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An Assessment Of The Influence Of Economic Drivers Of Land Use Change On Nitrate Concentrations In The Red River Of The North Basin

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AN ASSESSMENT OF THE INFLUENCE OF ECONOMIC DRIVERS OF LAND USE CHANGE ON NITRATE CONCENTRATIONS IN THE RED RIVER OF THE NORTH BASIN

by

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This thesis, submitted by Brent Silvis in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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This thesis is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

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Brent J Silvis
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ABSTRACT

In recent years there have been dramatic increases in crop prices, which would be expected to have resulted in greater production of crops and increased nitrates in surface water from increased use of fertilizer. The objective of this study was to test the hypothesis that changing crop prices influence crop production and, consequently, water quality. To do this, the study intended to identify changes in crop cultivation within the Red River of the North Basin, assess whether these crops have contributed to nitrate concentrations and identify how nitrate concentrations would be influenced by alternative economic scenarios. Requisite data were obtained including observed nitrate concentrations within the basin, historical farm economic and production data and physical data such as stream discharge. From these data, two models were developed, a land use – water quality model which identified relationships between the extent and type of crop and nitrate concentrations, and an economic – land use model which predicted land use under various economic scenarios. The projected land use under a specified economic scenario could then be provided to the land use – water quality model to assess how changing economic conditions related to nitrate concentrations in the Red River of the North Basin.

CHAPTER I

INTRODUCTION

Policy changes, such as the Energy Independence and Security Act of 2007 (EISA), have contributed to increased demand for ethanol and its feedstocks, primarily corn (Beckman et al., 2013). This increase in demand for corn has contributed to increases in corn prices, which have driven increased cultivation of corn crops in areas such as the extensively farmed Red River Basin of the North (RRB) (Lin et al., 2015). Corn requires considerable fertilizer inputs, such as nitrogen (Bierman et al., 2012). Studies have shown that surface waters in corn cropped areas tend to have higher concentrations of nitrates (Broussard and Turner, 2009).

The objectives of this study were to:

- Assess the change in land use in the Red River Basin from 2006-2014.
- Evaluate the influence of economic conditions, such as price increases, on land use, particularly the production of corn.
- Quantify the effect of land use, particularly corn cultivation, on nitrate concentrations in surface waters.

The Red River of the North

The Red River of the North (Figure 1) flows north through the states of South Dakota, North Dakota and Minnesota before entering Manitoba and eventually terminates at Lake Winnipeg (Lin et al., 2015). The U.S. portion of the Red River Basin (RRB) is approximately

9.2 million hectares, as delineated in this study, with a relatively low relief. The maximum elevation above sea level is 684 m and the minimum is 234 m (USGS, 2015a). The basin was once submerged beneath proglacial Lake Agassiz and, consequently, much of the area is clay and silt glacial till overlain with clay and silt lake deposits (Miller and Frink, 1984). The region experiences short summers and extremely cold winters, with an average January temperature of -18.3 ^{o}C and an average July temperature of 21.7 ^{o}C (Melesse, 2004). Approximately half of a meter of precipitation is received per year, mostly between April and September (Lin et al., 2015).

