Monitoring High-Risk Areas for Agricultural Impacts on Stream Water Quality

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A case study of the Michiana area

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I. Background

The industrialization of nitrogen (N) and phosphorus (P) fertilizer production has led to irreparable changes in global nutrient cycles and an overabundance of bioavailable N in natural ecosystems (Steffen et al. 2015, Galloway et al. 2003, Vitousek et al. 1997). Fertilizer application rates have increased considerably since the dawn of industrial fertilizer production, especially in the midwestern United States (Fig.1, Cao et al. 2018, Sinha et al. 2017). In agricultural landscapes, excess inorganic N and P move from fields to adjacent waterways via runoff, resulting in degraded water quality in downstream ecosystems (Fig. 2, Alexander et al. 2008, Royer et al. 2006, Gentry et al. 2000, Vitousek et al. 1997). Dissolved N loads in particular are high in areas with significant agricultural land use and are passed to downstream ecosystems at a continental scale (Manning et al. 2020). Excess nitrogen in freshwater systems catalyzes eutrophication events, negatively affecting biodiversity, and threatening drinking water supplies (Royer et al. 2006, Woodward et al. 2012, Vitousek et al. 1997). Thus, improving our understanding of nutrient inputs into stream ecosystems in midwestern agricultural areas is critical for protecting water quality and coastal ecosystem health.

Human impacts on river basins in the midwestern United States, especially due to agricultural land use and subsurface tile drainage (Gentry et al. 2000), are visible. Climate change will exacerbate anthropogenic effects on stream water quality via increases in the severity and frequency of precipitation events (Kelly et al. 2017, Coffey et al. 2019). Precipitation will cause higher nutrient fluxes into stream ecosystems (Fig. 3, Sinha et al. 2017), creating episodic N loads that can result in coastal algal blooms (Coffey et al. 2019). Including metrics of precipitation in stream nutrient load modeling is increasingly important, especially across broad geographic scales (e.g., Mississippi River watershed) (Kalkhoff et al. 2016).

Nutrient processing and transport is highly variable at the reach-scale, so it is very difficult to characterize at the watershed scale. Understanding data in geospatial terms allows for a more nuanced understanding of the different factors affecting nutrient loading in streams across regions, seasons and environmental conditions, making GIS an important tool for analysis.

The U.S. Geological Survey (USGS) has monitoring stations distributed in streams throughout the country that systematically monitor streamflow and water quality. These data have provided a backdrop for many geographic studies of water quality and discharge (discharge refers to the volume of water moving per unit of time). Wang and Yin 1997 used these data to investigate the relationship between land use and water conductivity using GIS and found that conductivity is related to the *cumulative* portion of land used for agriculture in upstream catchment areas as well as surrounding areas. Models of the effects of urban land use on stream water quality are another example of the power of spatial modeling in improving our understanding of factors affecting water quality (Hall and Hossain 2020). These studies highlight anthropogenic influence on stream biogeochemical cycling, especially agricultural nutrient inputs and the dominance of impenetrable surfaces in urban areas. Elliot et al. 2016 illustrate the potential for GIS modeling of stream nutrient loads using a Catchment Land Use and Environmental Sustainability (CLUES) model to evaluate management strategies rapidly at a national scale in New Zealand. Additionally, studies like Davies and Neal 2004 illustrate the potential for modeling nutrient-specific data with GIS, and its potential to inform both scientists and citizens of local water quality. There is great potential for improving our understanding of stream nutrient pollution by utilizing GIS frameworks.

The prevalence of tile drains in agricultural fields across the Midwest makes it difficult to monitor or collect data on all drainage points within watersheds like the Mississippi River basin

(Sugg et al. 2007). GIS-based analysis of land use and soil type has allowed for a better understanding of drainage points, and there is still more potential for increased precision and accuracy of drainage modeling (Valayamkunnath et al. 2020, Sugg et al. 2007). Additionally, nonpoint sources of nutrient pollution have remained elusive due to limitations in monitoring and the diffusive nature of nutrient inputs into streams. Nonpoint sources of nutrient loads in streams include agricultural runoff and animal feeding operations, which represent nutrient loads that are not well-regulated or consistent (Yang and Jin 2010). GIS provides a mechanism for maximizing inferences for the data that are available on hydrology and nutrient loads.

Proposed Project

In this study I aimed to create a pilot model for the identification of points within the Michiana area that are especially susceptible to high nutrient loading. I utilized data on regional crop cover (specifically corn and soybean row crop agriculture), average monthly precipitation and stream order. ArcMap software was used to generate a model that highlighted areas where nutrient loads could be exceptionally high. In constructing the model, I made several assumptions based on scientific literature cited above: 1) proximity to row crop agricultural fields increases potential nutrient inputs, 2) larger streams carry higher dissolved nutrient loads and 3) higher precipitation results in higher rates of nutrient runoff into stream ecosystems.

II. Methods and Results

GIS Methods

Hydrologic and precipitation data can be slow to process over large areas, so I narrowed down the pilot study to a specific, familiar region to increase my ability to cross-check results. South Bend straddles the Mississippi River watershed and the Great Lakes watershed, which makes it an area of importance in a very expansive hydrologic region. Broadening the scope from including only South Bend to including all of Michiana allowed for the incorporation of more suburban and rural agricultural sites in my model. The importance of agriculture in the wider region of the midwestern United States makes this an ideal pilot study area.

There are many variables and metrics that play a role in determining freshwater quality throughout river systems. The EPA uses the Freshwater Quality Index developed by Washington Department of Ecology's Stream Monitoring Program to categorize stream quality. This index is based on temperature, dissolved oxygen, pH, fecal coliform bacteria, total nitrogen, total phosphorus, total suspended sediment, and turbidity data (Hallock 2002). Due to data access restraints and the study area selected for this pilot model, I did not include any of these point-specific metrics, but all are related to hydrology and dissolved nutrient loads and future models would benefit by incorporating more thorough data.

