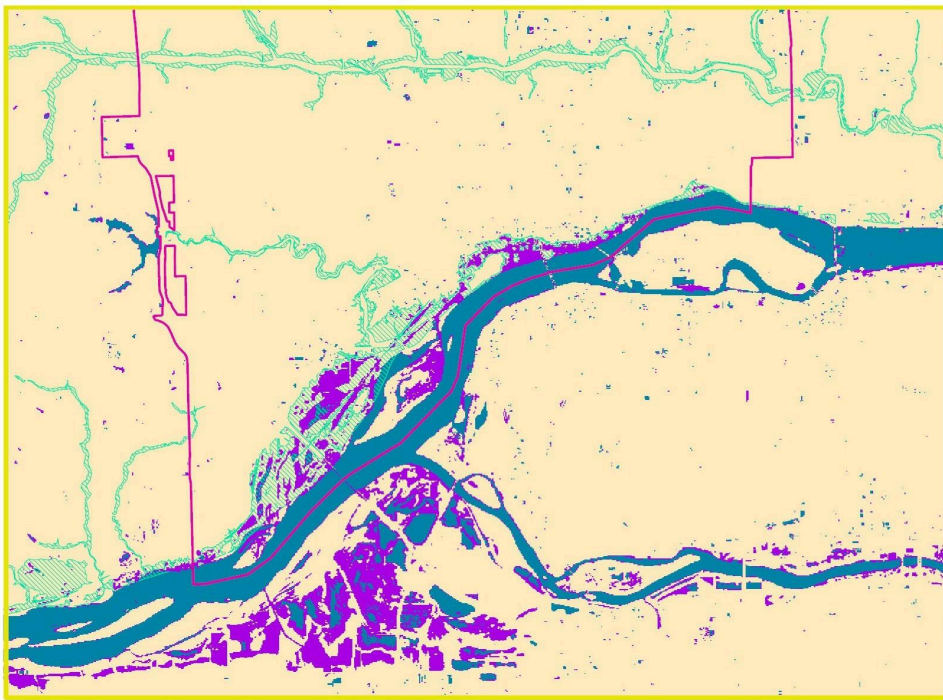


Figure 13: Flood extent results for the April 9th 2019 study date alongside a comparison to the baseline extent measured in June 2018 and FEMA's 1% annual chance flood zones.