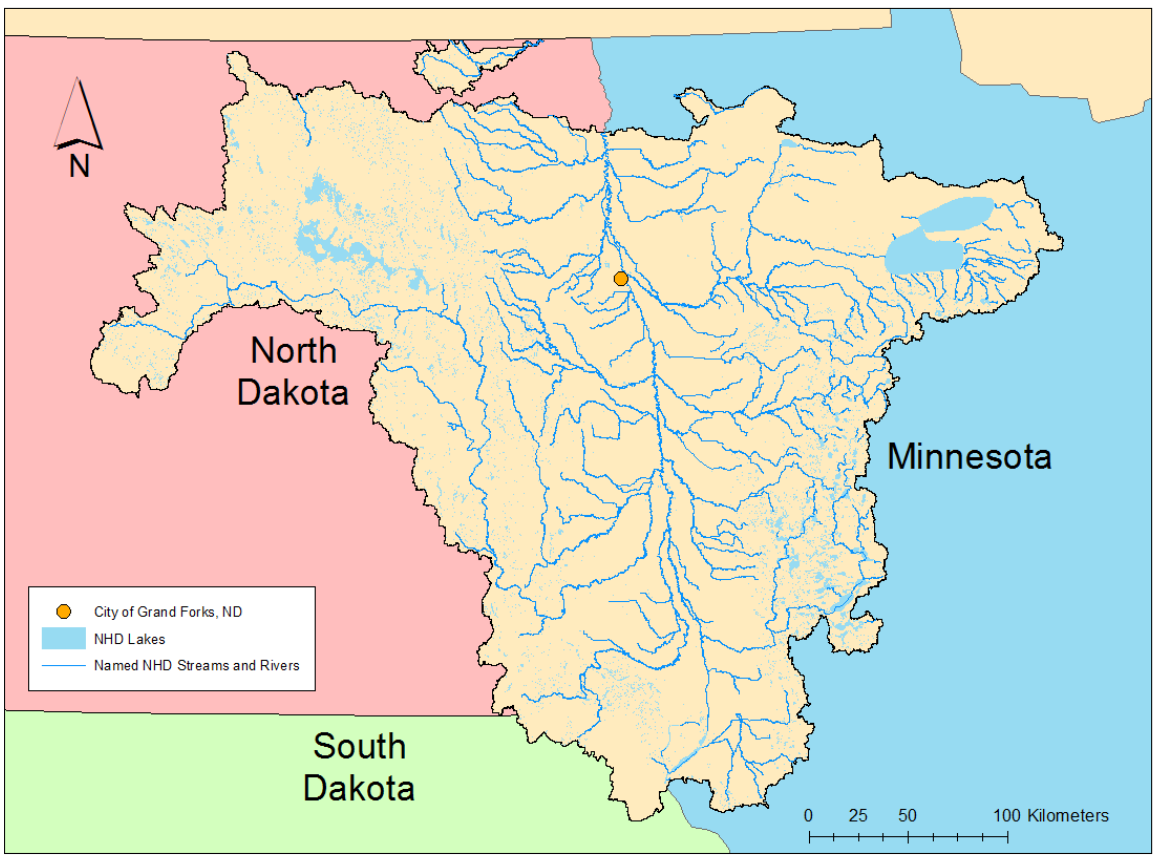


Figure 1. The Red River of the North Basin. The area of interest, as delineated in this study.

The RRB falls within the Prairie Pothole Region and, as one would expect, once contained numerous wetlands and prairies; many of which have been converted to cropland. In 2014 about 58% of the basin was cropland; 45% of that cropland was soybeans, 22% wheat and 17% corn, as identified by this study. The Red River Basin is sparsely populated, with a population of about 630,000 (excluding the city of Winnipeg), equivalent to about 14 people per square mile (Hearne, 2007).

An area of particular interest within the Red River Basin is Devils Lake. This terminal lake lies within a 9,800 km^2 (980,000 ha) basin in the northwest portion of the RRB (Kharel and Kirilenko, 2015). This basin comprises about 11% of the Red River Basin. The location and extent of the basin, as defined by The National Map, are shown in Figure 2. The lake is terminal until its surface reaches an elevation at which it spills into a tributary of the Red River, which did not occur during the period of land use and water quality assessment used in this study, 1997-2014 (Kharel and Kirilenko, 2015).

The Red River of the North provides an interesting study area for several reasons. It is heavily farmed which would be expected to influence nitrate concentrations in the area's surface waters. The region is suitable to a variety of crops including corn, which is the primary feedstock for ethanol in the United States. Policy and economic forces that impel ethanol production are suspected to have been some most influential drivers of corn production in recent years. Furthermore, the Red River of the North drains into Lake Winnipeg, which has experienced problems with algal blooms related to in increased loads of nutrients such as nitrates (Kling et al., 2011).