In order to target areas where it might be beneficial to add monitoring equipment or target specific management methods to reduce stream nutrient pollution, I developed a model that highlights reaches in the Michiana region that are especially close to cash crop agricultural fields, are high-order (i.e., several tributaries will flush dissolved nutrients into the reach), and receive high precipitation inputs. Together, these layers were combined to produce a model of relative risk for nutrient pollution. All mapping was conducted with ArcMap 10.8.2 software and maps were prepared for export using the "Layout View" feature.

Establishing the study area: I used a layer detailing the watersheds in the Michiana region as a backdrop for my model, then added in a layer mapping out the hydrology of the region (i.e., stream systems) (Fig. 4). I used a DEM of hydrology in the Michiana region (intersection of St. Joseph County, Indiana and Berrien County, Michigan) for the first layer.

First, I filled in Sinks in the hydrologic raster layer using the Spatial Analyst Fill tool to avoid inaccuracies in flow accumulation derivation. I then created flow direction and flow accumulation rasters from the sinkless DEM using Flow Direction and Flow Accumulation tools in the Spatial Analyst Hydrology toolbox. I then created a vector layer to model drainage with polylines by reclassifying the vector layer to include data on drainage from at least 50 pixels. I saved this raster layer for use in building a stream order layer. Additionally, I placed the study site in context by mapping its location relative to the regions of Michigan and Indiana (Fig. 4).

Proximity to cash crop agricultural fields: I used crop cover data from the USDA's Cropland Data Layer (CDL) on Cropscape (Boryan et al. 2011). I chose to use crop data from 2021 given that data were easily accessible for each layer during this time window. Having added the raster layer with data for every crop to my map, I then delineated regions with corn and soybean row crop agriculture specifically (Fig. 5). There were over 100 crop types included in the dataset, so I reclassified the data into corn/soybeans versus all other crops. I assigned a value of 1 to cash crop sites and 0 to all other crop sites to target row-crop agriculture where fertilizer inputs and runoff levels are especially high. I saved the reclassified raster as a new layer, then used this layer to calculate the euclidean distance from row crop agricultural areas in Michiana. I classified distance from corn and soybean fields into 10 classes (although Figure 6 shows a continuous scale to aid visualization) with farther distances classified as lower numerical values to simulate decreasing nutrient loads with increasing distance from fertilizer runoff zones (Fig. 6). I saved this reclassified euclidean distance layer as a new layer for use in model calculations.

Stream order: I used the drainage raster layer for this layer, and calculated stream order for streams in Michiana region using the Stream Order tool in the Hydrology Spatial Analyst

Toolbox (Fig. 7). Streams of order 1 through 6 were present in the study area. I did not reclassify the values associated with each stream order, given that one of the model assumptions in this study is that stream nutrient loads scale positively with stream order (not per unit flow, but in terms of the magnitude of nutrient load which is sufficient information in this model).

Precipitation: I accessed precipitation data from NOAA and Oregon State University's PRISM Climate Group via the ESRI platform for building this layer. I used average monthly precipitation data from 2020-2021 for the study area (Fig. 8). The Michiana region was split between two precipitation regions (3-4 and 4-5 inches of precipitation per month, respectively). I created a polygon feature using the Draw Polygon and Autocomplete Polygon tools to delineate these two precipitation regions and assigned a value of 3 and 5 to the two zones. Given the assumption that higher precipitation washes more nutrients into stream ecosystems (here, too, looking at nutrient load mass rather than concentration in water), the reclassified values of 3 and 5 were appropriate inputs for the model. I saved this reclassified raster layer for use in model calculations.

Creating the model: I used the Raster Calculator tool in the Map Algebra Spatial Analyst toolbox to create my model. I used the function:

*(2*distance to cropland)*(seasonal precipitation)*(stream order)* Equation 1

to derive relative estimates of the risk for nutrient pollution in each stream reach in the Michiana region. I weighted distance to cropland to have the highest impact of the three model inputs, given that it affects both the degree of nutrient loading in precipitation runoff and the loads in streams of all sizes. The model output yielded a continuous scale of streams at risk for nutrient loading (Fig. 9). The histogram in Figure 9 represents the distribution of different relative risk scores in the model output. High risk areas are fewer in number than low risk areas, which indicates that the model successfully outlined *specific* areas for directed management or monitoring strategies to be applied.

Interpretation of Results

The output of the model was satisfactory in its indication of especially high-risk areas for high nutrient inputs into stream reaches. The model is limited in scope (both in terms of studied region and level of precision excluding very small streams) but represents an effective pilot. Areas at high risk of nutrient pollution based on proximity to cropland, precipitation and flow number less than 200, indicating the model has potential to inform land management or placement of water quality monitoring sites (Fig. 9).

The crop data layer could be expanded to include more than just soybeans and corn, especially in regions where other crops are more prominent (Fig. 5). The calculation of euclidean distance from row crop agricultural fields was adequate, but with the caveat that those areas with lowest scores (i.e., furthest away from row crop land use) were generally associated with urban centers (Fig. 6). The effect of urban impervious surfaces on runoff adds complexity to the issue, given that waste output from cities is often high in dissolved nutrient loads as well (Hall and Hossain 2020). Future models would benefit from incorporating a metric for urban areas, especially surrounding waste treatment facilities or registered point sources of pollution, to indicate potential nutrient inputs from metropolitan systems.

Finally, the average monthly precipitation data were limited both temporally and in terms of specific precipitation types (Fig. 8). Seasonal precipitation measurements could improve this model, and allow for forecasting of nutrient loading throughout the year. Some areas might especially benefit from monitoring during heavier rain seasons, while others might be more affected by snowmelt (Kalkhoff et al. 2016). This brings up the issue of precipitation type:

snowmelt represents an important input of high-nutrient runoff into stream ecosystems and is difficult to account for across large areas with differential melting rates and various levels of fallow season cover cropping (Schneider et al. 2019). Breaking down precipitation into different types could help with inferences of when snowmelt will end up reaching streams. As a pilot model, this study was effective. Many improvements could be made to the design of future studies, and several metrics could be added to increase the precision and accuracy of similar studies at larger scales.

