USING A GROUNDWATER FLOW MODEL TO EXPLORE OBJECTIVE-BASED SCENARIOS IN THE PINELAND SANDS AQUIFER REGION

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LIST OF ABBREVIATIONS

Abbreviation	Name/Term
EPA	Environmental Protection Agency
MN DNR	Minnesota Department of Natural Resources
MPCA	Minnesota Pollution Control Agency
NO_3-N	Nitrate-nitrogen
NRS	Nutrient Reduction Strategy
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
U.S.	United States
USGS	United States Geological Survey
USDA	United States Department of Agriculture

Introduction

The Pineland Sands Aquifer region in north central Minnesota is an important area for agricultural production, fishing and recreation, and is home to many communities, including the Anishinaabe Peoples of White Earth Nation. As with many regions that rely heavily on groundwater resources, ensuring an adequate amount of clean water for all of its uses creates complex management challenges. The geology of the area is characterized by sandy soils that provide high infiltration capacity for irrigated crops such as potatoes (Stark, Busch, & Deters, 1991) (Stark, Armstrong, & Zwilling, 1994). However, the sandy glacial deposits also increase the potential of contamination of nitrate-nitrogen (NO3-N) in drinking water and surface water (Killpack & Buchholz, 2022). Nitrogen's primary anthropogenic source of nitrogen in intensive agricultural landscapes is nitrogen fertilizer (Ward, et al., 2018). A study conducted by the United States Geological Survey's National Water Quality Assessment on public and private drinking water supply aquifers across the United States (U.S.) between 1988 and 2015 found that groundwater below agricultural land had nitrate concentrations almost three times the national background level of 1 mg L^{-1} NO_3-N (Ward, et al., 2018).

The maximum contaminant level for NO_3-N for public supply wells set by the U.S. Environmental Protection Agency (EPA) is 10 mg L^{-1}. At concentrations above this level, infants are at risk for developing blue baby syndrome, which is also known as infant methemoglobinemia (Ward, et al., 2018). There have been numerous studies that have shown other negative effects from high NO_3-N concentrations such as congenital birth defects (Holtby, et al., 2014), bladder cancer (Jones, et al., 2016), and pancreas cancer (Quist, et al., 2018). Alongside human health concerns, there is also risk of contamination affecting aquatic life found in water bodies. The Straight River, one of the major rivers flowing within the study area, is a cold-water trout stream. McGurk et al. (2006) observed lake trout weight being impacted by chronic exposure to NO_3-N levels above 6.25 mg L^{-1}. In Minnesota, draft ecological chronic exposure standards for salmonid and non-salmonid waters are set at 5 mg L^{-1} NO_3-N and 8 mg L^{-1} NO_3-N respectively (Monson, 2022).

As stated in the project background of the main report, Protecting Minnesota's Headwaters of the Mississippi and Pineland Sands, the project area has seen an increase in intensive agricultural practices and irrigation. The study area is near the headwaters of the Mississippi River. To help address the Gulf of Mexico dead zone caused by excessive



nutrient runoff from the Mississippi River, states with contributing watersheds have created Nutrient Reduction Strategies (NRSs). In 2014, the State of Minnesota aimed to reduce nitrogen loading into the Mississippi River by 45% by 2040 (MPCA, 2014). According to the update in the 2025 Minnesota NRS report, NO_3-N concentrations within rivers across the state showed no trend in most of the sites between 2008 and 2022. In order to reach the (NRSs) goal, there needs to be a lot more nitrate reduction over the next remaining 15 years (MPCA, 2026).

A groundwater flow and nitrate transport modeling framework, combined with uncertainty analysis and multi-objective optimization, was used in this study to examine groundwater flow in the Pineland Sands region and the sustainability of agricultural management practices with respect to NO_3-N levels in drinking water and important water bodies. The framework evaluated tradeoffs between farmer social equity, protection of nitrate concentrations in drinking water and trout streams, and agricultural productivity. More detailed information on the framework, methods, results, and other possible uses can be found in the paper by Margarit et al. (2025).

