Cows in a feedlot near Arlington, Minnesota. Photo by Tony Webster.

Flowing from Feedlot to Faucet:

A Geospatial Analysis of Nitrate Pollution in Four Southeast Minnesota Counties

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Advanced Geospatial Analysis

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0. Abstract

Nitrate pollution is a complex issue that requires an interdisciplinary approach to investigate. It threatens water quality, affects ecosystems, and poses health concerns to communities through drinking water. To answer the question of what risk nitrate pollution poses to Southeastern Minnesota and Twin Cities Metropolitan Area communities, we attempted to model the associations of human and environmental variables with nitrate pollution levels in wells in four Southeastern Minnesota counties.

We approximated nitrate pollution using the results of hundreds of well tests from 2022 to 2024 obtained through the Minnesota Department of Health. These were spread across four counties: Dakota, Goodhue, Wabasha, and Winona. We processed these tests and then tested for spatial autocorrelation, finding highly significant results at both global and local levels. We also utilized advanced watershed modeling techniques to better understand pollution flow through local environments. Finally, we worked to incorporate the test results into a broader model using spatial linear regression. Environmental variables for this model were based on geology and soil types within the region, as well as hydrologic variables like the depth to the water table. Ultimately, we found that soil type (and spatial lags of soil type) can be a statistically significant predictor of a good amount of the variance in nitrate concentrations. A more robust model incorporating elements such as feedlot presence, demographics, and other variables could be more successful.

1. Problem Statement

Nitrate is a chemical compound that forms when nitrogen mixes with oxygen in water. Drinking water with high levels of nitrates can cause "blue baby syndrome" — which causes potentially fatal effects on the body's ability to carry oxygen — and is linked to thyroid and other cancers (McVan, 2023). While the federal safe drinking water limit is 10 milligrams of nitrate per liter (mg/L), meta-analyses of health studies have found adverse effects may begin when drinking water contaminated with 5 mg/L of nitrate or even less (Conrad, 2023). Nitrogen is found in many fertilizers and manures that are liberally applied to Minnesota croplands, where the nitrogen can become nitrate (or nitrite, which also causes health problems) and leach into rivers and groundwater (Marohn, 2023; Masters, 2023). Nitrate contamination in wells, aquifers, and groundwater systems in Minnesota has been occurring for decades, but increasing nitrate levels have prompted new calls in the past year — including from the EPA — to regulate fertilizer application and punish violators more harshly (LaDuke, 2024). Nitrate pollution in Minnesota comes not just from crop field runoff but also from concentrated animal feeding operations (CAFOs or feedlots), which store manure and wastewater in on-site "lagoons" that can leach or overflow during floods (Stanley, 2024).

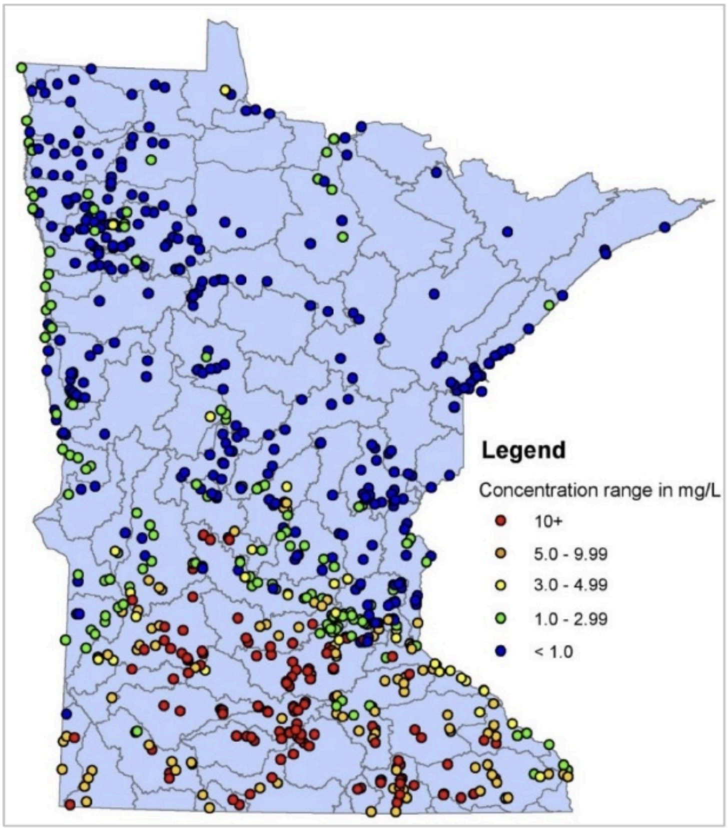
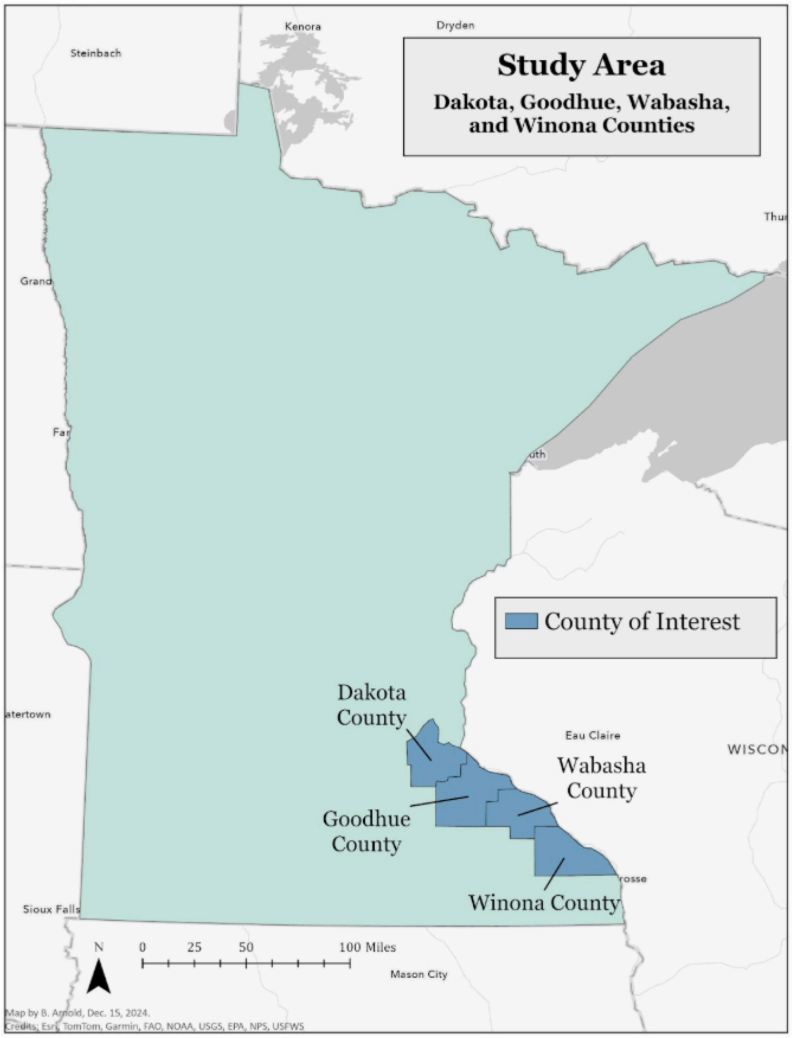


Figure 1. An example of the broad statewide patterns of nitrate contamination, taken from a report analyzing 700+ river and stream sampling sites from 2000 to 2010 by the Minnesota Pollution Control Agency (2013).

Nitrate contamination also heavily depends on local geology, which determines how water and water-borne contaminants cycle through the environment. Two soil variables strongly influence the chance of water contamination: Hydrologic Soil Group and Depth to Water Table. The Hydrologic Soil Group is based on how quickly the soil soaks up water when it is not protected by vegetation or is already saturated. The slower the infiltration is, the higher the runoff potential. Runoff gathers pollutants, including chemicals and polluted sediment. It either reaches surface water (lakes, rivers) or infiltrates into groundwater when it reaches soil with a quicker infiltration rate (Environmental Protection Agency). Runoff can carry excess fertilizer and pesticides with nitrate and sediment treated with nitrate-based chemicals. Depth to the Water Table provides a measurable distance from the surface to the location of the water table, an entirely saturated zone separating surface soil from groundwater. Generally, "shallow groundwater" is defined as groundwater where its water table is less than three feet from the surface (Shallow Groundwater). Most of Minnesota falls within this category. The main concern with shallow groundwater is Infiltration Best Management Practices and "lagoons" in industrial and farming areas. Minnesota laws require a three-foot separation from the bottom of the BMP to the highest seasonal water table (Shallow Groundwater). Some pollutants can be removed within this gap, but with less separation, there is a high probability that the pollutant will infiltrate the groundwater.

This project aims to perform a risk analysis of nitrate pollution in Southeastern Minnesota by focusing on four counties in particular: Dakota, Goodhue, Wabasha, and Winona (Figure 2). The following report will use spatial autocorrelation analyses, advanced watershed modeling techniques, and spatial regression modeling to examine the relationships between nitrate pollution, soil data, hydrologic data, and other human and environmental variables.



Map by B. Arnold, Dec. 15, 2024.
Credits: Esri, TomTom, Garmin, FAO, NOAA, USGS, EPA, NPS, USFWS

Figure 2. This report's study area.

1.1 Project Requirements

Table 1. Itemized list of project requirements.