III. Conclusions

This study represents a successful pilot model of targeting stream areas with high risk of nutrient pollution in the Michiana region. GIS provides the potential for spatial analysis and modeling that would not be possible with field-based data collection and analysis alone, and this study is a small example of the potential for geospatial modeling of nutrient loading in stream ecosystems.

Given limitations in geographic scope, precision and analytical capacity, there is great potential for future studies based off of the model proposed here. Data on tile drain distribution have been collected and geographically analyzed (Fig. 10, Valayamkunnath et al. 2020). Similarly, in the state of Indiana data on cover crop acreage during the fallow season is accessible to the county level (older data down to the catchment level) and studies have modeled cover crop impact on reducing nutrient inputs into stream ecosystems (Yeo et al. 2014). Cover cropping impacts are often dependent on soil characteristics and temperature, so adding these metrics to my spatial model would also improve its predictive power (Yeo et al. 2014). Utilizing tile drain and cover crop data as additional layers and model inputs in future studies would add to the predictive power of this model, as tile drains shunt nutrient-rich water into stream ecosystems and cover crops reduce nutrient losses from agricultural fields.

Spatial modeling in GIS further highlights the analytical power of using geospatial data in stream water quality analyses. For example, a case study in Iowa featured spatial modeling of nutrient loads with spatial correlation of uptake coefficients in watersheds (Yang and Jin 2010). Expanding such a model to a broader region and incorporating land use and precipitation contexts into characterization of stream ecosystems has the potential to greatly advance our understanding of the dynamics of nutrient uptake in the present, and under future climate scenarios. There are countless options for application of water quality monitoring and trending tools using geographic data.

While this study was only a pilot study, the model represents a starting point for region-wide monitoring of trends in water quality by proposing a baseline for where monitoring should occur and what regions are at particularly high risk of intense nutrient loading in stream ecosystems. The model highlights the potential of GIS-based analysis for identifying points and ecosystems of interest in a region with high variability between and within stream reaches. With additional metrics and future analyses, it could be scaled into a project that informs watershed management and water quality monitoring in the Michiana region and beyond, both under current conditions and models of future conditions.

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V. Figures

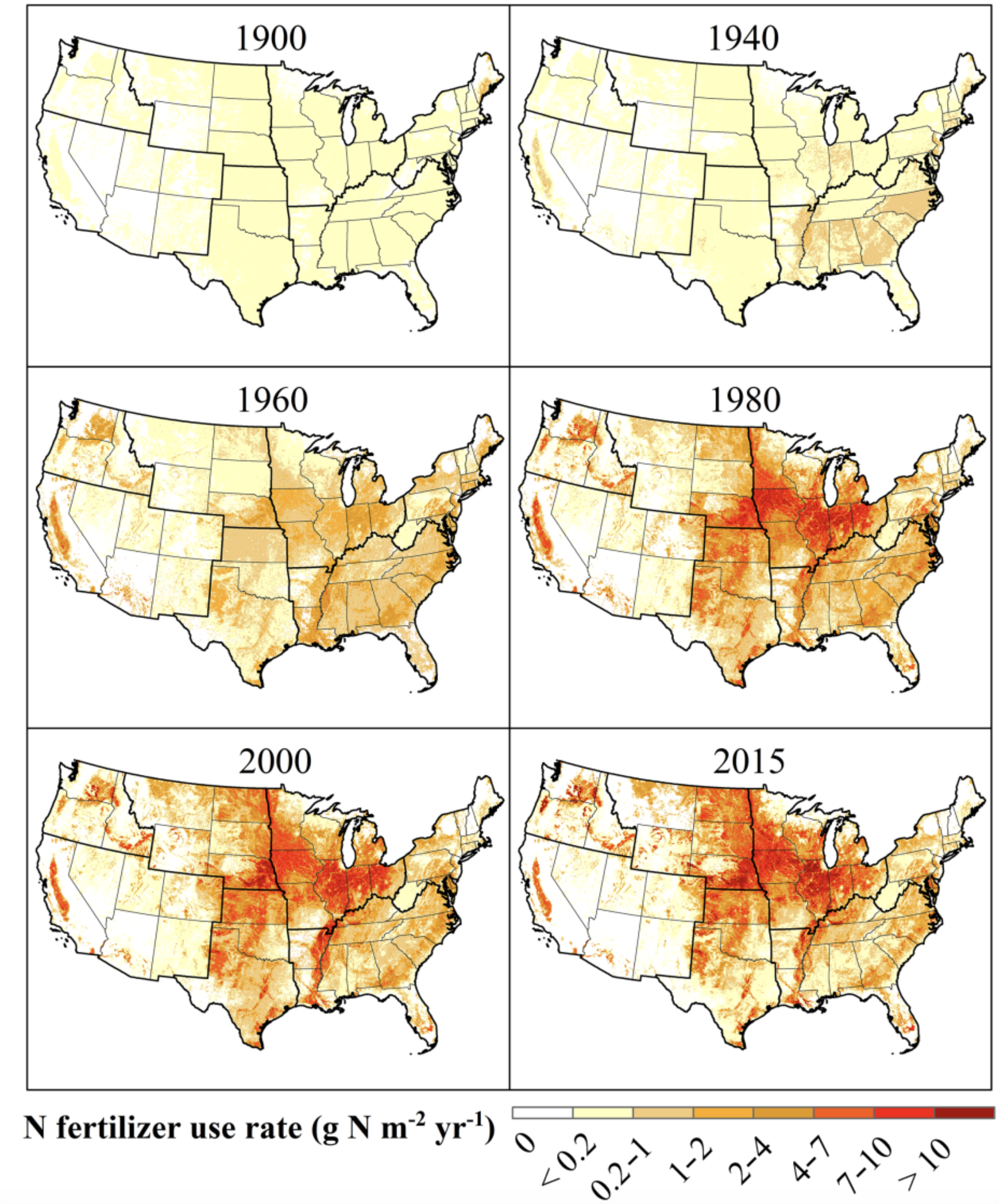

Figure 1. Maps from Cao et al. 2018 detailing the historical increase in fertilizer application rates across the continental United States.