Project Objectives and Study Area

The objective of the study is to develop a framework that can be used to assist in finding nitrate management outcomes along with their tradeoffs between economic, social, and environmental objectives under uncertainty.

Methods

Method Description

A groundwater flow model was made using MODFLOW-NWT, a Newton-Raphson formulation for MODFLOW-2005 created by the U.S. Geological Survey (USGS) (Niswonger, Panday, & Ibaraki, 2011). NO_3–N transport was simulated using MT3D-USGS (Zheng & Wang, 1999). The model covers the northern Pineland Sands Aquifer region. It is broken down into three layers and has a 200 m x 200 meter (m) cell size (Figure 1). The three layers were modeled after the Central Sands regional groundwater model in Wisconsin by the USGS because the two regions have similar glacial deposits (Fienen, Haserodt, Leaf, & Westenbroek, 2022). The first layer in the model is a composite of the surficial quaternary layers. Upper glacial aquifer layers make up the second layer. And the third layer is made of lower undifferentiated material.



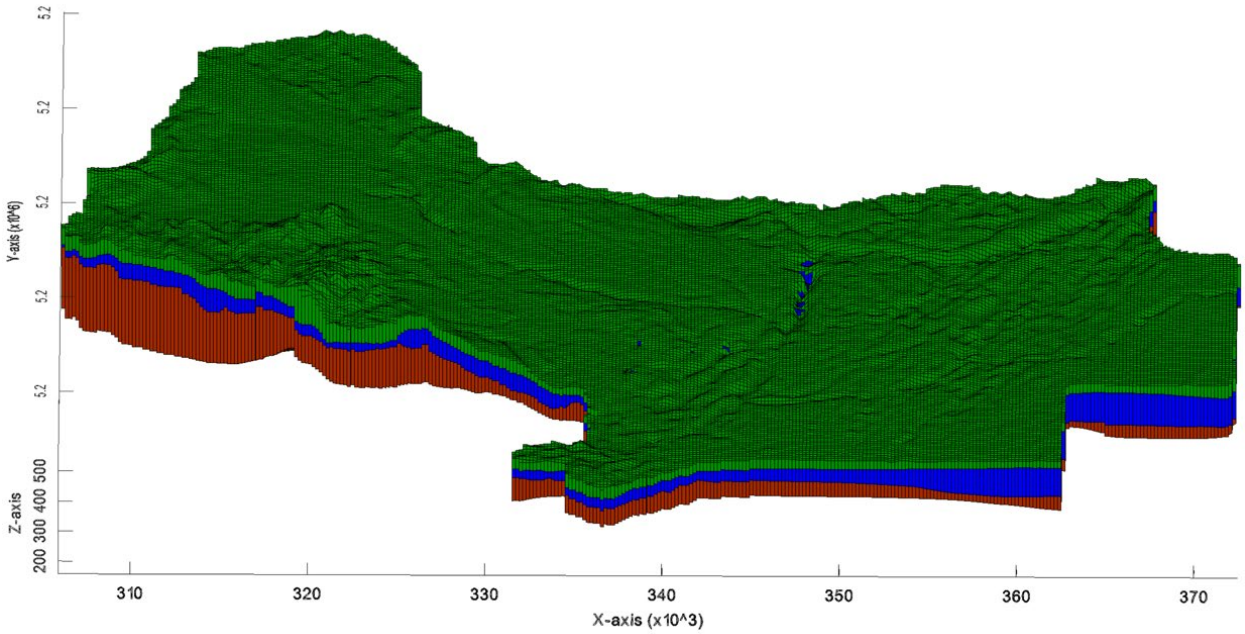

Figure 1: Three-dimensional view of the model's geologic layers and surface. There is a vertical exaggeration of 20x (Margarit et al., 2025).