Requirement	Defined As	(Spatial) Data	Attribute Data	Dataset	Preparation
Define project extent	Create a polygon that represents the spatial extent of the project.	Project Extent (polygon)			
Data acquisition	Acquire appropriate watershed, DEM, basic and analyzed soil, groundwater, and Nitrate Risk data.	LiDAR, Shapefiles	Nitrate levels, Soil Survey attributes	USGS DEMs, Groundwater Atlas, USDA Soil Survey, What's in my Neighborhood	Explore data and determine specific attributes that are most relevant.
Process Data	Prepare datasets for subsequent analysis and enable interoperability between datasets from different counties	Shapefiles, CSVs	Nitrate Levels, Soil Survey Attributes	Nitrate Tests, Tests with Well Locations, USDA Soil Survey	Narrowing observations to relevant tests and manually de-jittering well locations.
Autocorrelation Analysis	Perform local and global autocorrelation to find possible clustering.	Shapefiles, CSVs			
Global Multivariable Spatial Regression	Determine possible spatial correlation between demographic variables and nitrate pollution.	Numbers	Test Statistics	Previous Autocorrelation Data and Processed Nitrate Data.	Completed previous steps.
Basic Watershed Modelling	Use ArcGIS Pro Geoprocessing tools to model Minnesota Watersheds	DEMs	Elevation	USGS DEMs	
Advanced Watershed Modelling	Implement other variables (soil composition, pollution vulnerability, feedlot location) into the watershed model. The goal is to determine a pollution sensitivity or risk factor.	DEMs, Shapefiles	Elevation, Soil Survey Attributes, Depth to Water Table, etc.	USGS DEMs, Soil Survey,	
Zonal Statistics	Calculating statistics for nitrate pollution across all watersheds.	Numbers	Statistics	Watershed Modelling Data, Demographic Data, Feedlot Data	

2. Input Data

Table 2. Input Data as of Dec. 17, 2024

	Title	Purpose in Analysis	Spatial Datatype	CRS	Link to Source
	Nitrate-Nitrogen Tests for Minnesota Wells, 1999-2024	Jittered (spatially-scrambled) data on the results of well nitrate concentration tests from 1999-2024. Used to demonstrate nitrate pollution at well sites and estimate broader pollution levels.	Shapefile	NAD 83 UTM Zone 15	Minnesota Dept. of Health, via personal comm. with Mary Coburn
	Max Nitrate with County Well Index (CWI)	Shapefile of well locations in Minnesota that was used to unify and un-jitter the jittered well tests from the Minnesota Department of Health.	Shapefile	NAD 83 UTM Zone 15	MnGEO, with processing assistance from Mary Coburn, MDH
	Minnesota County Boundaries	Used in Select by Location to extract only observations of feature classes within the area of interest.	Shapefile	NAD 83 UTM Zone 15	MnGEO
	Minnesota City and Township Boundaries	Used for Select by Location and for Summarize Within to get city/township-level statistics.	Shapefile	NAD 83 UTM Zone 15	MnGEO
	US Department of Agriculture Gridded Soil Survey Geographic (gSSURGO) Database	Includes the soil features that determine groundwater pollution sensitivity for entire counties (not just specifically tested aquifers).	Shapefiles and CSV files are both provided.	NAD 83 UTM Zone 15	US Dept of Agriculture – Database from Soil Scientist
	Nitrate Risk to the Water Table Aquifer	Includes ranked risk maps of nitrate-nitrogen pollution across Minnesota.	Shapefiles and/or ESRI File GDB	NAD 83 UTM Zone 15	MnGEO
	USGS DEM	Includes a raster of a digital elevation model (DEM)	Raster	WGS 1984	USGS DEM

3. Methods

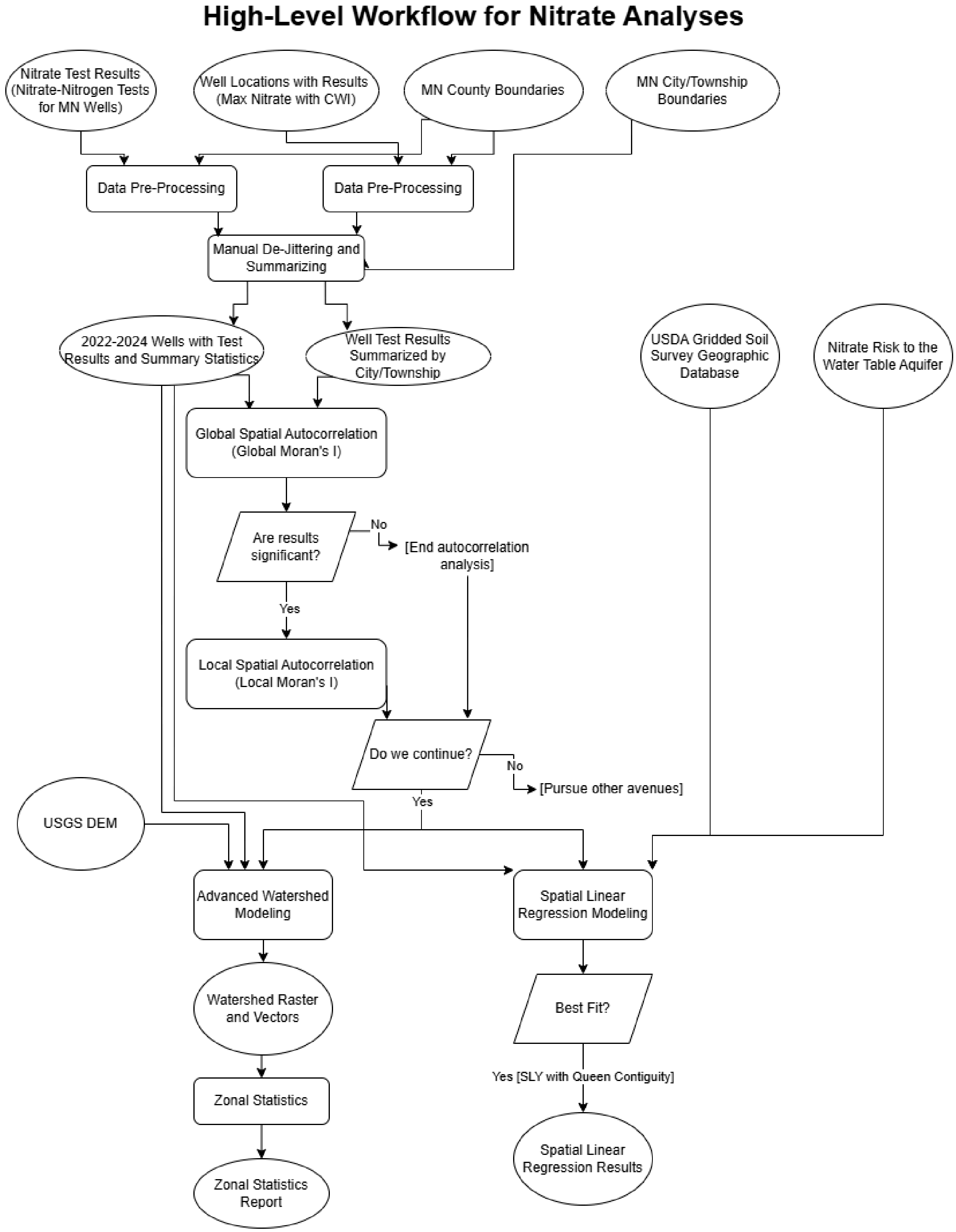


Figure 3. High-level workflow for this report's analyses.

3.1 Data Pre-Processing

3.1.1 Nitrate and Well Data Pre-Processing

Data pre-processing for the nitrate and well data required significant manual data entry and manipulation but utilized more automated geoprocessing tools. The combined pre-processing workflow is shown in Figure 4. First, Dataset 3 is imported, and Select by Attributes and Export Data are run to isolate the four counties in the area of interest (Dakota, Goodhue, Wabasha, and Winona). Next, Dataset 1 (the full nitrate test dataset) is run through a series of tools that decrease and limit the number of observations to those that only meet certain criteria: Select by Location to the tests in the four counties; Select Rows and Delete Rows to remove observations with erroneous or NoData test results; and Select by Attributes to produce a dataset with only the tests between 2022 and 2024 (the past three years, chosen for recency and data quality), which list 'NITRATE + NITRITE NITROGEN, TOTAL' (for methodology consistency), and which measured in the standard units of mg/L. Then, these test results -- whose locations were, according to MDH staff, displaced or 'jittered' by up to 500 meters from the wells' real locations -- were compared with the known well locations in Dataset 2. All but 1 set of tests could be linked to specific well locations. A new feature class was created with the 'de-jittered' locations of wells with tests, including manual data entry of the following attributes: total tests, maximum test result, mean test result, number of tests above 3 mg/L, 5 mg/L, and 10 mg/L. Finally, percentage statistics were derived by normalizing the threshold (above X mg/L) fields by the total number of tests using the Field Calculator (Add Fields). The final result was a feature class of all wells tested for nitrate using the standard methodology between 2022 and 2024, with each observation including summary statistics about those tests.

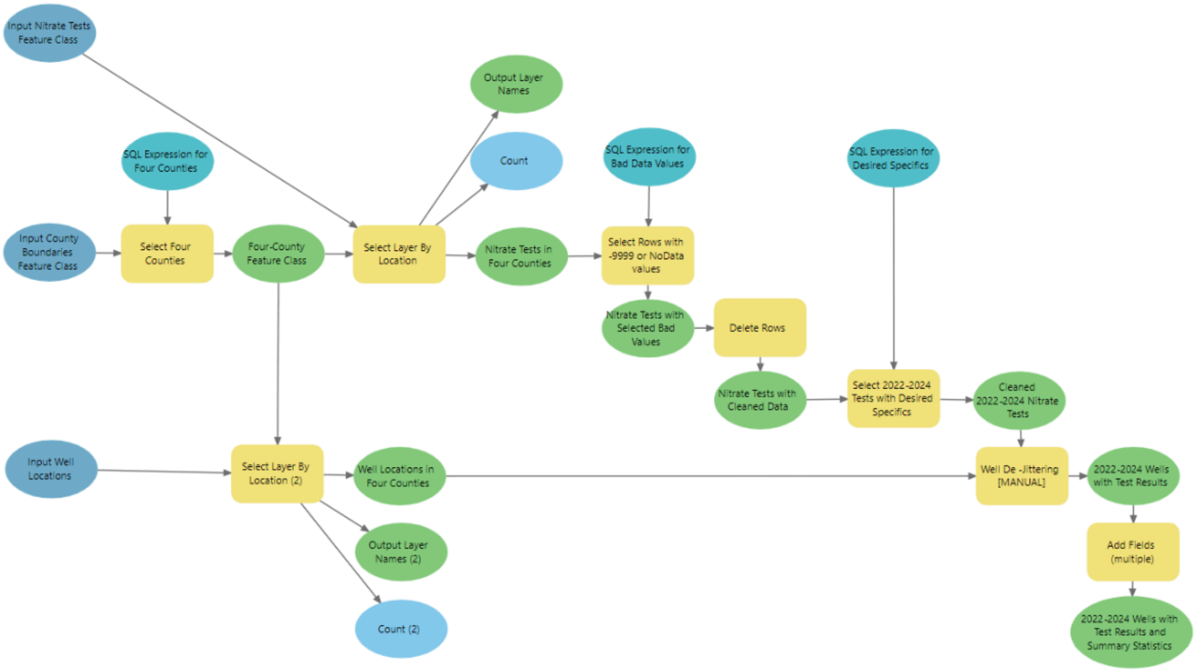


Figure 4. Workflow for data pre-processing of nitrate and well data.