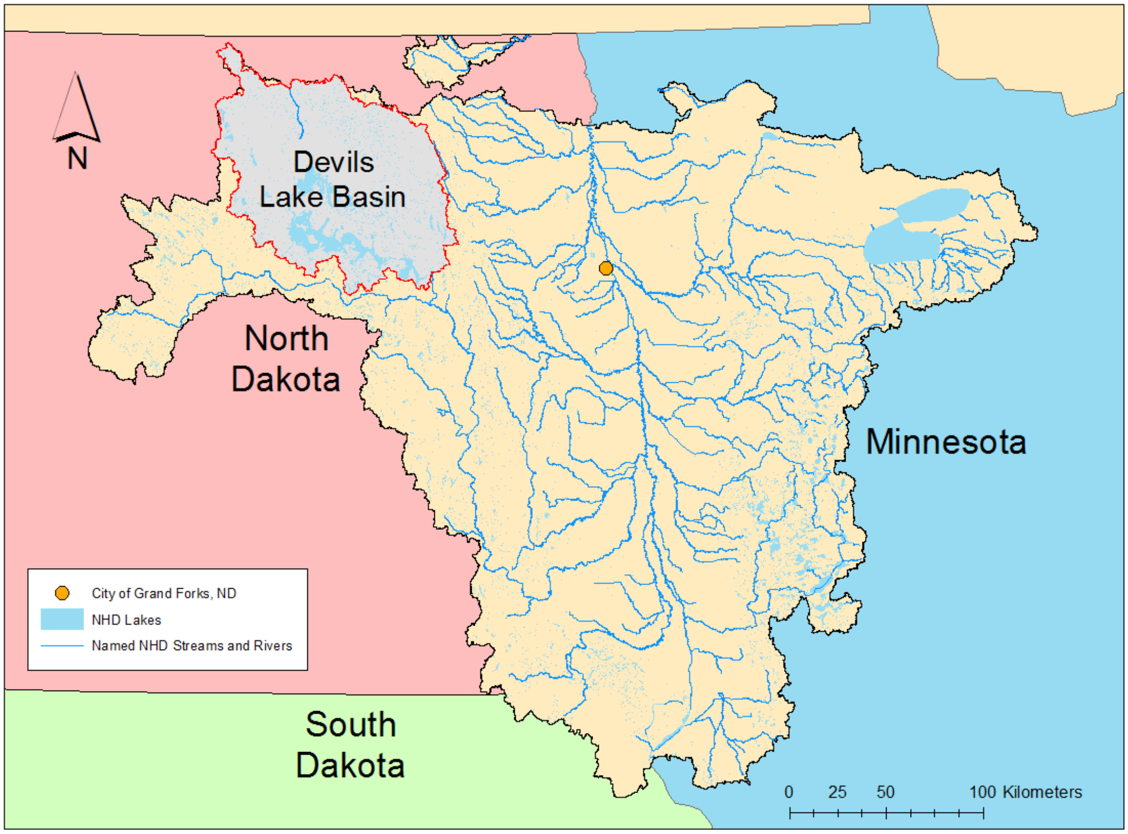


Figure 2. Location of the Devils Lake Basin within the Red River Basin.

Nitrates and Water Quality

Clean water is essential to humans in many different ways. It is the foundation of a healthy biosphere and provides many critical services. It is required for consumption, sanitation, industry and a range of other human needs. Many human activities can have a profound influence on both the quantity and quality of surface waters. An appreciation of the importance of clean water and healthy aquatic ecosystems has grown over the years, most notably with the Clean Water Act (CWA) of 1972. As a result, programs to monitor water quality and implement corrective actions when problems are detected have been developed.

Elevated concentrations of nitrogen in water can have adverse economic, health and environmental impacts. Among these are eutrophication, which is excessive growth of algae and cyanobacteria (Smil, 1997). As an example, Lake Winnipeg, into which the Red River drains, has seen a dramatic increase in algae since the 1960s (Kling et al., 2011). This can lead to anoxia (no oxygen) or hypoxia (low oxygen) which can have adverse impacts on biodiversity and fish populations (Vitouske et al., 1997). The Red River of the North contributed an average of 31,476,000 kilograms of nitrogen per year to Lake Winnipeg between 1999 and 2007 (Lin et al., 2015). Additionally, nitrates in drinking water pose a health hazard. The EPA has set a maximum allowable concentration of nitrate in drinking water of 10 mg/L (Mueller and Helsel, 1999).

This study is concerned with the specific effects of land use on the nitrates levels in surface waters. It has been shown that there is a strong positive correlation between nitrate loads in surface waters and the extent of agricultural land use (Lam et al., 2010). Agricultural land use in the states of Minnesota and North Dakota is substantial: in 2012 there were 21,597,136 and 27,147,240 respective acres of cropland (USDA, 2014a). Other potential land uses in the study area are pasture, forestry and conservation.

Nitrogen Cycle and Pathways

Nitrogen is a highly reactive element and, as such, moves quickly and easily through the environment in the form of several species (Peoples et al., 2004). Nonreactive nitrogen is dinitrogen gas (N_2), which is found in the atmosphere. Other atmospheric nitrogen species include the reactive inorganic species ammonia (NH_3), nitrogen oxides (NO_x) and nitrous oxide (N_2O) (Follett and Hatfield, 2001; Galloway et al., 2003; Peoples et al., 2004). Within soils can be found organic nitrogen, such as biomass and urea (CH_4N_2O), along with other inorganic species including ammonium (NH_4^+), nitrite (NO_2^-) and nitrate (NO_3^-).

Nitrification occurs when ammonia or ammonium are oxidized to nitrate, which can then move easily from the soils to surface waters by runoff or leaching through the soils (Baird, 1999). Atmospheric deposition also contributes a small amount of nitrate to surface waters; 5-10 pounds (2.3 – 4.5 kg) per acre per year in Minnesota (Lamb et al., 2014). Fluxes of nitrogen from surface waters include denitrification to the atmosphere or uptake by aquatic organisms (Galloway et al., 2003).