The groundwater model was run under steady state conditions. Flow directions within the regional aquifer are assumed to not change much between different seasons. Nitrate transport was simulated over 100 years, which was the amount of time needed for NO_3-N to become stable within the model area. Most of the packages used in the model were created and visualized using the software Groundwater Modeling System. A package is an individual module that is designed to represent specific hydrological processes or boundary conditions within a groundwater model. The Minnesota Soil Water Balance Model was used to determine groundwater recharge inputs using data averaged from 2002 to 2015. This period corresponds to the available data from the Soil Water Balance Model and is long enough to capture climate variability. The 2019 National Land Cover Database was used for land use data. The U.S. Department of Agricultural Soil Survey Geographic Database was used for soil information. Geology and hydrogeology data came from the Minnesota County Geologic Atlas for Hubbard, Wadena, and Becker counties. Lakes, rivers, and streams were represented using the River package was used. For external model edges, the General Head Boundary and Drain packages were implemented. The Multi-Node Well package was used to represent irrigation and pumping wells. These packages are often used in groundwater modeling for the model setup.

Water level observation data for the groundwater heads of 541 observed wells were gathered from the Minnesota Department of Natural Resources (MN DNR) Cooperative Groundwater Monitoring program. Daily stream discharge data from the MN DNR Cooperative Stream Gaging Network Database was collected for two stream gages along the Straight and Shell Rivers and used during calibration. A Lynn-Hollick baseflow separation filter was used on the discharge data hydrographs to get baseflow values. Observation wells and stream gaging stations are shown in Figure 2.