April 9th 2019 Flood Extent



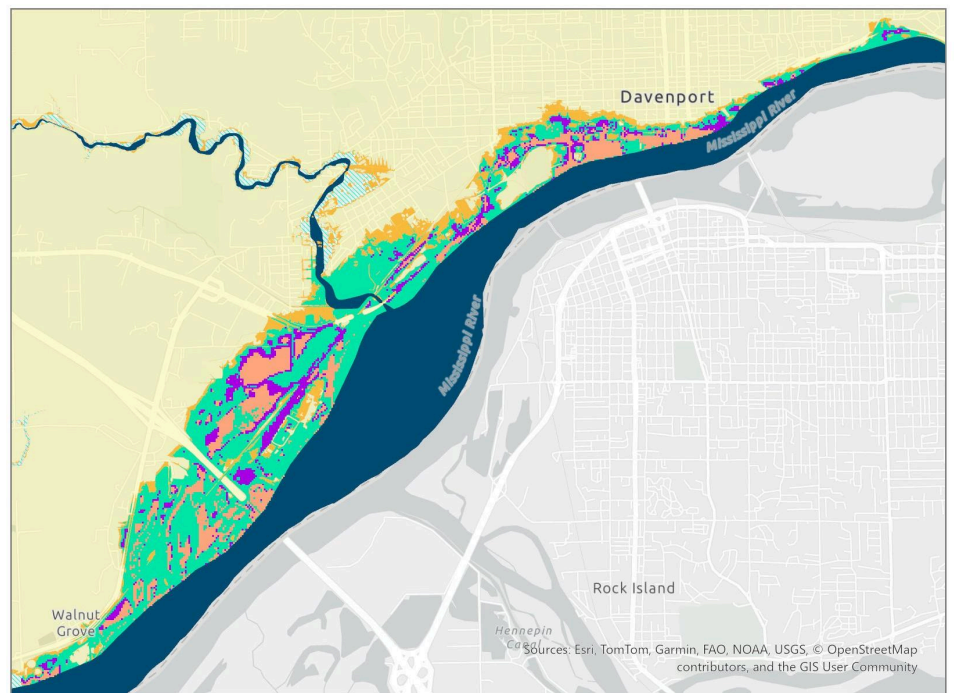
May 4th 2019 Flood Extent

Study Area
 Davenport
 1% Annual Chance Flood Hazard Zone
 Land (MNDWI < 0)
 6-3-2018 Baseline
 5-4-2019 Flood Extent

Figure 14: Flood extent results for the April 9th 2019 study date alongside a comparison to the baseline extent measured in June 2018 and FEMA's 1% annual chance flood zones.

Figure 15: A close-up comparison of FEMA flood zone and mapped flood extent.

3.3 Comparison to FEMA Flood Hazard Layer
 Comparing my flood extent measurements to FEMA's Flood Hazard Zones layer, it's clear that neither of these floods exceeded the level of the 1% annual chance flood, although they were significant and record-breaking in other respects. To quantify this, I calculated the total area of



1% Annual Chance Flood Hazard Zone Along the Mississippi
 Excluded 1% Annual Chance Zones
 0.2% Annual Chance Zones
 Area of Minimal Flood Hazard
 Floodway
 4-9-2019 Flooding in Davenport
 5-4-2019 Flooding in Davenport

Flooding in downtown Davenport compared to FEMA Flood Zones

0 0.5 1 2 3 4 Miles

the 1% annual chance flood polygons that were directly adjacent to the Mississippi river – in other words, those that overlapped the area affected by this flood. See Figure 15 for a visualization of these areas. Their total area was 638 hectares. This means that the April 9th and May 4th floods inundated about 38% and 53% of these areas, respectively.

3.4 Accuracy Assessment and Validation

For my accuracy assessment, I used 100 equalized stratified random points for each date and compared them to the RGB imagery from the same Sentinel-2 acquisition. I didn't do more points because I wasn't sure of the validity of this means of accuracy assessment, anyway, since I used the same exact imagery to set the threshold through manual observation. However, I still wanted to know roughly how well my classification performed. I was particularly curious if there was a big difference between dates with more and less vegetation, since that was one of my big concerns going in.

The confusion matrices were similar and the accuracy was fairly high. While probably not very meaningful, as expected, the accuracy was slightly lower for May 4th, 2019, the date with the most inundation and also the most vegetative growth.

June 3rd, 2018:

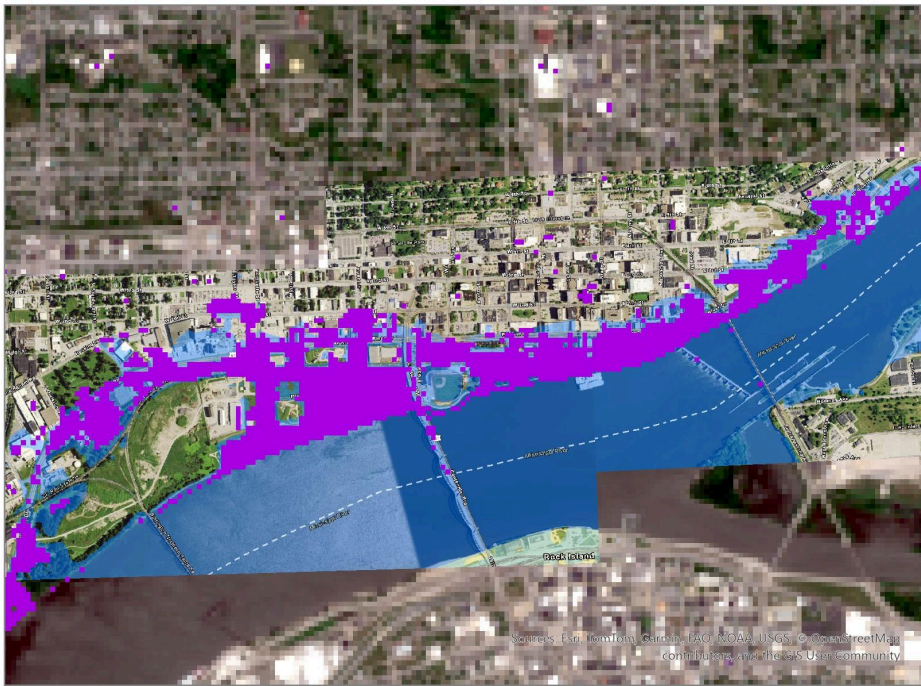
ClassValue	Land	Water	Total	U_Accuracy	Kappa
Land	48	2	50	0.96	0
Water	1	49	50	0.98	0
Total	49	51	100	0	0
P_Accuracy	0.9796	0.961	0	0.97	0
Kappa	0	0	0	0	0.94