Nitrogen loss, for the purpose of this study, is the export of either applied or residual nitrogen, in the form of nitrates, from the soils to the surface water. Nitrate being the dominate nitrogen species in water, it is usually the species of interest in studies of nitrogen loss (such as Booth and Campbell, 2007; David et al., 1997; Tiemeyer et al., 2006). The rate of nitrogen loss is influenced by a variety of variables such as land use, slope, soil types and amounts and timing of precipitation (Randall and Mulla, 2001). The influence of these factors can be interrelated. For example, rains immediately after tilling or fertilizer application will likely produce greater nitrate loss (Power et al., 2001).

Studies have produced mixed results regarding the effect of these various physical variables. A study by Lam et al. (2011) found that groundwater is the primary flux of nitrates to the channel in lowland basins, defined as areas with “low flow velocity, a high groundwater table, and flat topography”, typical of this study area. Conversely, in a study in west-central Minnesota, it was found that very little nitrate is returned to surface water once it has reached the aquifer (Galloway et al., 2003). It is unusual to find studies which identify runoff as the primary pathway of nitrates from the landscape to surface waters. A study by Booth and Campbell

(2007) did use multivariate regression to develop a model nitrate to surface water flux which included a positive runoff variable and did not include a baseflow variable. That model had a coefficient of determination of 0.84. The coefficient of determination (R^2) is the amount of variance explained by a model, with 0 indicating no variance is explained, and 1.00 indicating that the independent variables fully account for the changes in the dependent variable (Helsel and Hirsch, 2002).

Sources of Nitrate in Surface Waters

Nitrate is very mobile and water soluble (Puckett, 1994). It most often originates from the nitrification (oxidation) of ammonia and ammonium by biological processes (Baird, 1999). Sources of ammonia and ammonium include:

- Ammonia applied to crops as fertilizer.
- Biological nitrogen fixation (BNF), in which bacteria convert dinitrogen to ammonia or ammonium (Johnson et al., 2005).
- Organic nitrogen from biomass and human and animal waste, is converted to inorganic ammonium by the enzyme urease (mineralization) (Follett and Hatfield, 2001).

Various studies have found that over 95% of nitrate export to waters originates from nonpoint sources (Schilling and Wolter, 2009; Lam et al., 2010). Nonpoint sources of nitrogen are those that have diffuse and numerous origins, such as fertilizer runoff, manure and atmospheric deposition (Puckett, 1994). Examples of point sources are septic systems and wastewater treatment plants (Schilling and Wolter, 2009).

Most modern agricultural operations rely heavily on the input of synthetic fertilizers to provide crops with necessary nutrients such as nitrogen. This nitrogen input has become critically important to meet the world’s food demand. To illustrate, the economically optimal input of nitrogen on winter wheat in Europe (192 kg N/ha) will produce 9.3 tonnes (tonne = 1000 kg, or about 2200 pounds) of wheat per hectare; without fertilizer, the wheat production would be 2.1 tonnes per hectare (Erisman et al., 2010). Without synthetic fertilizers, world food demand could not be met.

A result of all this additional nitrogen is elevated concentrations of nitrates in surface waters. Lam et al. found that basins with greater agricultural use had a positive correlation with average nitrate loads within the basin (r= 0.63), and basins with greater forest coverage had a negative correlation (r= -0.71) when regressing nitrate loads with percent land cover of eight different land use types within subbasins of northern Germany (Lam et al., 2010). In 1994, Larry Puckett, of the USGS, wrote “In watersheds that are largely agricultural, such as the Red River of the North in North Dakota and Minnesota and the Palouse River in Washington, nitrogen from commercial fertilizers accounts for 84 and 87 percent, respectively, of the total nitrogen added to the watersheds.” Stoner et al. (1998) also found that streams in the Red River Basin tended to have higher nitrate concentrations when they passed through heavily cultivated areas.

Crop Choice and Water Quality

A fundamental decision for farmers is the choice of crops. The conditions in the study area are conducive to a variety of crops, including grains, beans, vegetables, sunflowers, beets, potatoes and hay (USDA, 2014a). Projected prices and actual prices paid fluctuate annually and a farmer’s crop choice is influenced by this. Additional considerations will include the use of fertilizer, tillage, cover crops, crop rotation and the selection between perennial and annual crops.

Crop choice has a major influence on nitrogen retention or loss. Some crops, such as corn and wheat, require high levels of nitrogen input. For example, harvesting 250 bushels of corn will result in the removal of approximately 175 pounds of nitrogen (Lamb et al., 2014). If yields are to be maintained, this nitrogen will need to be returned to the soil, usually by application of synthetic fertilizers. Others crops, particularly alfalfa, do not require nitrogen input and instead contribute to an increase of the available nitrogen in the soil. To illustrate, South Dakota State University recommends the following unadjusted rates of nitrogen application: 0 lbs. per bushel of alfalfa, 1.2 lbs. per bushel of corn, 0 lbs. per bushel of soybeans and 2.5 lbs. per bushel of wheat (SDSU, 2005).