3.1.2 Soil Data Pre-Processing

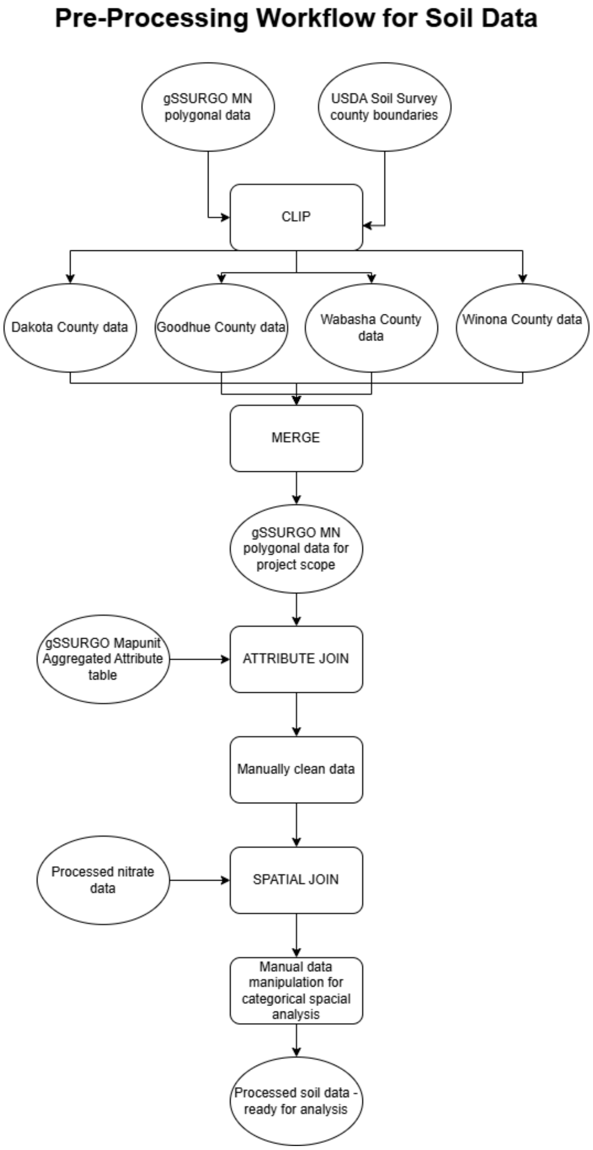


Figure 5. Workflow for data pre-processing of soil data.

Data from gSSURGO was downloaded as polygonal data provisioned by the state with associated CSV tables for specific data categories collected by the U.S. National Cooperative Soil Survey staff and local state agencies. To preprocess the large data formats, the polygonal data (MUPOLYGON) was clipped to the boundaries of the counties, as provided by the USDA Soil Survey, as data for each county is managed slightly differently. The county-clipped layers were merged for easy data analysis and then joined with the Mapunit Aggregated Attribute table (MUAGGATT). Furthermore, this data was cleaned only to include the information that would be analyzed, including Water Table Depth - Annual – Minimum (wtdepannmin) and Hydrologic Group - Dominant Conditions (hydgrpdcd). The new, project-specific feature layer was spatially joined with the processed nitrate data. This spatial join was conducted with the polygon features as the target features and the point data of the nitrate well tests as the join features, with the join operation as join one to many, as some soil units contained multiple wells. It was completed with the "contain" match option. This created copies of features with the same soil attributes but with data specific to each contained well. To complete the exploratory analysis, the Hydrologic Group - Dominant Conditions variable, initially defined by categorical text, was broken into columns with binary values. Each feature had an attribute for each category of the hydrologic group, with 1 indicating that the unit matched the group and 0 indicating it did not. For example, a unit that was defined as "A," would have a 1 under the "A" column and 0 for all other categorical hydrologic columns. This process is shown in Figure 5.

3.2 Exploratory and Descriptive Analysis

3.2.1 Wells and Nitrate Tests Exploratory Analysis

Exploratory nitrate/well data analysis was conducted mainly by measuring potential spatial associations. Each well's mean test result was used in a Global Moran's I, and when the Global Moran's I was found to be significant ($p < 0.05$), an Anselin Local Moran's I (a Local Indicator of Spatial Association test, or LISA) was run on the dataset as well. Test results were also summarized at the city/township level using Dataset 4. Using a normalized field representing the percentage of well tests in the city/township at or above 5 mg/L, another Global Moran's I and Local Moran's I were run. The workflow for this process is shown in Figure 6 below.

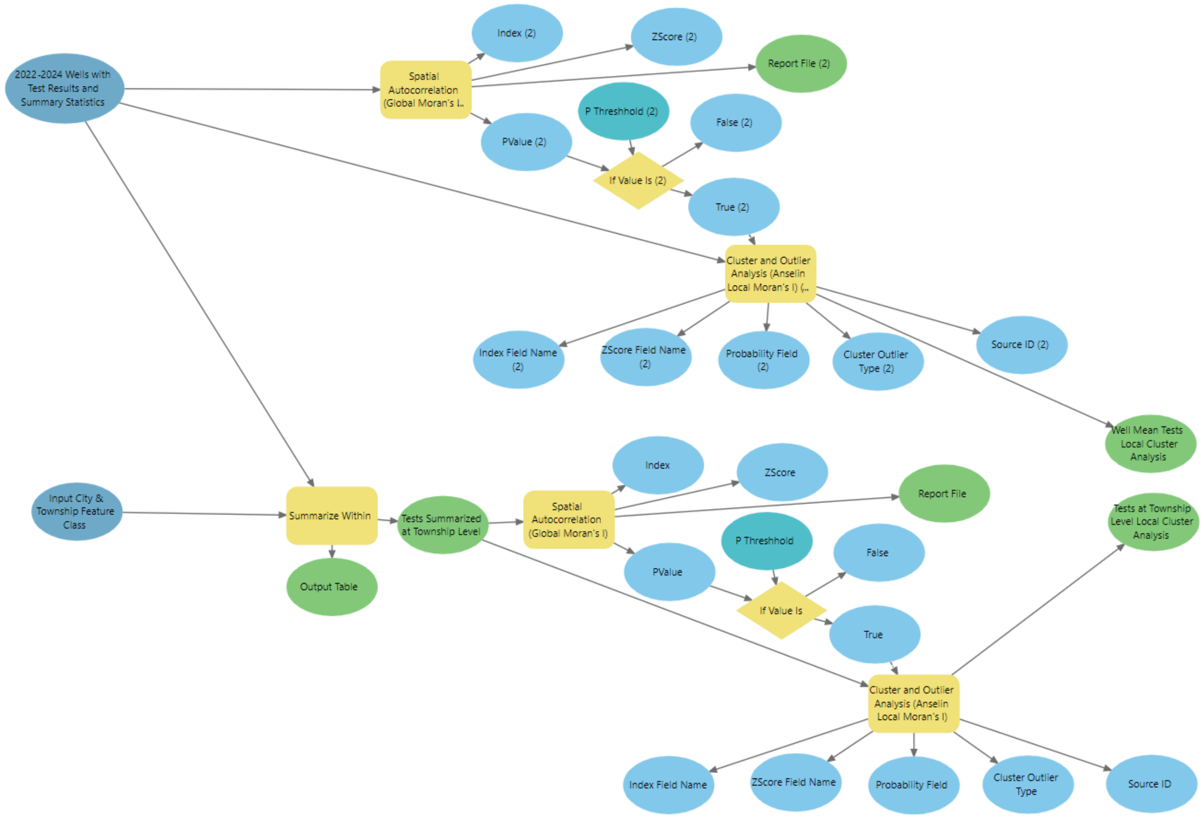


Figure 6. Workflow for exploratory analysis of nitrate tests/well data.

3.2.2 Soil Exploratory Analysis

Exploratory analysis (Figure 7) for the gSSURGO data began with drafting symbolized maps (Figures 14-16) of each variable of interest, noticing a visual relation between small distances to the annual minimum water table and moderate to slow infiltration rates as characterized by the hydrologic groups. Additionally, higher mean nitrate well tests correlated with moderate infiltration rates. Generalized Linear Regression (Spatial Statistics Tool) was completed with nitrate levels as the dependent variable and the soil variables as the independent or explanatory variables. From this, there appeared to be some correlation or clustering between high nitrate levels and specific soil variables. Next, an iterative autocorrelation analysis was completed, and similar results were obtained. From these tests, it was clear that while soil variables didn't perfectly explain nitrate levels in full, statistical significance was low, and there did seem to be a relationship. From here, the goal was to complete various spatial regression models to determine a best-case scenario or see which variable had the most influence on nitrate levels.