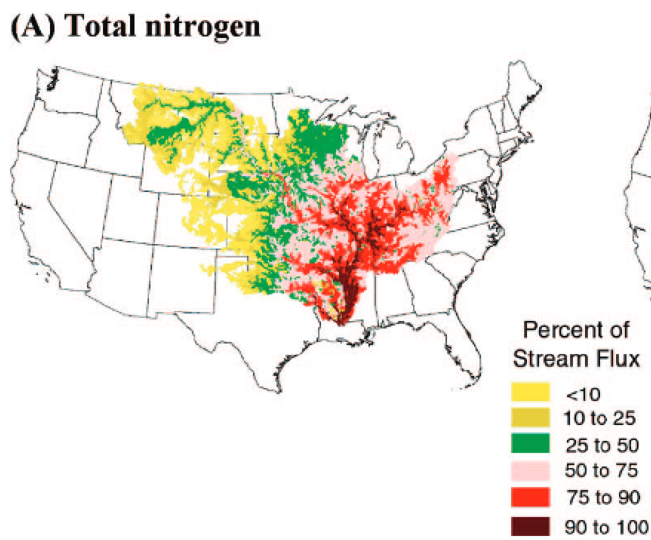

Figure 2. Percent of stream nutrient load delivered to the Gulf of Mexico (Alexander et al. 2008). Maps indicate that as loads increase down the watershed, stream biofilms are not able to remove as much of the N load.

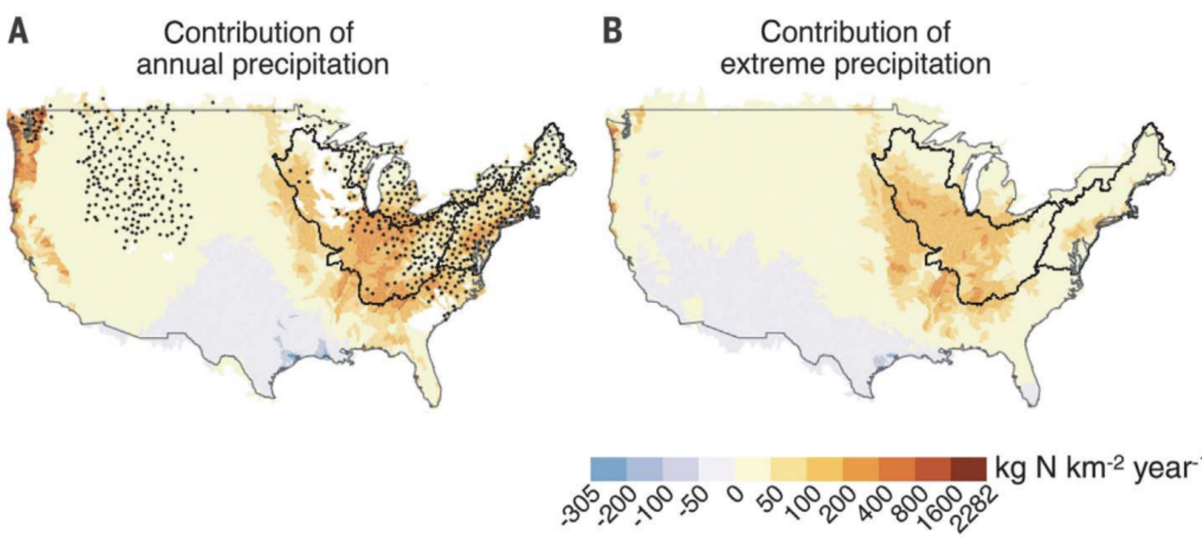

Figure 3. Maps delineating the contribution of precipitation to change in mean total nitrogen flux from Sinha et al. 2017. From the paper: "Stippling indicates watersheds with a robust change in total nitrogen flux (i.e., more than 50% of the models show a significant change and more than 80% of the models agree on the sign of change)... The black outlines highlight the upper Mississippi Atchafalaya River Basin and the Northeast region."