April 9th, 2019:

ClassValue	Land	Water	Total	U_Accuracy	Kappa
Land	49	1	50	0.98	0
Water	2	48	50	0.96	0
Total	51	49	100	0	0
P_Accuracy	0.961	0.98	0	0.97	0
Kappa	0	0	0	0	0.94

May 4th, 2019:

ClassValue	Land	Water	Total	U_Accuracy	Kappa
Land	47	3	50	0.94	0
Water	4	46	50	0.92	0
Total	51	49	100	0	0
P_Accuracy	0.922	0.939	0	0.93	0
Kappa	0	0	0	0	0.86



Comparison of May 4th flood to georeferenced images found on weather.gov provided by Scott County GIS
 0 0.25 0.5 1 1.5 2 Miles

As an alternative means of validation, I found two maps produced by Scott County GIS of the April 30th flash flood caused by the breach of temporary flood barriers. I georeferenced these and compared them to my May 4th flood extent map. While the flooding was slightly higher in these maps, overall the extents matched pretty closely.

Figure 16: Validation using georeferenced flood extent maps from local GIS. ([US Department of Commerce, n.d.](#))

4. Discussion

4.1 Contributions and Limitations

These results show that MNDWI thresholds are a valid method for flood extent mapping. Furthermore, they support prior research that suggests remote sensing methods for detecting flood extent can be simplified and automated. In addition to applications for disaster response, experts should consider more regularly incorporating these methods into flood hazard map production for both insurance and public communication purposes. While the methods used in this study were not groundbreaking, they do highlight some considerations that future researchers may use when selecting techniques for specific use cases. In particular, I was impressed with the performance of the SWIR-based index in an urban environment.

One of the biggest limitations of this study was availability of imagery for dates of interest. I initially intended to use SAR data, but it was not available for most of the 2019 flood peaks. I started pre-processing SAR data for other dates, but technical issues and a desire to examine specifically the 2019 events led me to pivot to MNDWI classification. This highlights the

importance of being agile in method selection depending on the conditions. However, because no cloud-free data was available for the late-May/early-June flood event, I did attempt to classify flooding on these dates using SAR imagery in order to evaluate the instructions given on the

page [Step-by-Step: Recommended Practice: Flood Mapping and Damage Assessment Using Sentinel-1 SAR Data in Google Earth Engine \(UN-SPIDER Knowledge Portal, n.d.\)](#). This page

provides a Google Earth Engine script. I used a similar baseline date (June 4th, 2018) and was able to use a Sentinel-1 acquisition from May 30th, 2019, when water levels were close to peak. The script provided an automatic classification. I was not impressed. I think for this use case, MNDWI with Sentinel-2 imagery is much better suited.