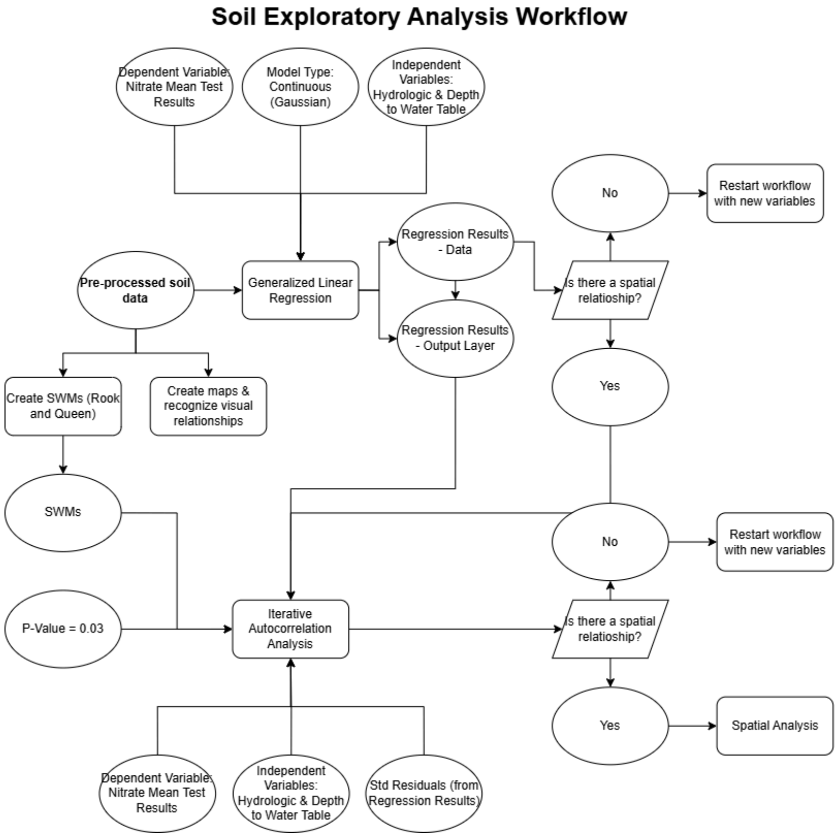


Figure 7. Workflow for exploratory analysis of soil data.

3.3 Watershed Modeling

Watershed modeling was conducted using the un-jittered pour points and the USGS Dynamic Elevation Model (DEM). ESRI has a robust set of tools that fill small holes that could disrupt simulated flow, model flow direction, model water accumulation, and create watershed boundaries. The un-jittered wells were used as pour points, but a relatively high maximum snapping distance was needed for the Snap Pour Point tool (300m). The pour point ID field was preserved across the process, which allowed for it to be joined back to the well data, allowing for visualization of nitrate content for the well that each watershed is theoretically flowing into. This process is shown in Figure 8 below.

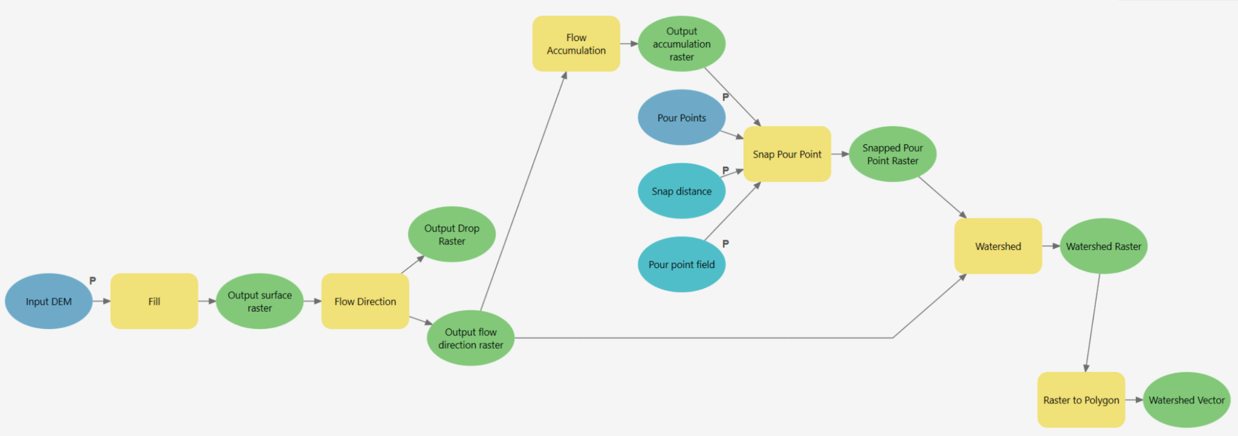


Figure 8. Workflow for watershed modeling.

3.3 Spatial Analysis

Using Pysal's OLS, linear regression was performed with both the Spatial Lag of X and the Spatial Lag of Y. X, or the independent variables were defined as the categorical, binary, hydrological group attributes and the annual minimum depth to the water table. Y, the dependent variable, was defined as the mean nitrate test results. Both were analyzed using both queen and rook contiguity. The same was also completed with only the Hydrologic group of C/D as the independent variable, as this attribute showed the most importance with the initial spatial regression models. Results of the best-fit model, SLY with queen contiguity, are shown in Table 3.

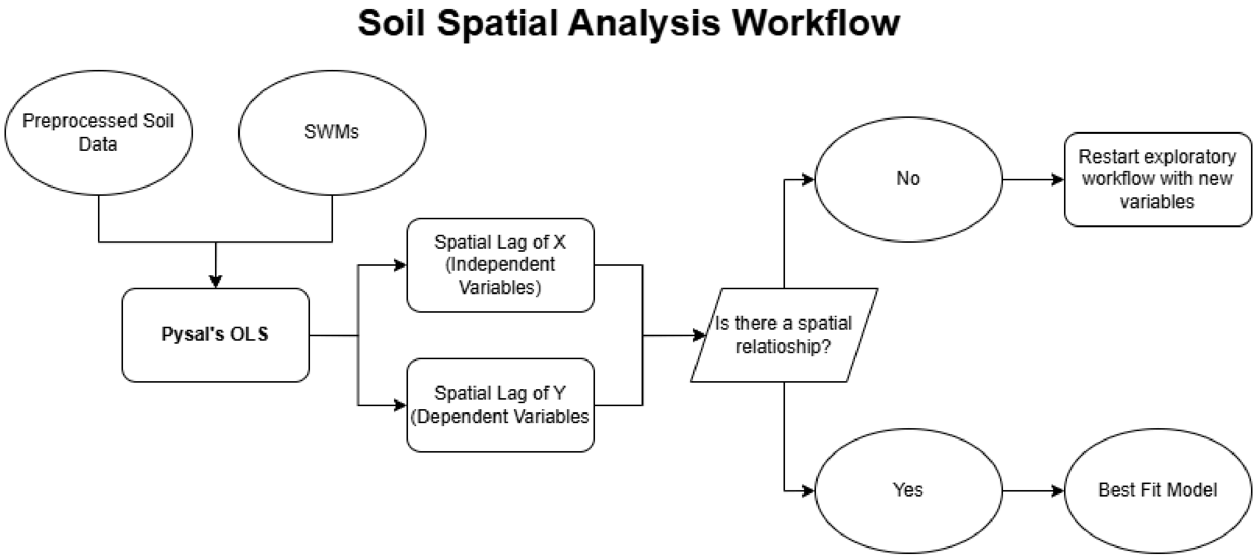


Figure 9. Workflow for spatial analysis for soil data.

4. Results

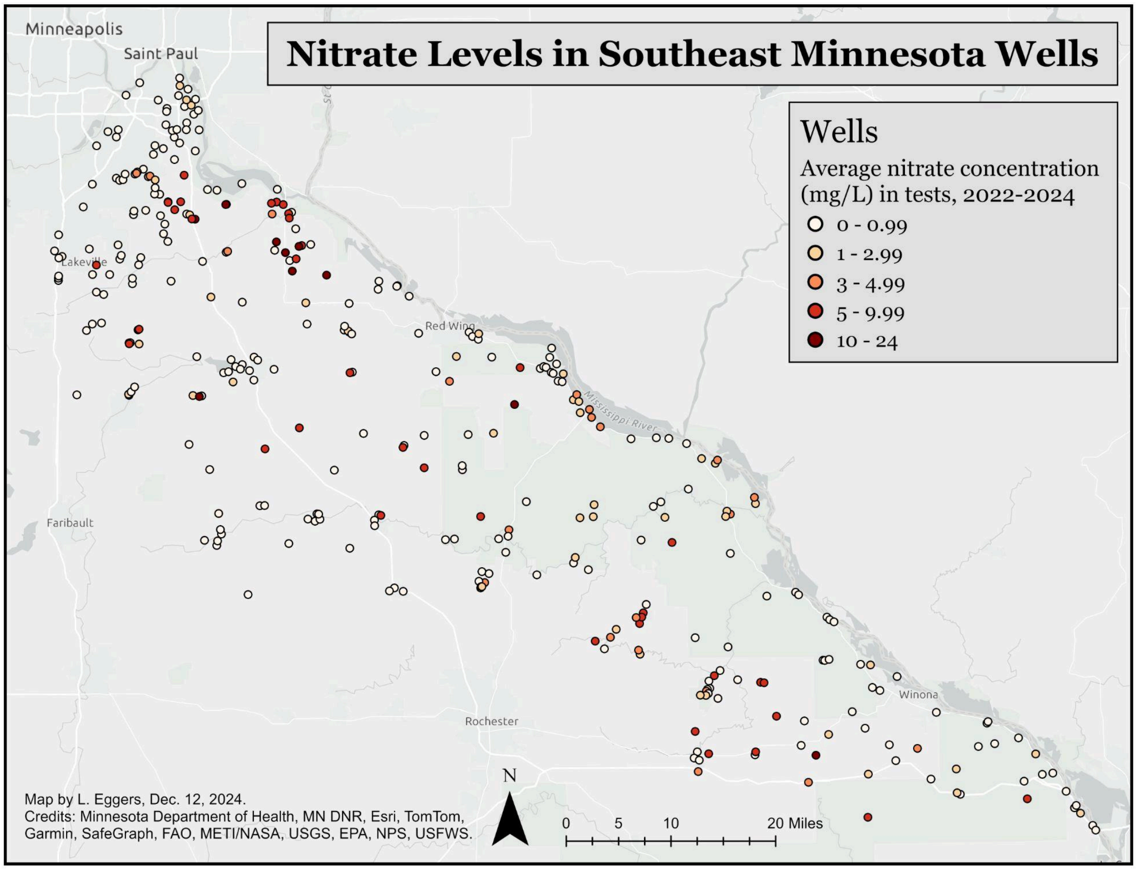
The results of initial and exploratory analyses, both at the well level (Figure 10) and at the city/township level (Figure 11), visually suggest clustering dynamics. In particular, Figure 11 seems to exhibit a ‘middle-band’ pattern where wells with high nitrate levels make up the largest proportion of wells, specifically in areas slightly spatially removed from the blufflands and the Mississippi River. This strikes us as somewhat counterintuitive, as we might expect nitrate concentrations to accumulate and build as we progress further through the river network. We might have expected to see higher proportions of nitrate-heavy wells right along the Mississippi River.