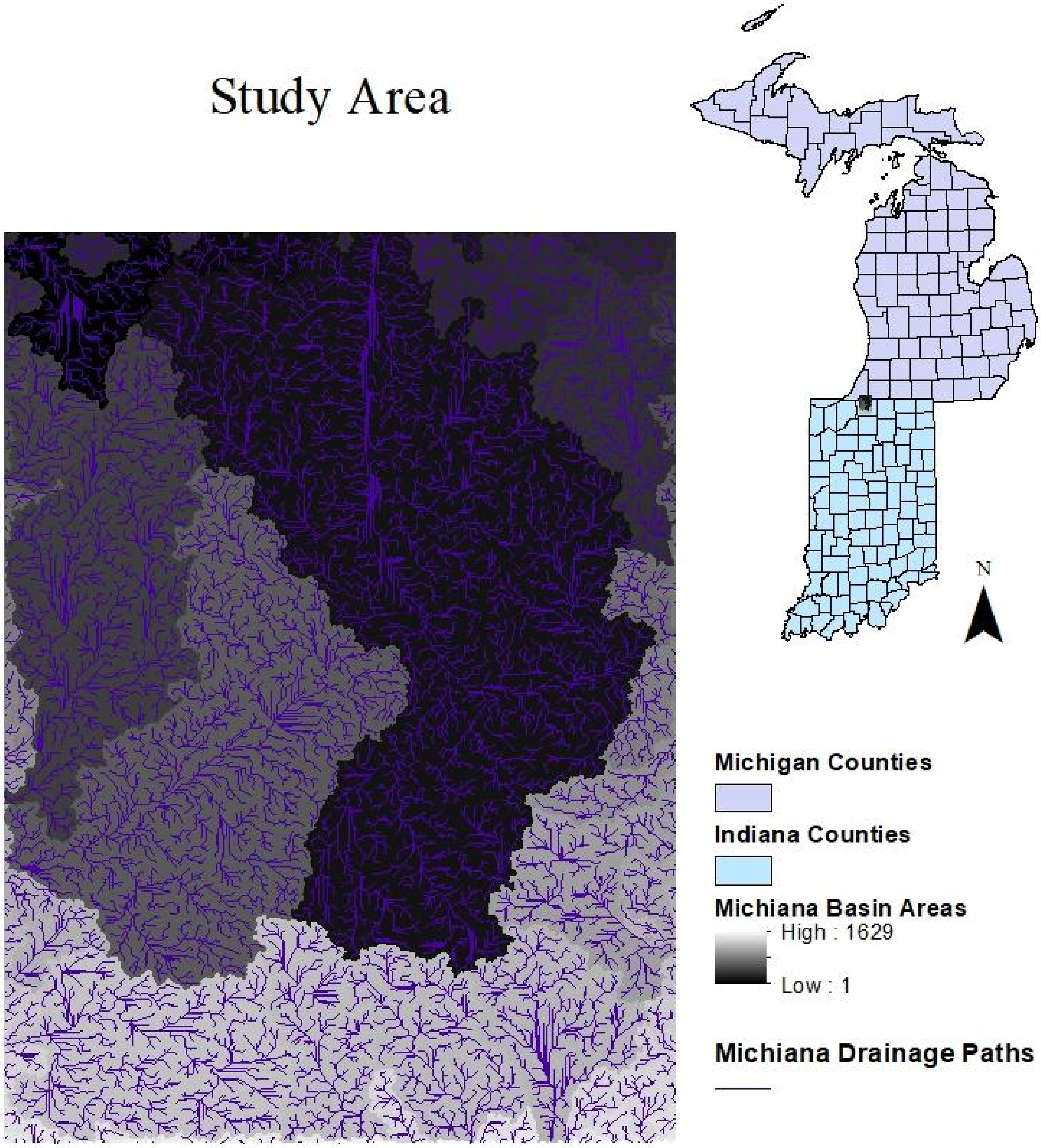

Figure 4. Map of the study area for this pilot analysis of streams at risk of high nutrient loading in the Michiana region. The water basins included in the region are colored in grayscale, with GIS-derived drainage paths outlined in purple. The larger geographic context of the region is displayed on the right, with Michigan counties colored purple and Indiana counties colored blue.

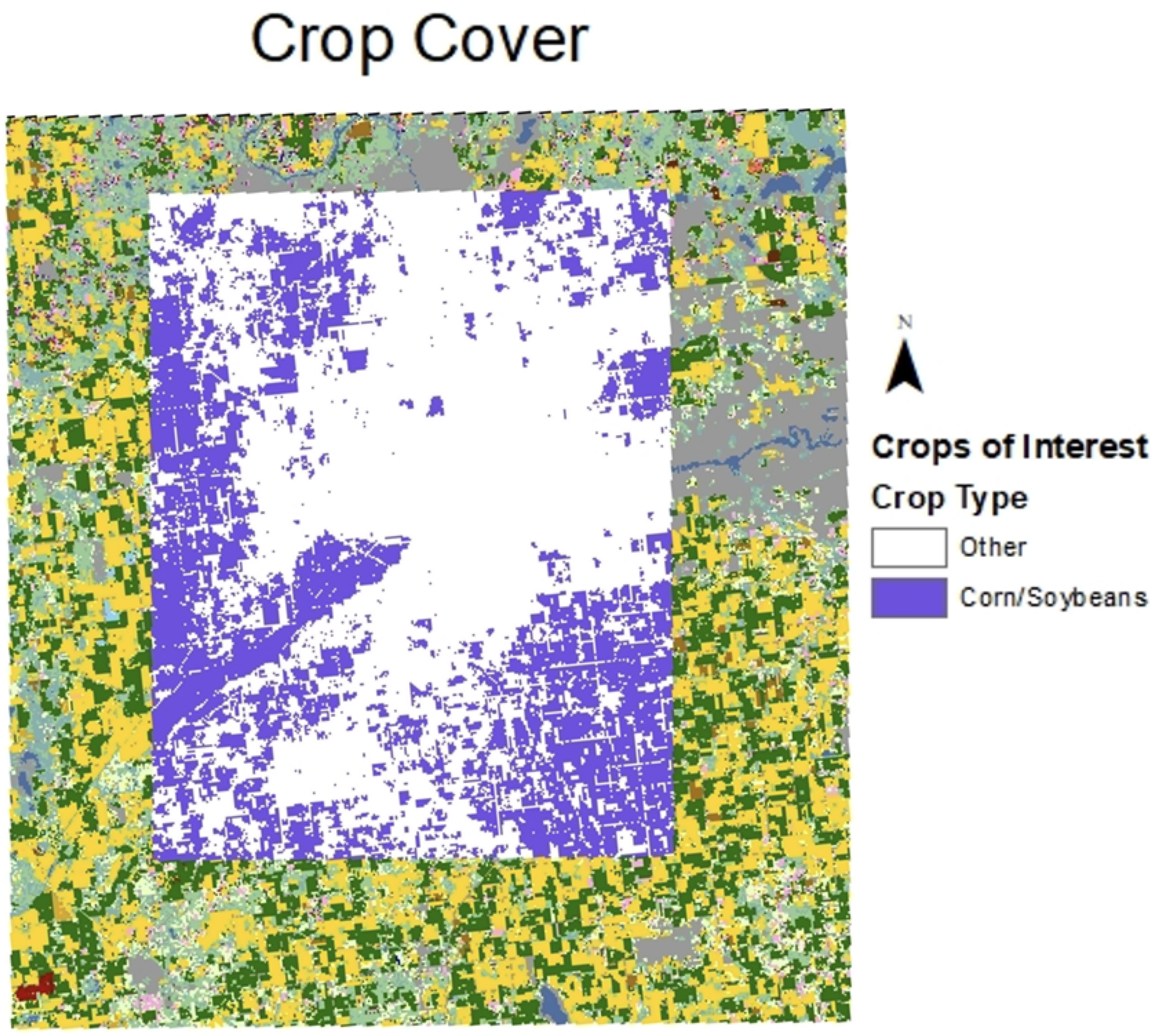

Figure 5. Map of the crop cover in the study region. Area outside of the study area was included as a reference for what the original CropScape dataset included. Each color represents a different crop. The study area includes only reclassified measurements of areas with corn and soybean crops versus areas without. *Source: USDA National Agricultural Statistics Service Cropland Data Layer. 2022. Published crop-specific data layer [Online]. Available at http://nassgeodata.gmu.edu/CropScape/ (accessed 03.23). USDA-NASS, Washington, DC.*