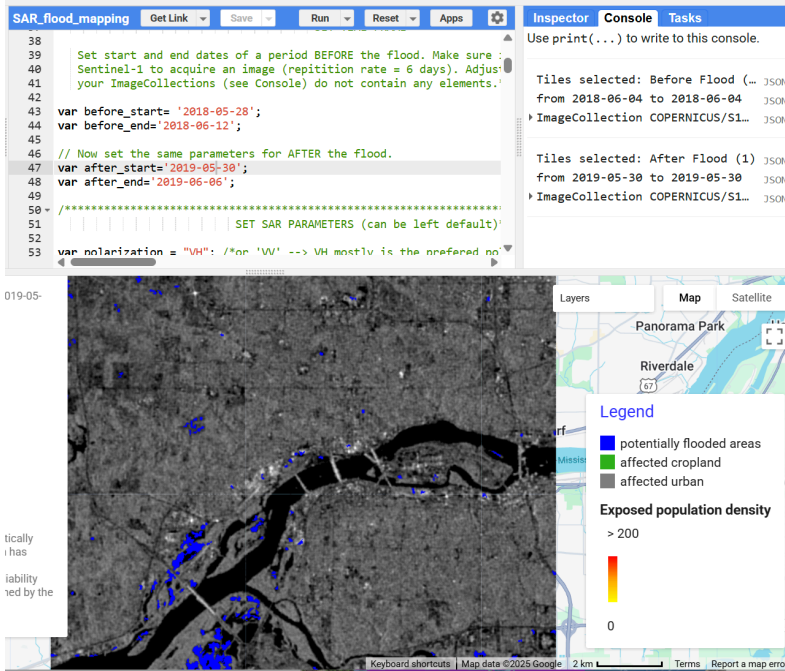


Figure 17: SAR classification using UN-SPIDER methods in Google Earth Engine.

Further research should measure the extent of flooding during flood events of other years, including 1993, 2011, 2023, and 2024. Methods for filtering noise should be explored. The relationship between these results and the methods currently used to produce NFIP maps should be examined and compared to other means of measuring contemporary flood events.

4.2 Implications for Flood Hazard Mapping in Davenport

Although neither of these events exceeded the 1% annual chance flood level, their extended and/or repeated nature (depending on how you want to frame the relationship between river crests) was unprecedented in 2019. However, Springs of 2023 and 2024 both saw similar extended patterns of high water levels, although slightly less extreme. The question then becomes: is this now a “typical” event? Is some other designation needed for this rather large subsection of the 1% chance zone? Are those that build in this zone sharing the same risk with everyone else in the 1% annual chance zone?

Notably, the flood zones adjacent to bodies of water in the study zone other than the Mississippi did not experience any flooding at all. In fact, Duck Creek, the 1% chance flood zone visible bisecting the city east-west just north of downtown, did not seem to even contain visible water in *any* of the three dates indexed. The MNDWI values for this area weren't even close to the threshold to be classified as water. The same was true for Black Hawk Creek, the 1% chance flood zone to the west of the wide portion of the Mississippi. This highlights that FEMA flood hazard maps may be out of date in multiple ways at once and also do not communicate anything about seasonal variation. While they may be suitable for calculating insurance rates to a limited degree, they are also widely used for communicating flood risk to the public, a role which they are much less equipped to fulfill.

Although the results of this study and others like it are not enough by themselves to make recommendations about the methods used to create flood hazard maps, they do point to alarming trends and the need for further investigation. They also suggest that efforts to remedy misconceptions about flooding and underestimation of risk by the general public must go beyond merely clarifying the definition of a "100 year flood." Not only *can* floods of this magnitude happen multiple times a year or multiple years in a row, they should in fact be expected to. A year later, mayors of towns along the Mississippi presented a report to federal lawmakers that detailed over \$20 billion of flood damage in 2019 ([Mott, 2020](#)). The design firm Sasaki Associates was engaged to completely overhaul Davenport's floodplain and flood management infrastructure according to feedback from the public ([Sasaki Associates, Inc., 2020](#)). Lawmakers and the general public must begin preparing now for flood events of increased risk to life and property, and cities must make haste to plan changes to their infrastructure — we unfortunately cannot wait for hazard mapping practices to eventually catch up and give us more precise data.

5. Reflection

I enjoyed reviewing my peers' papers. I drew inspiration from seeing their project ideas and progress, and we comforted each other through our struggles and uncertainties. I think that slightly more specific paper requirements could have helped make the feedback rubric more meaningful and fruitful. I also think requiring an abstract at the beginning of the semester that is allowed to evolve over time could be really worthwhile too. I noticed that students who were doing projects with similar subject matter may have gotten more out of the peer review process, so that could be something to consider when creating groups in the future. One of my favorite parts was seeing how people's methods evolved over time as they ran into technical difficulties that they either could or could not solve.

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