Global Moran’s I tests at the well level (e.g., wells shown in Fig. 10), which were run using the wells’ mean nitrate concentration test and the inverse distance method, returned statistical significance values for clustering at $p < 0.000001$. Anselin (Local Moran’s I) tests on the same dataset revealed statistically significant high-high clusters around Hastings and Elgin and significant low-low clusters on the western extremities of our area of interest (Figure 12).

Figure 13 shows watersheds modeled for each well, as well as the mean nitrate test for a well in that watershed from 2022-2024. Visually, there appears to be a clustering of high nitrate tests, particularly in Wabasha and Winona counties. Dakota, which has the most wells that have been tested, has much smaller watershed subdivisions than the other counties. Interestingly, there are high nitrate concentrations in some of these small subdivisions but not many of the nearby ones. Given more time, autocorrelation and multivariate regression could be performed to show clustering and possible relationships quantitatively. Additionally, incorporation with the other data could provide insight into more isolated high nitrate wells.

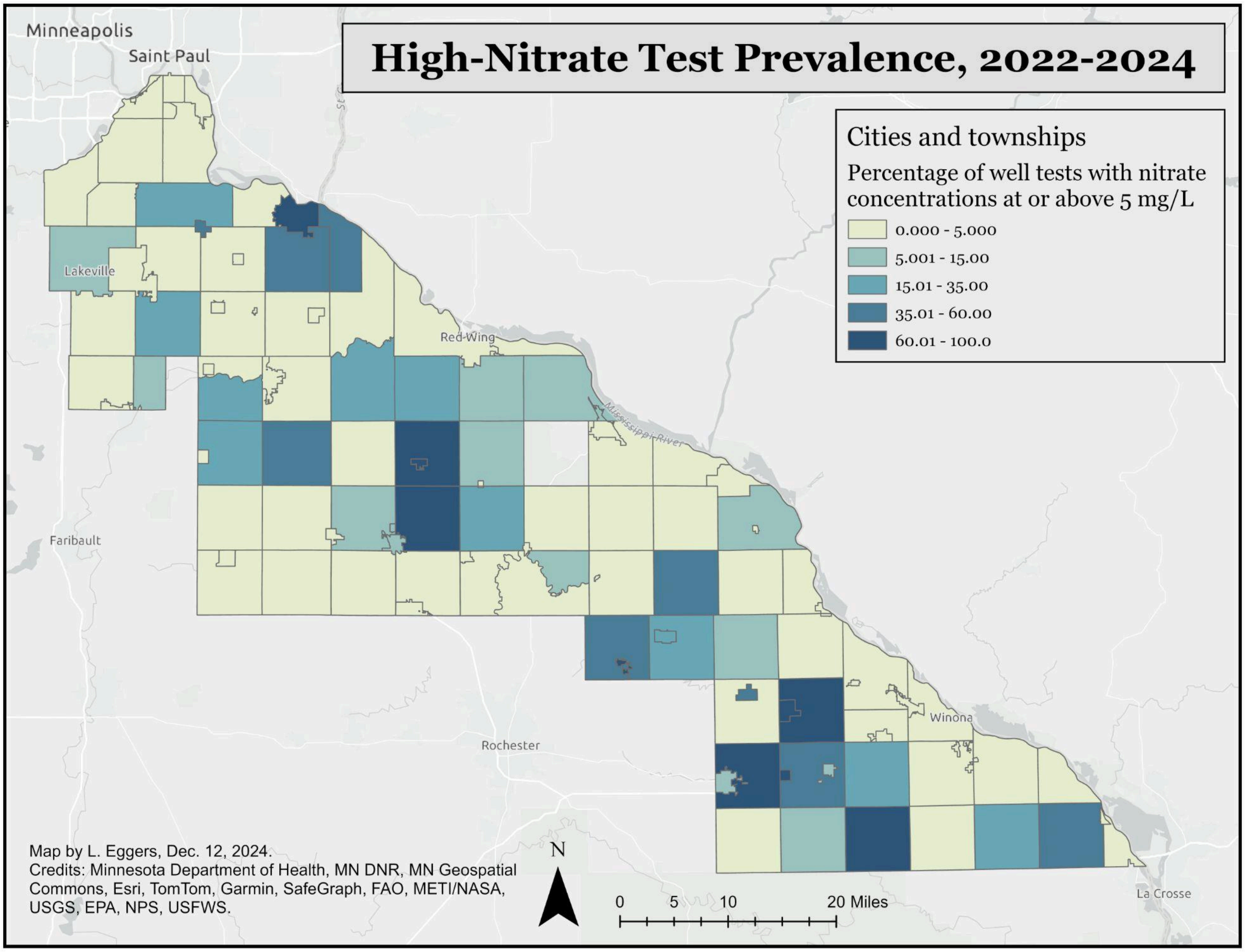
From the initial visualization of nitrate test results aggregated to the soil unit as defined by the county and the USDA (Figure 14), it is clear there are increased nitrate levels in the middle of Goodhue County and the southwest corner of Winona County. With the context of the annual minimum depth to the water table (Figure 15), these regions correspond with shallow depths. Shallow groundwater is defined as any area where the water table is located less than 91 cm or 3 feet from the surface (Shallow Groundwater). These targeted regions of increased nitrate pollution correspond with the shallow groundwater definition. These regions also correspond with a range of hydrologic conditions (Figure 16) between B and C/D. This indicates that these regions have moderate to slow infiltration rates with moderate to high runoff potential. This would suggest that polluted water would not quickly infiltrate the soil but move to other regions as polluted runoff. This may result in wells being polluted by runoff from other soil units or areas, meaning there is a low spatial correlation between soil units and nitrate levels in wells.

The spatial lag regression model has weak explanatory power, with a pseudo-R-squared of 0.0163 (Table 3). However, the spatial lag of the mean nitrate test results for the soil units is more significant (coefficient = 0.3347, p-value = 0.0446). While this model does not independently explain nitrate levels with conclusiveness, it does provide insight into the limitations of using a few chosen variables in an attempt to describe something as complex as nitrate pollution.


Nitrate Levels in Southeast Minnesota Wells

Map by L. Eggers, Dec. 12, 2024.
Credits: Minnesota Department of Health, MN DNR, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS.

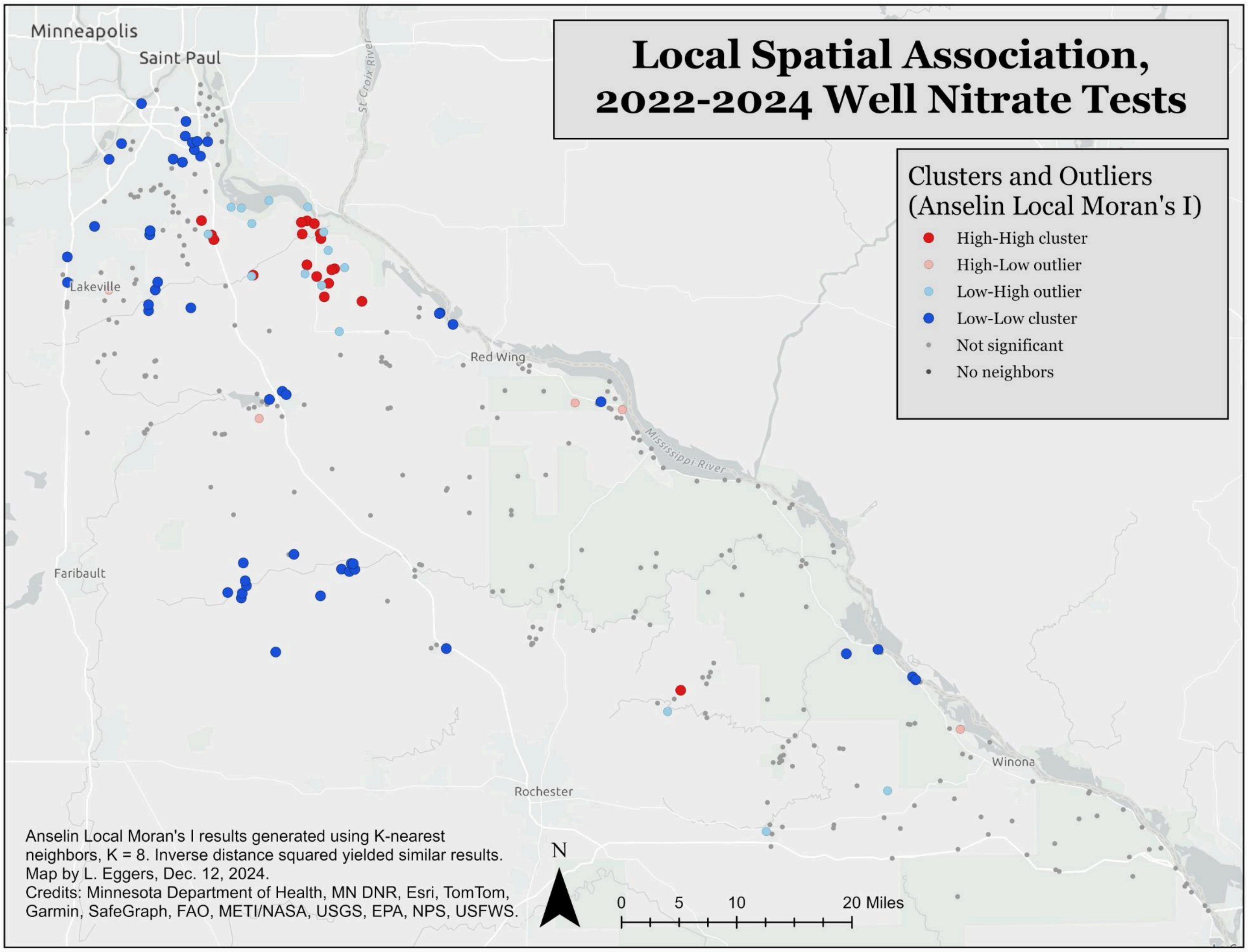
Figure 10. Average nitrate test results for wells in Area of Interest, 2022-2024.