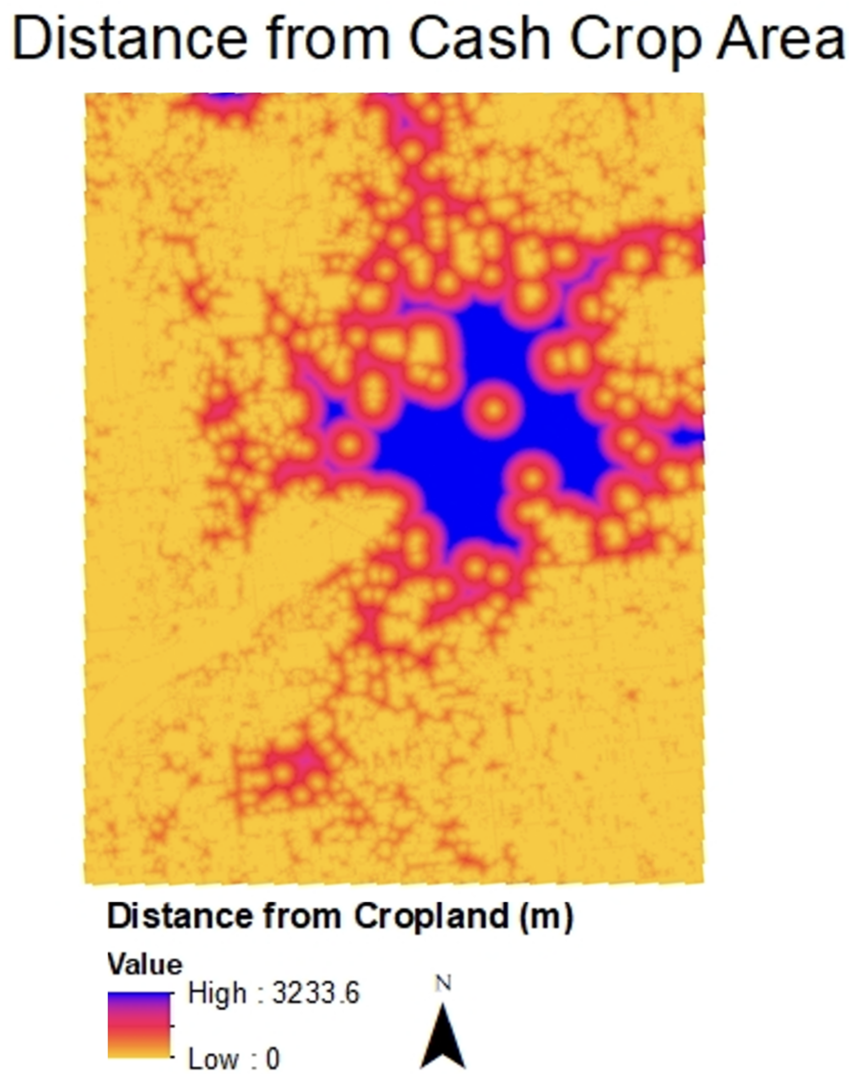

Figure 6. Map of the euclidean distance from cash crop agricultural runoff zones. Areas further from these agricultural areas are considered "high" distance. This scale was inverted and reclassified for incorporation into the model.