Obviously, greater nitrogen export will occur in fields which are heavily fertilized (Lam et al., 2011). Numerous studies have explored this relationship and found that nitrate losses are highest in fields planted with continuous corn, lower with fields planted in soybean and corn rotations and lowest when planted with alfalfa, a perennial legume (Randall and Mulla, 2001). A Minnesota study found that total nitrate loss in tiled fields over a four year period was 217 kg/ha when planted with continuous corn and 7 kg/ha when planted with alfalfa (Randall and Mulla, 2001).

Management Practices and Water Quality

There are a variety of land management techniques which can influence rates of nitrogen export. In addition to choice of crop, managers can vary fertilizer type, quantity, and timing and method of application, choose from various tilling techniques, elect to use tiling or irrigation or adopt any of a range of "best management practices" (BMPs), or alternative farming practices, which are intended to minimize inputs and preserve or enhance ecosystem services. The University of Minnesota Extension provides a variety of references detailing BMPs relevant to the study area (Bierman et al., 2012) and the scientific literature contains examples of many studies which investigate the effectiveness of these practices. Some common alternative farming practices include the use of cover crops, crop rotation, buffer strips and reduced tillage.

Alternative farming practices, such as those that employ less synthetic fertilizers, can reduce nitrate export to waters. Oquist et al. (2007) found that alternative practices resulted in 8.2 mg of nitrate-nitrogen per liter discharge in tile flow compared to 17.2 mg per liter when conventional practices were used and a study in Norway found similarly that 42% more nitrogen was lost under conventional methods than alternative practices in a tiled study. The choice to explore alternative practices may be due to personal values, policies that promote such practices or economic drivers, such as increases in fuel and fertilizer costs (Beckman et al., 2013).

Cover Crops

Cover crops can be used as an alternative to leaving fields fallow after harvest. These crops can reduce erosion, potentially replenish lost nutrients by facilitating processes such as nitrogen fixation and reduce the amount of nitrate leaching by nitrogen uptake during the months between harvest and planting (Kaspar et al., 2012). One study found that nitrate leaching decreased about 80% when rye cover crops were used after harvesting corn (Di and Cameron, 2002) and another study in Minnesota found an 11% decrease in nitrate loss (Strock et al., 2004).

Crop Rotation

Crop rotation is a commonly used strategy for nutrient management. Typically this involves following plantings of high nitrogen demand crops such as corn and wheat with nitrogen fixing crops like soybeans and alfalfa. Over a four year period, annual average nitrate losses in Minnesota under four cropping systems found the highest nitrate loss in fields planted in continuous corn and the lowest in fields planted in alfalfa, as illustrated in Table 1 (Randall and Mulla, 2001).

Table 1. Annual nitrate loss over a four year period under different crop rotations. Data source: Randall and Mulla, 2001

Crop system	Average annual nitrate loss (mg/L)
Continuous corn	32
Corn-soybean	23
Soybean-corn	26
Alfalfa	2

Buffers

Buffers are areas left to native vegetation in sensitive areas, particularly near water features. This vegetation can provide filtration of pollutants before they enter surface water (Vigerstol and Aukema, 2011). This is accomplished through denitrification within the anaerobic soils, by reducing the velocity of surface flow which allows nutrients and sediments to precipitate and through various biological mechanisms including uptake of nutrients by the plants in the buffer (Lam et al., 2011). The modeled influence of the addition of a ten meter buffer to a study area was a 12.9% reduction in nitrogen output (Lam et al., 2011). When comparing the denitrification potential of soils in restored buffers to agricultural land, it was found that the buffers were capable of denitrifying 42.4 ng N per grams of soil per hour and agricultural soils were able to denitrify only 5.3 ng N per grams of soil per hour (Marton et al., 2014).

Tilling

There are a variety of tilling techniques available, including moldboard, chisel, contour, ridge and no-till. Although no till farming is commonly perceived as an alternative practice with less environmental impact, various studies have produced mixed results regarding the impact on nitrate export (Randall and Mulla, 2001; Lam at al., 2011). This seems particularly true of lowland catchments, where runoff is not the primary pathway to the channel (Lam et al., 2011). Some studies have even observed increased nitrogen loss in untilled fields, possibly due to greater porosity within the soil (Di and Cameron, 2002).