High-Nitrate Test Prevalence, 2022-2024

Map by L. Eggers, Dec. 12, 2024.
Credits: Minnesota Department of Health, MN DNR, MN Geospatial Commons, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS.

Figure 11. Cities and townships are symbolized by the percentage of 2022-2024 well tests that returned nitrate concentrations at or above 5 mg/L.



Anselin Local Moran's I results generated using K-nearest neighbors, K = 8. Inverse distance squared yielded similar results.
Map by L. Eggers, Dec. 12, 2024.
Credits: Minnesota Department of Health, MN DNR, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS.

Figure 12. Anselin Local Moran's I results on wells' mean nitrate levels, 2022-2024.

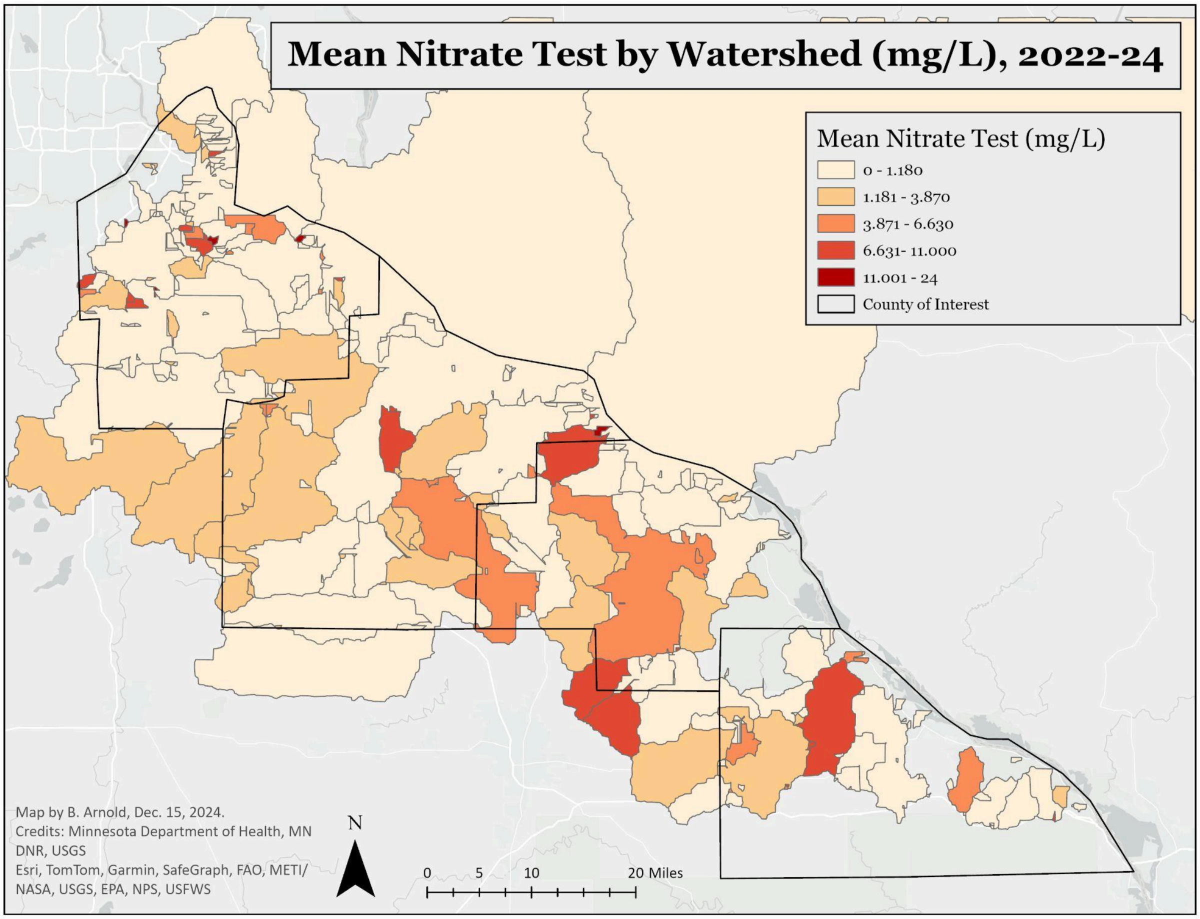


Figure 13. Mean nitrate testing results from 2022-24, visualized by watershed.