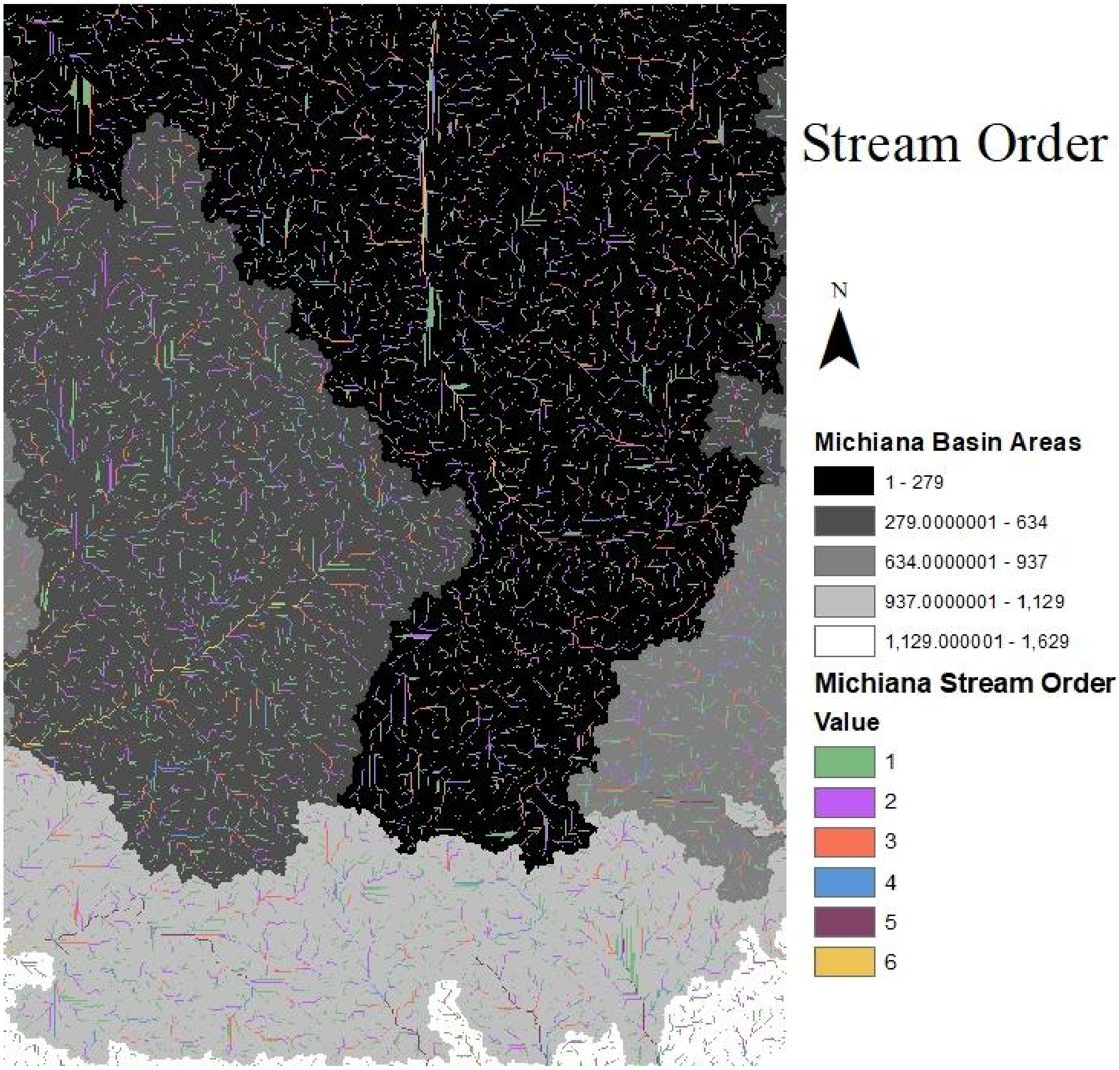

Figure 7. Map of derived stream order values in the study region. Each value of stream order (1-6) is associated with a unique color. Basins included in the study area indicated in grayscale.

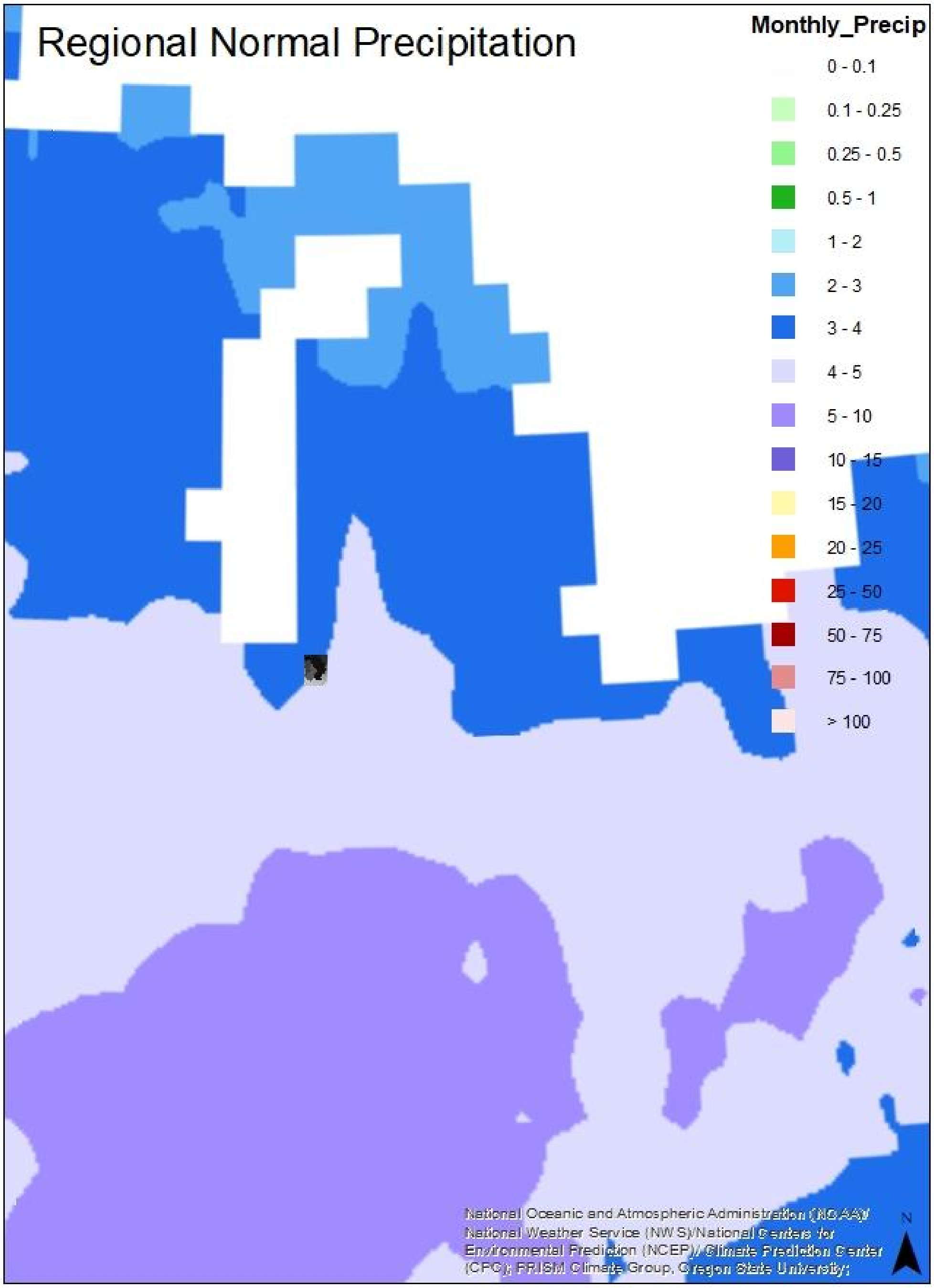

Figure 8. Map of precipitation data for the region. The study area is indicated by the greyscale box with watersheds delineated. It is apparent from this map how the region was split between two zones of average precipitation (colors light purple and blue indicate average monthly precipitation in inches).