To summarize the extent and impact of farming practices within Minnesota, Table 2 draws from various sources to provide a very brief overview of the more common alternative practices in the study areas and their evaluated influence on nitrate reduction. Crop rotation is the most widespread practice, although this has likely declined due to the biofuel industry's demand for corn (Stern et al., 2012). It appears that cover crops offer the greatest potential for reduced nitrate loss. The assessed impact of the various practices can vary considerably between studies. It can be expected that the effectiveness of these practices is influenced by things such as soil type, precipitation, topography and other variables. The extent to which these practices are utilized varies as well. The profitability of a practice will contribute greatly to its popularity and the profitability can be influenced by factors such as government incentives and cost savings due to reduced inputs.

Table 2. Examples of findings of various studies regarding the prevalence and effectiveness of some alternative farming practices.

Practice	Prevalence	Nitrate reduction
Buffers	11.9% (Napier and Tucker, 1999)	12.9% (Lam et al., 2011)
Cover crops	5.1% (Singer et al., 2007)	11-80% (Strock et al., 2004; Di and Cameron, 2002)
Crop rotations	80.4% (Napier and Tucker, 1999)	28% (Randall and Mulla, 2001*)
No till	5.2% (Napier and Tucker, 1999)	5% (Randall and Mulla, 2001)

*adapted from Table 1 (difference between continuous corn and corn-soybean rotation).

Fertilizer and Nitrogen Management

The application of synthetic fertilizer on cropland provides a source for nitrogen export to surface waters. The type, timing and amount of this application are important factors. University of Minnesota Extension and South Dakota State University provide nitrogen fertilizer guidelines (Table 3). However, neither resource contains guidelines for all the common crops within the study area. The UMN guidelines rely heavily on soil testing, and the recommendations are for nitrogen application. The SDSU guidelines are more useful, as they provide recommendations for soil nitrogen content. Contributing to the variability of the guidelines, the suggested nitrogen application and content are adjusted for considerations such as expected yield and soil properties.

Table 3. Nitrogen application and soil content recommendations. NDSU data source: Franzen, 2013. UMN data source: Kaiser et al., 2011. SDSU data source: Gerwing and Gelderman, 2005.

	NDSU Soil Content Recommendation (lb/acre)	UMN Application Recommendation (lb/acre)	SDSU Soil Content Recommendation (lb/acre)
Corn	90-240	0-150	96-240
Sugar Beets	130	0-130	no recommendation
Soybeans	0	0-75	0
Sunflowers	50-125	no recommendation	50-150
Canola	65-150	0-70	65-162
Alfalfa	0	0-30	0
Wheat	0-250	0-170	75-250
Dry Beans	40	0-120	50-150

It is intuitive that greater amounts of applied nitrogen will result in greater nitrogen export. However, the relationship is not strictly linear. Di and Cameron (2002) found that the rate of potentially leachable nitrogen (N_{PL}) to nitrogen leached (N_L) was

$$N_L = 0.000143(N_{PL})^2 - 0.0229(N_L)$$

indicating that, once a threshold is reached, the rate of loss increases at a greater rate than the rate of application (R^2=0.95). When considering the cost of fertilizer and the point of diminishing returns of application, it can be seen that the profit-maximizing application of fertilizer may not be the quantity that maximizes yield (Lam et al., 2011).

The timing of nitrogen application can also influence yield and nitrogen loss. In a study comparing four tiled corn fields treated with identical amounts of fertilizer over four years, those fields with spring fertilizer application showed the least nitrate loss (177 kg/ha) (Randall and Mulla, 2001). Fall application resulted in the highest nitrate loss (264 kg/ha) and lowest crop yield (8.0 Mg/ha) (Randall and Mulla, 2001). Bierman et al. (2012) surveyed Minnesota corn farmers regarding their use of nitrogen fertilizer in the 2009 growing season. It was found that in northwest Minnesota, where much of the Minnesota portion of the study area lies, 89.2% of farmers apply their primary nitrogen application in the spring, 10.8% in the fall and none as sidedressing.

Additional information regarding the type and quantities of fertilizer used in the study area is not readily available. Some studies have used the type and quantity of fertilizer sold in their respective study area as a variable in water quality models (Randall and Mulla, 2001), but these data are usually available for a fee from entities such as The Fertilizer Institute and these data were not obtained for this study. Some fertilizer sales data were obtained for Minnesota, but the author was strongly cautioned against its use since the method of data collection changed over time and the quantity of fertilizer sold in a given area did not seem indicative of the quantity used (Bruening, 2015).

Subsurface Drainage and Irrigation

The study area generally receives sufficient rainfall to produce crops without the use of irrigation. In 2012 only 2% of Minnesota farm lands and less than 1% of North Dakota farm lands were irrigated (USDA, 2014a). In fact, much of the study areas falls within the prairie pothole region, an area heavily interspersed with wetlands, and the region is prone to spring flooding. Of greater interest than irrigation is the need to drain excess water from farmland through the use of subsurface drainage tiles, or “tiling”.