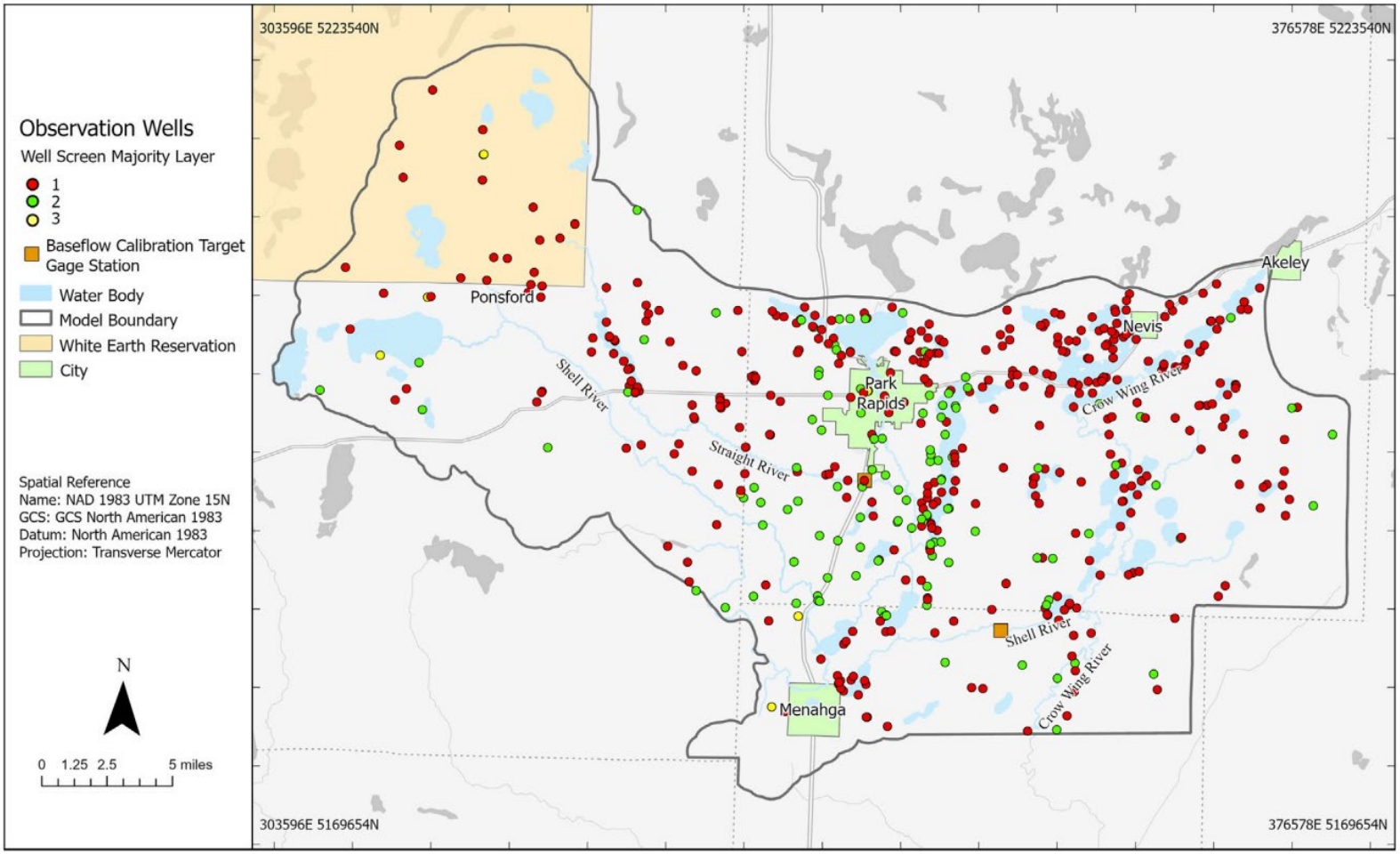

Figure 2: Map of observation wells and stream gaging stations used in the calibration dataset in Margarit et al. (2025).

Pilot points distributed at 271 places around the model area were used to account for spatial heterogeneity of aquifer properties, conductance, and denitrification rates. Pilot points are specific locations throughout a model where parameter values are estimated and then interpolated across the rest of the model area. Distributions of these parameters were defined with best estimates from literature. This introduced uncertainty. Each set of different possible parameters formed a possible "prior parameters realization" of the aquifer system's properties. In simpler terms, they each formed a plausible realistic way the groundwater system could have behaved before the model was fitted to observed data with model calibration.

For model calibration, our study used PESTPP-IES[1], which is an iterative ensemble smoother that uses a Bayesian history-matching approach to calibrate. It updates an entire group (ensemble) of parameter realizations instead of single parameters at one time (White, 2018). Through this calibration, parameters were adjusted to match groundwater head and flow data. The output of the model calibration was a final ensemble of 475 posterior parameter realizations. To put simply again, it resulted in 475 possible groundwater models that were matched to historic observed data. Uncertainty in groundwater predictions was addressed by sampling the posterior parameter distributions and putting them through an optimization framework so that nitrate concentration constraints under various risk tolerance levels were estimated probabilistically.

Groundwater flow was simulated flowing from the northwest to the southeast towards the Crow Wing River of the model area. There were constraints with the model. One of them was that there was insufficient observed field data for denitrification to be able to accurately calibrate for it. As part of this study, the model was chosen to be used in an optimization under uncertainty framework to look at tradeoffs between agricultural economics, farmer social equity, and risk aversion to enforce nitrate concentration limits in drinking water and rivers.

The resulting groundwater model realizations from the calibration were used in a framework in which multi-objective optimization under uncertainty was used. The software PEST++ multi-objective optimization under uncertainty (PESTPP-MOU) implemented

[1] PEST is the name of a software package that enables users to conduct model-independent parameter estimation and uncertainty analysis.

the framework. The framework aimed to explore how management of nitrate contamination in drinking water and rivers can create tradeoffs with landowners in the way of agricultural production (allowable nitrate leaching) and farmer equity (making sure the majority of nitrate reductions does not fall on a small number of landowners). There were three different trade-offs used in this study. The first one is economic profit from agricultural practices. The second is nitrate concentrations in streams and drinking water. And the third is a social aspect aimed at making sure there is fairness in splitting nitrate reduction measures across farms in an area.