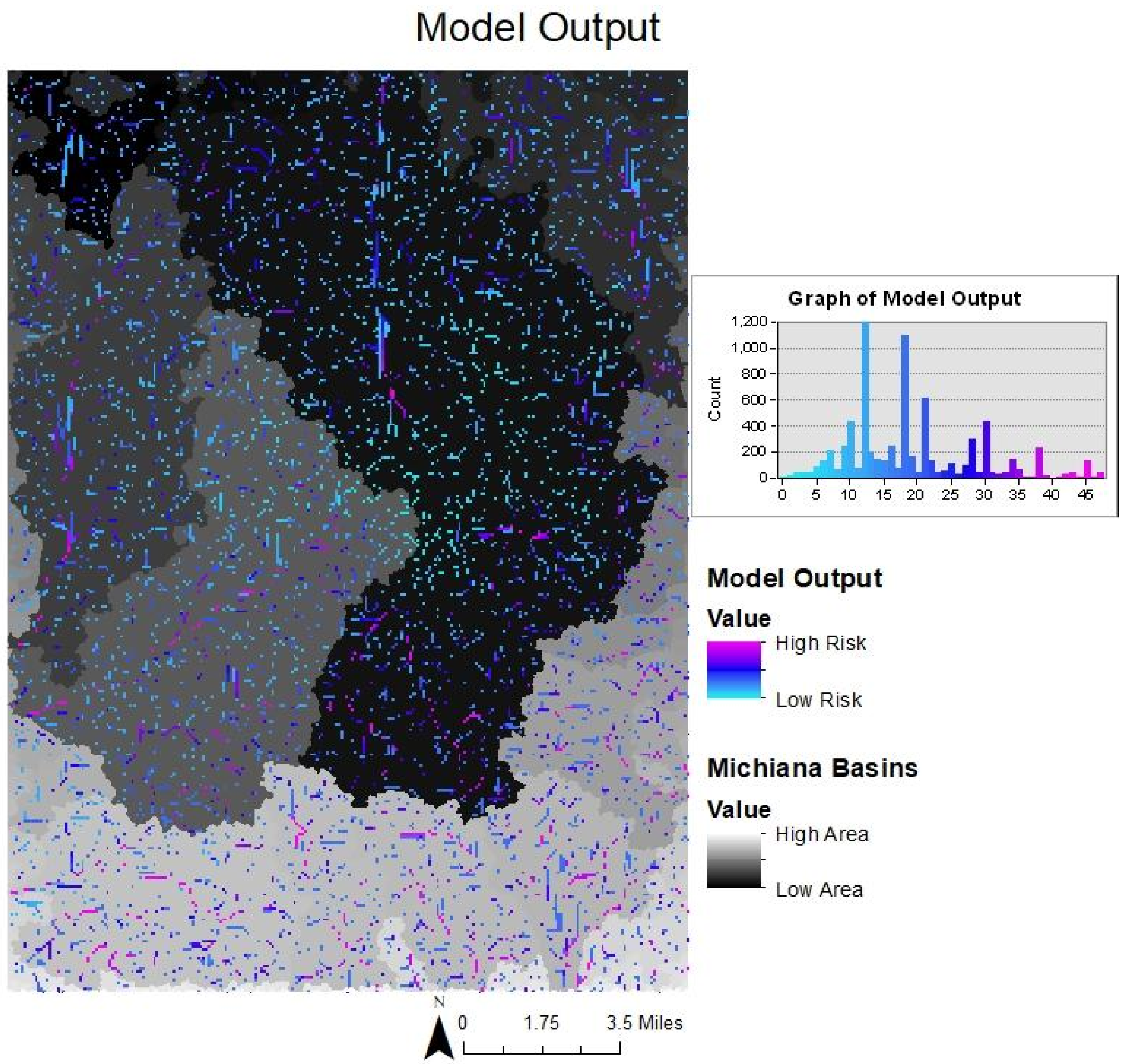

Figure 9. Map displaying model output, with relative risk scores categorized on a continuous scale from low risk to high risk alongside a graph of the frequency of each of 6 subset intervals of relative risk score from the model. Higher risk seems to be concentrated on the left hand side of the graph, which is largely explained by the predominant land use in the area being attributed to cash crop agriculture.

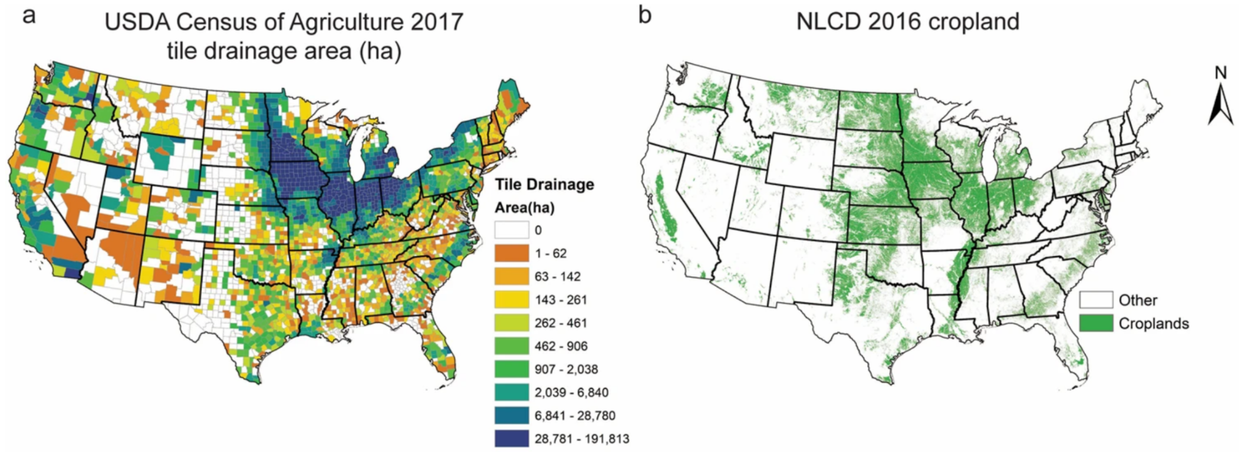

Figure 10. Geographic data on tile drain coverage from Valayamkunnath et al. 2020. These data could be incorporated as another layer in the model if the study area were increased to encompass a broader region, as tile drains shunt nutrient-rich runoff into streams and are especially common in Indiana.