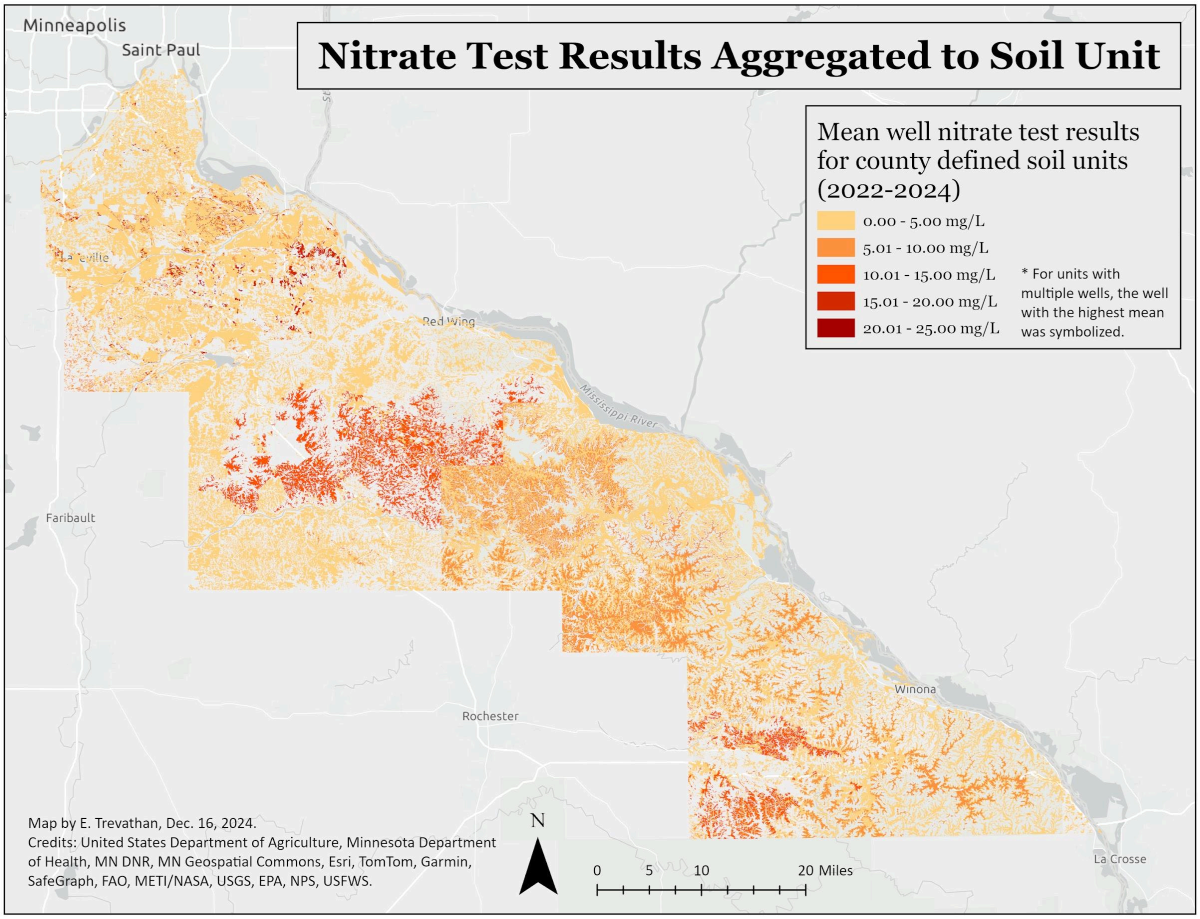
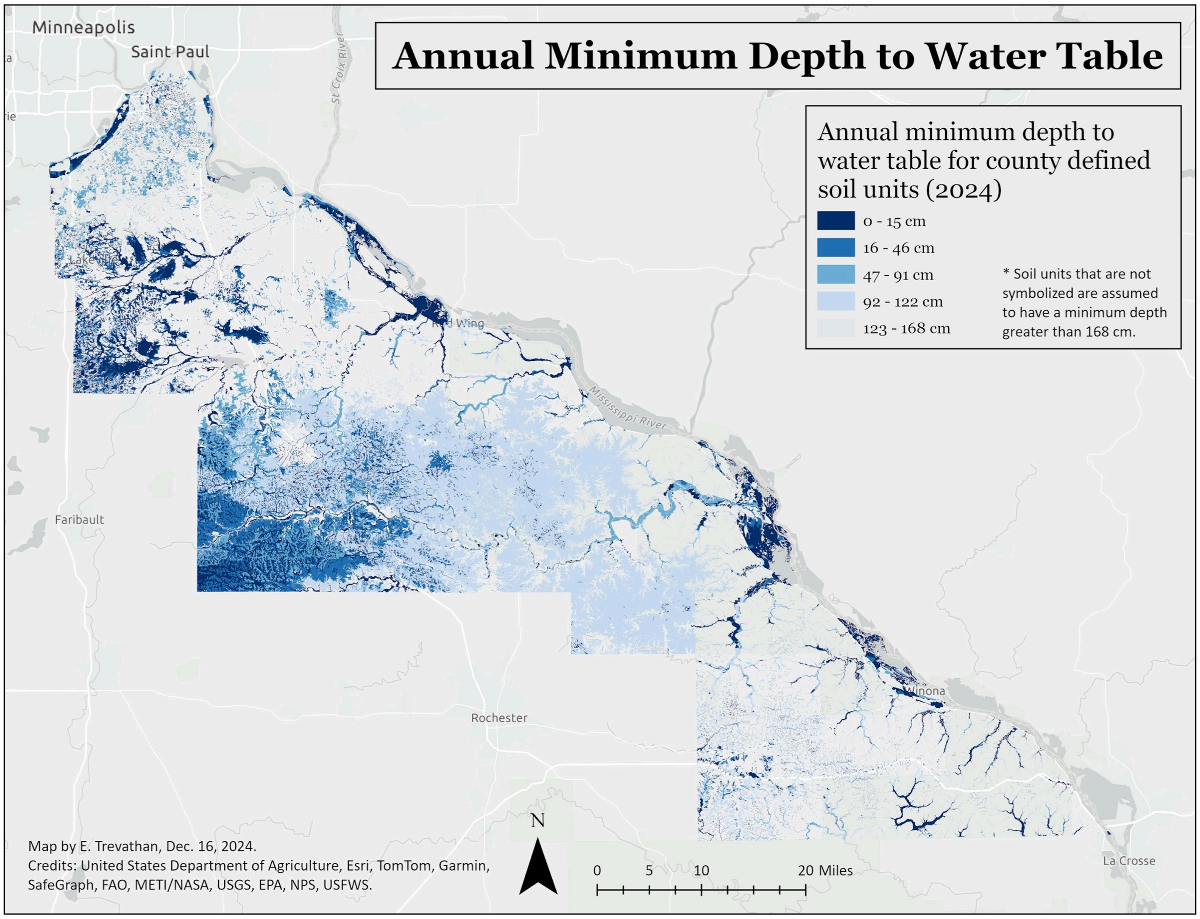
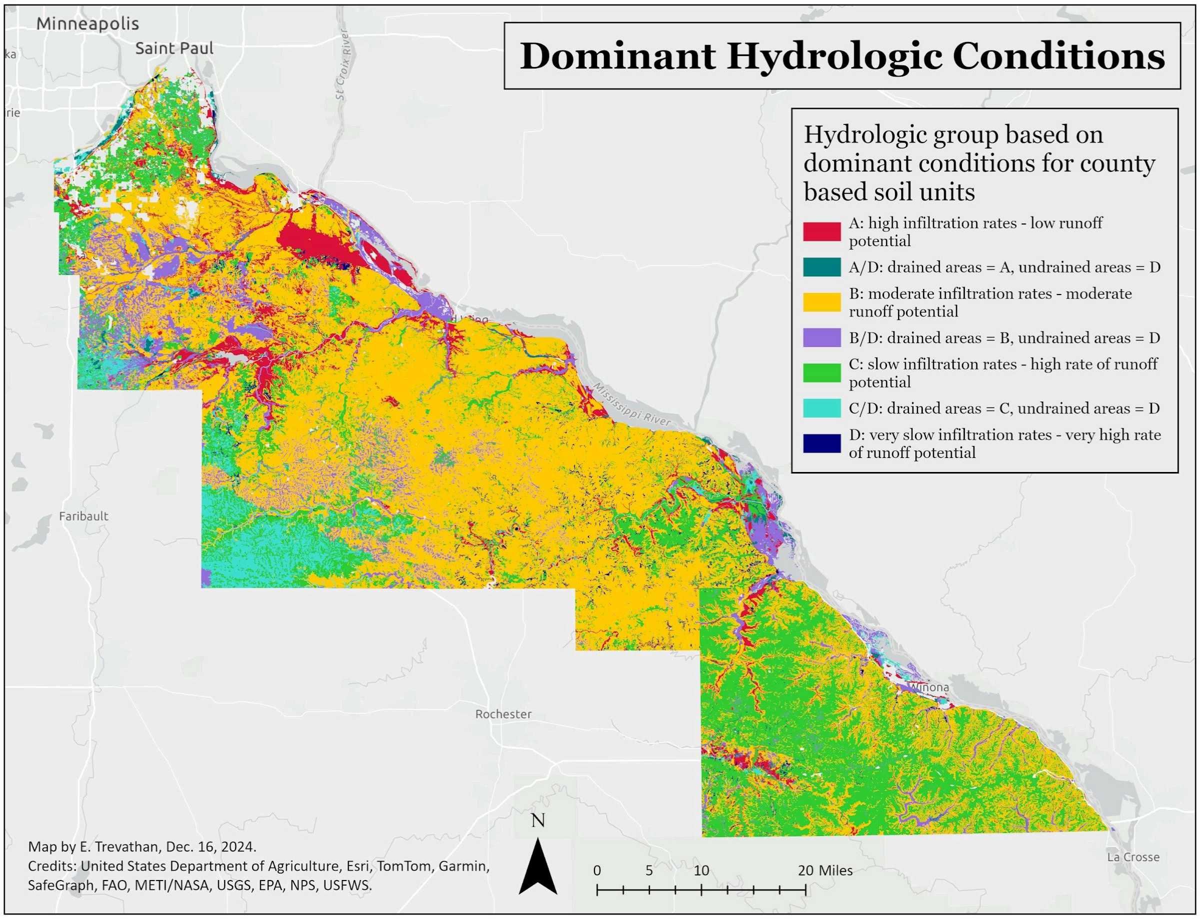


Figure 14. Soil units, as defined by the county, are symbolized by the containing well with the highest mean nitrate concentration results during the 2022-2024 test period.



Map by E. Trevathan, Dec. 16, 2024.
Credits: United States Department of Agriculture, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS.

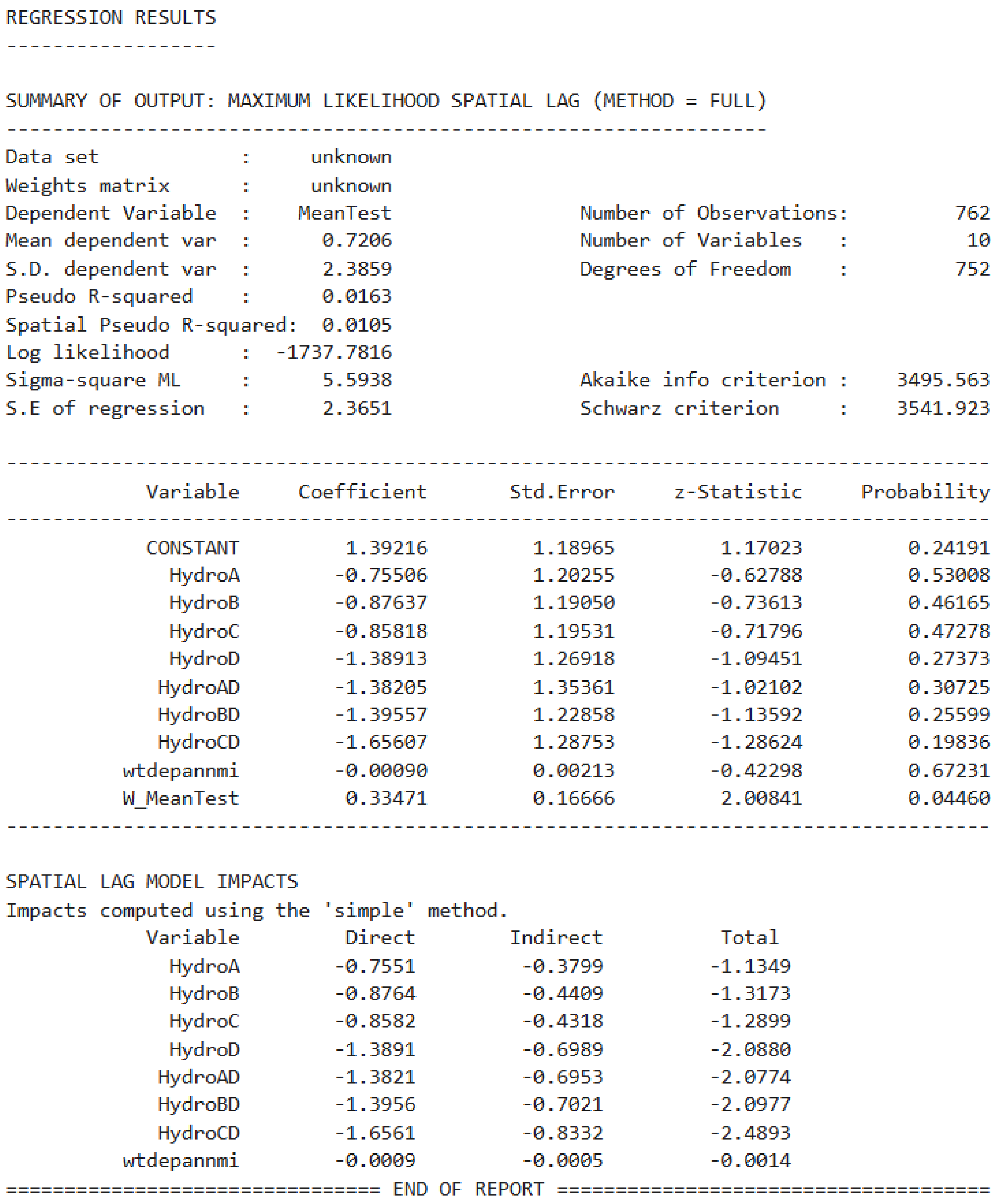
Figure 15. As defined by the county, soil units are symbolized by the annual minimum depth to the water table as calculated by the USDA Soil Survey staff, updated in October of 2024. Not symbolized areas are assumed to have a greater minimum depth than 168 cm. Shallow groundwater is defined as any area where the water table is located less than 91 cm (3 feet) from the surface. While located deeper than the water table, wells are considered "shallow wells" at any depth less than 3000 cm (100 ft).