PESTPP-MOU uses Particle Swarm Optimization and Non-Dominated Sorting Genetic Algorithm II for creating and analyzing a tradeoff curve called a Pareto Front. The framework includes decision variables, objective functions, and constraints. In this study, the decision variables are nitrate leaching rates specified at selected locations throughout the model area using pilot points. These rates can change depending on the different crop type used and model outcome used from calibration. The objective functions are used to implement the three tradeoffs, also known as objectives. The objective functions are mathematical formulas used to guide decision-making for uncertain key objectives. The first objective is the economic objective. This objective is to maximize the total leaching, and in other words, maximize farm revenue. The second is the social objective, which aims to ease farmer hardship and share nitrate reduction efforts across more farmland. The third is the environmental objective. In this objective, the main driver is to maximize constraint compliance, or in other words, reduce the risk of increased nitrate leaching. The goal for this objective is for a low chance of drinking water wells or rivers going above their constraint value for nitrate contamination. Upper and lower bounds for crop rotations were determined from literature. A crop rotation yield analysis with accompanying nitrogen application and NO_3-N leaching rates was completed. The crops considered for the analysis include corn, dry beans, potato, and kura.

Constraints are also part of the framework and are used as reference points to ensure nitrate values are kept below target levels. There are two constraints for the groundwater monitoring wells, 5.4 mg NO_3–N L^{-1} and 8.0 mg NO_3–N L^{-1}. These are concentrations that represent Mitigations of Level 1 and Level 2 respectively by the Minnesota Department of Agriculture to meet water quality limits for drinking water wells set by the MDA to reduce the need for mitigation (MDA, 2019). The constraint is for concentration in the Straight River



is 5 mg NO_3–N L^{-1}. The State of Minnesota has given salmonid waters a draft ecological chronic exposure standard at this concentration.

Location

The groundwater model was developed for the northern portion of the Pineland Sands Aquifer in Hubbard, Becker, and Wadena Counties by the University of Minnesota.

Results

Pareto Fronts for the different NO_3-N concentration constraints at the monitoring wells were created. Solutions are placed along the curves (Figure 3). As shown in Figure 3, the objectives compete against each other. As the nitrate leaching rates (agricultural production) increase, the risk aversion (chance of not keeping below the constraint concentrations in wells and the Straight River) decreases. And as risk aversion is increased, the farmer hardship also increases because to keep in accord with nitrate reduction for the constraints, certain farmers will have to reduce nitrate leaching. Risk aversion can be thought of as similar to percent chance. As risk aversion increases along the y-axis of the Pareto Front from 0 to 1, the percent chance of staying below the nitrate constraint in the drinking water wells and streams in a given land use scenario is higher. Allowable nitrate leaching is shown along the x-axis of the Pareto Front. As you go from 80 kg N ha^{-1} yr^{-1} to 150 kg N ha^{-1} yr^{-1}, more nitrate leaching is allowed to keep below the constraints, as long as the other two objectives are changed as well. As the farmer hardship value increases from 0 to 5000, it means that the brunt of the land use changes will be placed on a smaller amount of farms, mostly due to their close proximity to the stream or drinking wells. Pareto Fronts in Figure 3 show that the risk aversion is unable to reach a level of 1.0, meaning that staying below the constraint thresholds is never guaranteed. If the average decision variable nitrate leaching rate were to be extended to 0 kg N ha^{-1} yr^{-1}, then risk aversion might get closer to 1.0. When looking at the Pareto Fronts on the right side of the curve, where the solutions start to form a more vertical line could be seen as the point of diminishing return. Here, by mitigating NO_3–N leaching rates by as little as 5 kg N ha^{-1} yr^{-1}, farmer hardship can be largely reduced along with an increased risk aversion.