Tiling is a poorly regulated and inadequately studied practice of draining wetlands or areas of field which are too wet to cultivate. Tiling reduces the residence time of water within the soil, thereby facilitating transport of nitrates (Lam et al., 2010; Oquist et al., 2007). The rate of this nitrogen loss is influenced by crop and soil types and amounts and timing of precipitation (Randall and Mulla, 2001). Even in fallow fields with tiling and no nitrogen applied, elevated nitrogen losses can occur when wet years followed dry years. A field in Minnesota, which was left fallow and unfertilized for three dry years, was found to export nitrogen at an average rate of 57 mg/L when the fourth year experienced normal precipitation (Randall and Mulla, 2001). In Minnesota, subsurface drainage occurs mostly during the months of April through July and a study in southwest Minnesota found that 70% of nitrate loss occurs in April, May and June (Oquist et al., 2007).

Approximately 30% of Midwest cropland is tile drained (Power et al, 2001). One estimate of tile drainage in the counties within the study areas is about 5% tiling (Sugg, 2007). However, this estimate is based on soil characteristics and 1992 crop area data and would not reflect changes in area cultivated since then. Since there has been an increase in area cultivated, much of which may have occurred in marginal areas that may have required drainage, this is likely a significant understatement of the actual area drained. The shortage of data regarding this practice may preclude close scrutiny of its impact on nitrate loss.

Farmers' Decision-Making

Landowners and land managers are regularly faced with the decision of how to utilize the land. Within the Red River of the North Basin, the primary options available to them are to devote their land to some type of agricultural use or conservation. Ribaudo (2008) averred that land managers will nearly always use the land in a manner that maximizes their profit.

Using the information available, farmers will consider expected costs and benefits and calculate how to use their land to generate the greatest returns. Generally, land will be used in a way that maximizes income, such as choosing the most profitable crops based on price projections, and minimizes expenses, such as adopting a new farming technique that minimizes the application of fertilizer. A general formula showing the relevant considerations when deciding on optimal land use is below, where price is the per unit market price of a particular crop, yield is the farmer's expected yield for that crop in a particular parcel, cost is the per unit area direct cost associated with producing that crop and policy instrument denotes a tool, such as a tax or subsidy, intended to influence farmers' decisions.

$$profit = price * yield - cost +/- policy\ instrument$$

The farmer's objective is to maximize returns. Price is the expected market price for a crop. Yield is the attainable product per area, based on such things as soil, climate and fertilizer input. Direct costs can include inputs such as fuel, fertilizer and labor. With maximizing returns as the primary objective of land managers, their decisions will be contingent upon matters of cost, price and yield.

To illustrate some relative considerations, Figure 3 shows economic data for the period 2005-2012. It can be seen that, overall, crop prices increased nationally until 2012, after which they began to decline (University of Illinois, 2016). Also displayed, representative of a fairly volatile direct cost consideration for farmers, is the fertilizer index. The value of the index is the cost of fertilizer relative to 2011 costs (Gould, 2015). Prices and costs tend to follow the same trend. This type of information is relevant to land managers when deciding whether to cultivate their land, which crops to plant and which management practices to use.