Dominant Hydrologic Conditions

Map by E. Trevathan, Dec. 16, 2024.
Credits: United States Department of Agriculture, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS.

Figure 16. As defined by the county, soil units symbolized by the hydrologic group, as determined by its most dominant conditions, were updated in October of 2024.



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REGRESSION RESULTS
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SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)
-----------------------------------------------------------------
Data set            :     unknown
Weights matrix      :     unknown
Dependent Variable  :    MeanTest                Number of Observations:         762
Mean dependent var  :      0.7206                Number of Variables   :          10
S.D. dependent var  :      2.3859                Degrees of Freedom    :         752
Pseudo R-squared    :      0.0163
Spatial Pseudo R-squared:  0.0105
Log likelihood      :  -1737.7816
Sigma-square ML     :      5.5938                Akaike info criterion :    3495.563
S.E of regression   :      2.3651                Schwarz criterion     :    3541.923

------------------------------------------------------------------------------------
            Variable     Coefficient       Std.Error     z-Statistic     Probability
------------------------------------------------------------------------------------
            CONSTANT         1.39216         1.18965         1.17023         0.24191
              HydroA        -0.75506         1.20255        -0.62788         0.53008
              HydroB        -0.87637         1.19050        -0.73613         0.46165
              HydroC        -0.85818         1.19531        -0.71796         0.47278
              HydroD        -1.38913         1.26918        -1.09451         0.27373
             HydroAD        -1.38205         1.35361        -1.02102         0.30725
             HydroBD        -1.39557         1.22858        -1.13592         0.25599
             HydroCD        -1.65607         1.28753        -1.28624         0.19836
          wtdepannmi        -0.00090         0.00213        -0.42298         0.67231
          W_MeanTest         0.33471         0.16666         2.00841         0.04460
------------------------------------------------------------------------------------

SPATIAL LAG MODEL IMPACTS
Impacts computed using the 'simple' method.
            Variable         Direct        Indirect          Total
              HydroA        -0.7551         -0.3799         -1.1349
              HydroB        -0.8764         -0.4409         -1.3173
              HydroC        -0.8582         -0.4318         -1.2899
              HydroD        -1.3891         -0.6989         -2.0880
             HydroAD        -1.3821         -0.6953         -2.0774
             HydroBD        -1.3956         -0.7021         -2.0977
             HydroCD        -1.6561         -0.8332         -2.4893
          wtdepannmi        -0.0009         -0.0005         -0.0014
================================ END OF REPORT =====================================
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Table 3. Spatial Regression results from SLY analysis with all hydrologic variables and depth to the water table as independent variables, with a queen spatial weight matrix.

5. Discussion

As expected, nitrate pollution has many different variables that influence its spread and accumulation, which are difficult to model comprehensively. We tackled many different variables individually and paired with one or two others, but it is non-trivial to move from that to an accurate, multivariable model. Our early workflows and hypotheses proved helpful, as literature and prior knowledge supported us in finding variables to examine. Autocorrelation and spatial regression results did not always align with our expectations, but that further affirmed the complex determinants of nitrate accumulation in water.

Soil conditions have some relation to nitrate levels but are not enough to predict nitrate levels with significant confidence, or at least the tested soil variables. We believe there is a relationship that nitrate contamination risk factors are determined by many different variables, and soil features are one of them. The understanding of a correlation between soil variables and nitrate pollution is backed by larger-scale research, and these variables were chosen from the literature and from the variables that the USDA specifically tests within the concern of pollution. This analysis underlines that soil features are not the only variable that defines the probability of nitrate pollution. The best spatial regression model would include some hydrologic or water table variables, with the addition of other environmental variables such as soil type (sand/loam/etc.) and topographic variables. Other factors, such as well depth, would be interesting to investigate since wells are located a short distance underneath the water table. Shallow wells are located at any depth less than 3000 cm (100 ft), and as Figure 15 shows, most of the project's scope lies in regions with less than 168 cm to the water table (Reilly et al.). Despite the spatial model's clear limitations, it shows a spatial relationship within the mean nitrate test results, further backed by the exploratory analysis completed with the data. These results indicate that the nitrate results are not entirely dependent on the chosen soil variables, but nitrate levels have a spatial relationship with a greater host of variables.

Another insight gained came from how the results challenged our assumptions about pollution accumulation. Visual exploratory analysis and many of the varying autocorrelation tests we ran indicated high-high clusters in areas further upstream than expected, in regions of our area of interest that were neither the most upstream nor the most downstream (e.g., Plainview-Elgin). We expected to see the most pollution *either* in downstream areas *or* along the flatter land at the upstream end of our area of interest. The fact that we didn't see either of those kinds of patterns may have something to do with the bluff lands and local geological characteristics of this karst-heavy region.

If we had another 3 months to work on, we could make a more complex and comprehensive model that could better analyze the accumulation of nitrates across watersheds. This could be done by finding a more accurate way to define the watersheds for each well, either by using a more effective pour point methodology or using more general watershed boundaries determined by the USGS. We could then combine our data on water accumulation, soil types, depth to the water table, nitrate tests, feedlots, and other environmental conditions to simulate runoff and see if we can accurately model nitrate pollution in this region. Soil type is a variable that we hypothesize has a spatial relationship with nitrate levels. However, it is not currently a data variable in a form suitable for analysis. Each soil unit polygon has a short phrase or sentence explaining its conditions, including soil type. This information would have to be parsed out into its own categorical variable. Similarly to the hydrologic conditions, we would explore better ways to conduct spatial regression models with categorical data during this time. Additionally, we would be interested in examining whether nitrate pollution distribution relates to demographic variables, such as race and income.

Our rephrased problem statement in the form of a question is: Can we effectively model nitrate pollution presence in southeastern Minnesotan water systems as a function of human and environmental variables? Our answer to that would be that yes, modeling nitrate pollution is possible to some extent, though incorporating further variables like demographics, feedlot presence, and other environmental factors could advance modeling further.

6. References

Bullard, R., Mohai, P., Saha, R., & Wright, B. (2007, March). *Toxic Wastes and Race and Toxic Wastes and Race at Twenty*. United Church of Christ. https://www.ucc.org/what-we-do/justice-local-church-ministries/efam/environmental-justice/environmental-ministries_toxic-waste-20/

Conrad, I. (2023). *Nitrate pollution and the public health crisis in SE Minnesota*. Minnesota Center for Environmental Advocacy. https://www.mncenter.org/nitrate-pollution-and-public-health-crisis-se-minnesota

LaDuke, W. (2024, August 9). *Here's the choice: Cheap McDonald's fries or health of Anishinaabe village of Pine Point*. Minnesota Reformer. https://minnesotareformer.com/2024/08/09/heres-the-choice-cheap-mcdonalds-fries-or-health-of-anishinaabe-village-of-pine-point/

Marohn, K. (2023, October 31). *Southeast Minnesota struggles for common ground on nitrate pollution as health worries rise*. MPR News. https://www.mprnews.org/story/2023/10/31/does-nitrate-in-southeast-minnesotas-water-present-a-public-health-crisis

Masters, C. (2024, April 2). *High nitrate levels in southeastern Minnesota prompt aid plan at state capitol*. MPR News. https://www.mprnews.org/story/2024/04/02/high-nitrate-levels-in-southeastern-minnesota-prompt-aid-plan-at-state-capitol

McVan, M. (2023, November 10). *EPA says Minnesota needs to take more action on nitrates in drinking water. Minnesota Reformer*. https://minnesotareformer.com/2023/11/09/epa-says-minnesota-needs-to-take-more-action-on-nitrates-in-drinking-water/

Minnesota Department of Health. (2024). Nitrate-Nitrogen Tests for Minnesota Wells, 1999-2024. St. Paul, Minnesota.

Minnesota Pollution Control Agency. (2013). Nitrogen in Minnesota Surface Waters. https://www.pca.state.mn.us/sites/default/files/wq-s6-26a.pdf

MN Health Department. (2024a). *Nitrate Risk to the Water Table Aquifer—Minnesota Geospatial Commons*. https://gisdata.mn.gov/dataset/health-nitrate-risk

MN Health Department. (2024b). *Well Information from County Well Index for the General Public—Minnesota Geospatial Commons*. https://gisdata.mn.gov/dataset/water-well-information-non-pws

MN Natural Resources Department. (2024). *County Boundaries, Minnesota—Minnesota Geospatial Commons*. https://gisdata.mn.gov/dataset/bdry-counties-in-minnesota

MN Transportation Department. (2024). *City, Township, and Unorganized Territory in Minnesota—Minnesota Geospatial Commons.* https://gisdata.mn.gov/dataset/bdry-mn-city-township-unorg

Reilly, T. E., Dennehy, K. F., Alley, W. M., Cunningham, W. L., U.S. Department of the Interior, & U.S. Geological Survey. (2008). Ground-Water Availability in the United States. *Ground-Water Resources Program.* chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://water.usgs.gov/watercensus/AdHocComm/Background/Ground-WaterAvailabilityintheUnitedStates.pdf

Shallow groundwater - Minnesota Stormwater Manual. (2023, February 15). Minnesota Stormwater Manual. Retrieved October 10, 2024, from https://stormwater.pca.state.mn.us/index.php/Shallow_groundwater

Stanley, G. (2024, June 26). *Seventeen manure pits reportedly overflow at large feedlots in Southern Minnesota. Star Tribune.* https://www.startribune.com/manure-pits-reportedly-overflow-at-16-large-feedlots-in-southern-minnesota/600376074

Urbanization and Stormwater Runoff | US EPA. (2024, February 7). Environmental Protection Agency (EPA). Retrieved October 10, 2024, from https://www.epa.gov/sourcewaterprotection/urbanization-and-stormwater-runoff

USDA. (2024). *Gridded Soil Survey Geographic (gSSURGO) Database | Natural Resources Conservation Service.* https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database

USGS. (2024). *The National Map—Data Delivery | US Geological Survey.* https://www.usgs.gov/the-national-map-data-delivery