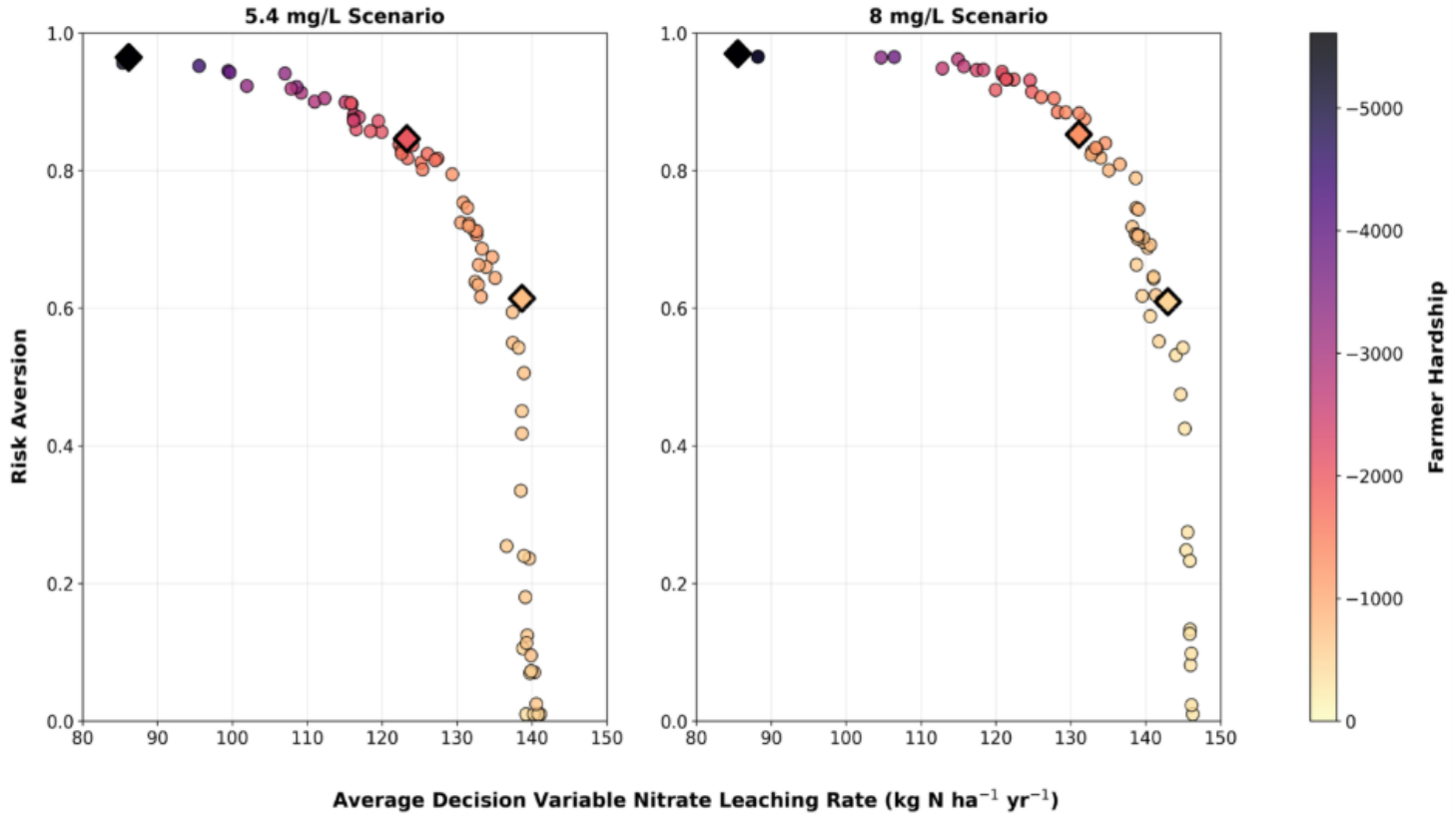

Figure 3: Pareto Fronts representing the tradeoffs between the objective functions. They are two different constraint scenarios calculated by PESTPP-MOU (Margarit et al., 2025).

Figure 4 includes proposed solutions, which are visually represented as diamonds in Figure 3. The diamonds in the 5.4 mg L^{-1} scenario Pareto Front graph correspond to scenarios A, B, and C in Figure 4. The diamonds in the 8 mg L^{-1} scenario Pareto Front graph then correspond to scenarios D, E, and F. The diamonds closer to a risk aversion of 1.0 match with A and D in Figure 4. Each of these solutions are composed of a different set of pilot point NO_3–N leaching rates. This shows which areas require the most reduction in NO_3–N leaching rates in order to comply with the constraints at the monitoring locations. Cooler colors represent lower allowable NO_3–N leaching rates, which result in lower farm revenue.

There are two main areas that are more affected by the limiting of NO_3–N leaching. That is the land area between the lower Shell River and the Fish Hook River in the East-Central part of the model, the area southwest of Park Rapids. They are both areas with a lot of farmland. So as a whole, each of the raster cells in these regions will need to limit their nitrate leaching rates because there are a lot of other cells around them also applying fertilizers. The region southwest of Park Rapids is also closer to the drinking water supply wells used for some of the constraints. Land use management changes in these areas could see the biggest impact in NO_3–N concentrations in public supply wells and the Straight River. Optimal land uses are also included in the pie charts. Crop managements that require less NO_3–N is more optimal in certain areas to lower NO_3–N leaching rate.

As you move from A to C and D to F in Figure 4, risk aversion increases. This also corresponds to a higher farmer hardship index value since certain areas will require more NO_3–N limiting. As you move from the top down in each constraint group, the percent land use optimal for high fertilizer requiring crops such as potatoes and dry beans decreases. Scenario D, with an 8.0 mg L^{-1} constraint, requires the least reduction in nitrate leaching compared to the other scenarios. It would also cause the lowest hardship on farmers and create the lowest risk aversion. Scenario C has the smallest constraint of 5.4 mg L^{-1}. It also would require the greatest reduction in nitrate leaching. This in turn would put the greatest hardship on farmers and create the highest risk aversion. The most ideal scenario to start off with would be D, because it would still be below the higher constraint but have the least amount of farmer hardship. But if a Mitigation I is needed, a scenario between A and C will be required to get nitrate reductions lower.



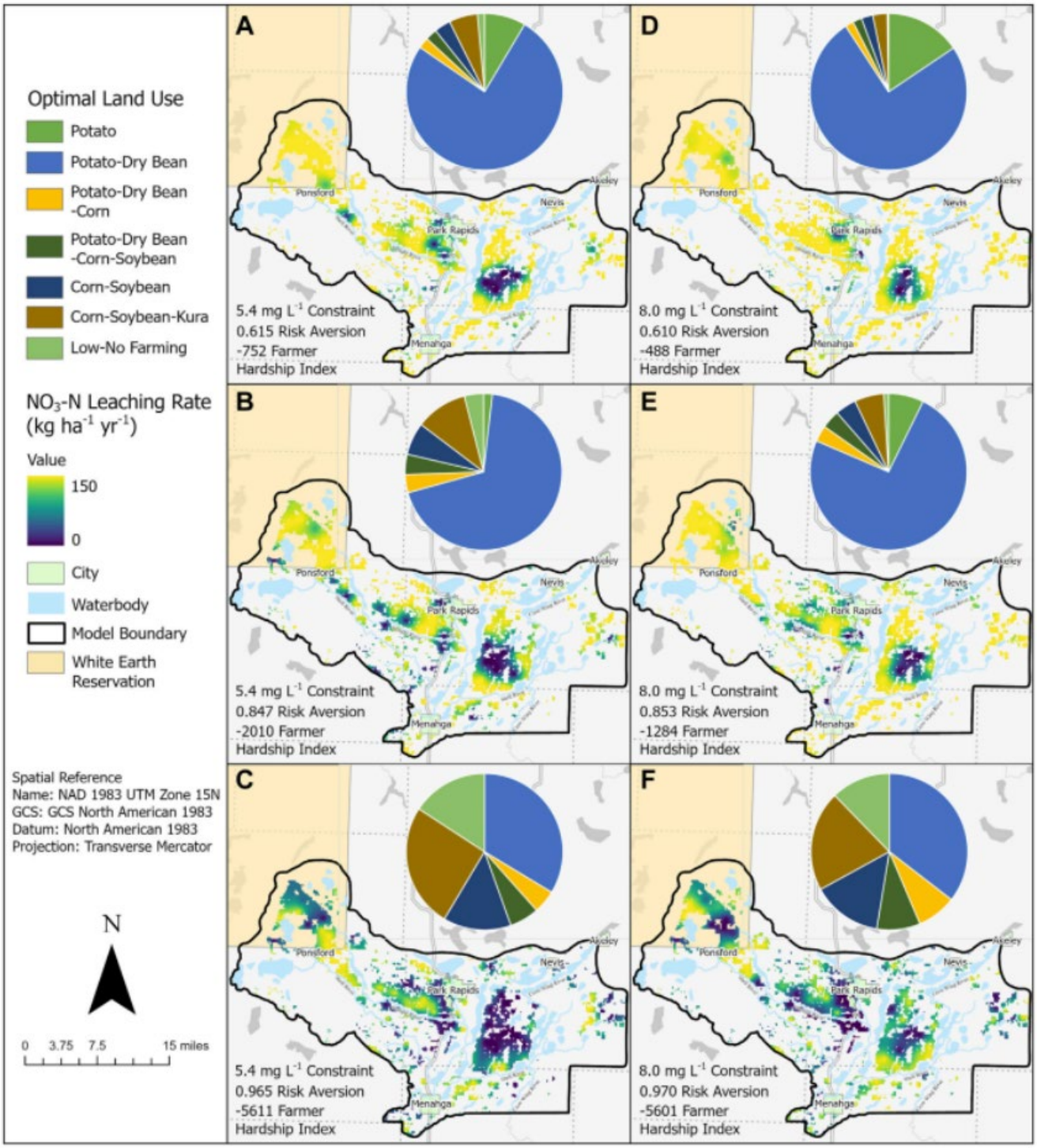

Figure 4: Optimization results of NO_3-N leaching rates for solutions indicated by diamonds from Figure 3. Land use pie charts for each solution are also depicted (Margarit et al., 2025).

Conclusion

The demonstration of the framework created in this study shows that constraint thresholds of NO_3-N for rivers and drinking water in the Pineland Sands Aquifer region can be made with farming management alterations. To lower NO_3-N leaching in the region, there are tradeoffs among the other objectives such as farmer hardship and risk aversion.

It is important to note that there are some limitations to the analysis. Because the groundwater model was made for steady state, NO_3-N concentrations are not changing over time. There is also some extra uncertainty included from averaging groundwater levels over time and denitrification calibration. Due to this, for future exploration, a transient model would be a good first step as well as the incorporation of ecosystem benefits. Further information on methodology remarks and uncertainties can be found in Margarit et al. (2025). The framework was made to be easily repeated and changed to include future changes in land use or different values.

This tool can be used for supporting decision-making and can allow for stakeholder input. Margarit et al. (2025) discussed how using a multi-criteria analysis method, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), could incorporate stakeholder preferences by assigning different weights of each objective based on constraint importance of stakeholders. For instance, local growers may put the importance of the economic objective higher than the environmental objective as compared to environmental or local government stakeholders. Borda score voting (Black, 1958) could then be used on the TOPSIS ranking results to give a winning solution with risk aversion, farmer hardship, and average decision variable NO_3–N values that can be inputted on a Pareto Front. This method would allow for a method for incorporating fairness between stakeholder input for management within a watershed.



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