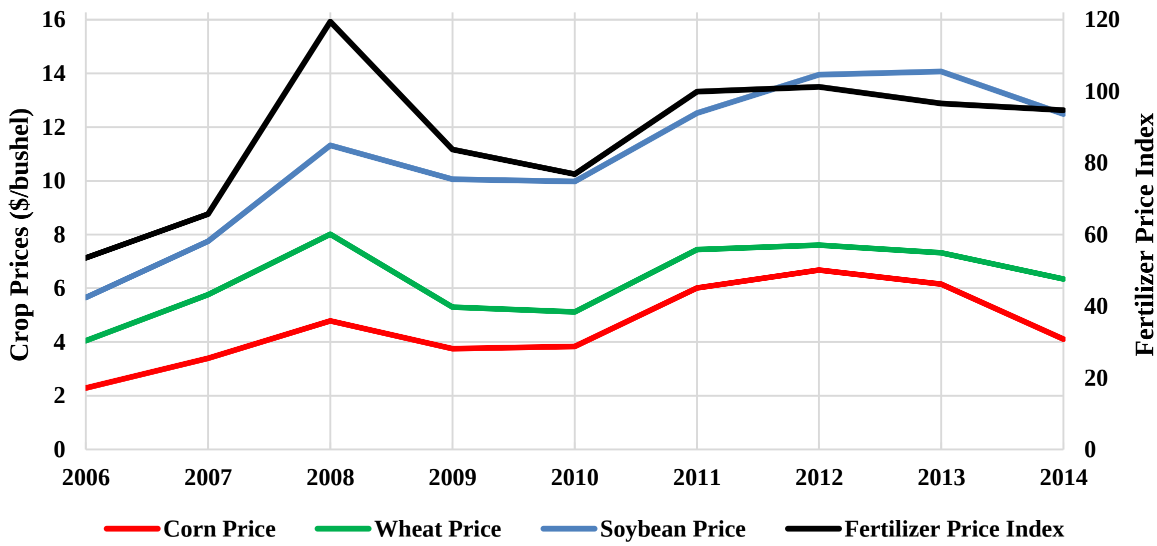


Figure 3. Changes in annual national crop prices and fertilizer index, 2006-2014. Crop price data source: University of Illinois, 2016. Fertilizer cost data source: Gould, 2015.

Ethanol

A number of recent market and economic forces have led to increased domestic production of ethanol. Ethanol is often perceived as being more environmentally friendly than fossil fuels and provides a domestic alternative to foreign oil. Probably the most significant policy that has driven ethanol production is the Energy Policy Act of 2005 (EPAct), which was amended with the Energy Independence and Security Act of 2007 (EISA). The EISA has a stated goal that 36 billion gallons of renewable fuels be produced per year by 2022 (Wu et al., 2012), compared to the 4.9 billion gallons of production in 2006 (USEIA, 2016a).

Figure 4 shows the mandated ethanol production from conventional sources, primarily corn (USEPA, 2015b). The maximum required volume of production from this source will have been reached in 2015. Generally, production has met the requirements of the mandate.

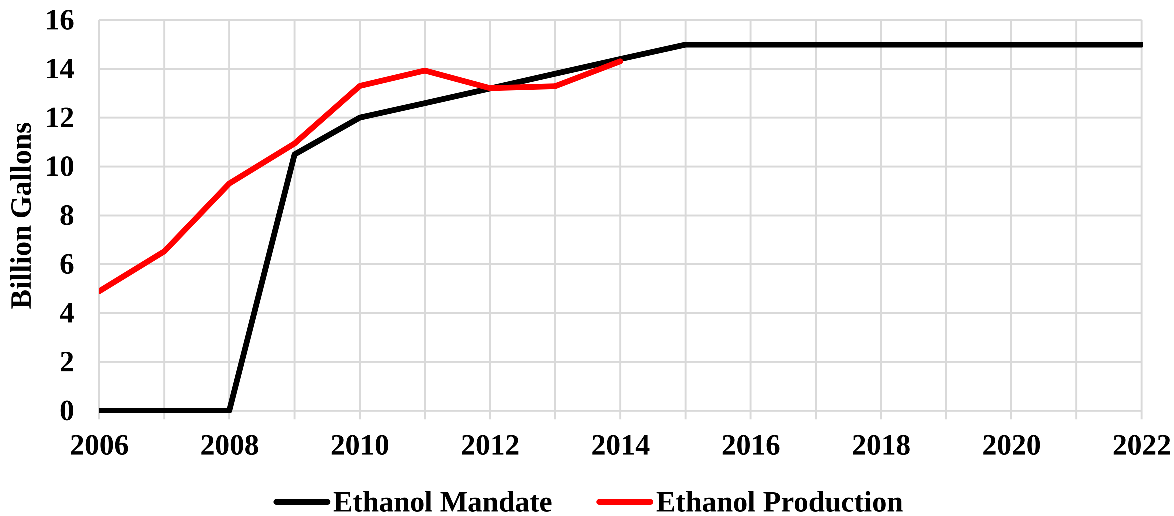


Figure 4. U.S. production of ethanol by year, 2006-2014, and production mandated by the EISA, 2009-2022. Mandate Data Source: USEPA, 2015b. Production Data Source: USEIA, 2016b.

The Role of Economics and Markets in Land Use Decisions

Corn is the primary feedstock of ethanol in the United States (Wu et al., 2012). 42 percent of U.S. corn production in 2012 was appropriated by ethanol production (Beckman et al., 2013). The mandated increase in ethanol production has created increased demand for corn, resulting in higher corn prices and greater cultivation of corn, which can impact water quality.

This impact of policies promoting biofuels is important. One study found that a scenario of increased corn production due to biofuel feedstock demand resulted in a one hundred percent increase in nitrate loads (Love and Nejadhashemi, 2011).

Figure 5 shows how U.S. corn prices changed over the period 2006-2014, compared with U.S. ethanol production. Prices followed production until a sharp price decline in 2009, corresponding with the recession. Prices gradually recovered, reaching a record high in 2012, before declining again. The 2013 price decline has been partially attributed to overproduction, perhaps in response to 2012 prices (Good, 2013).

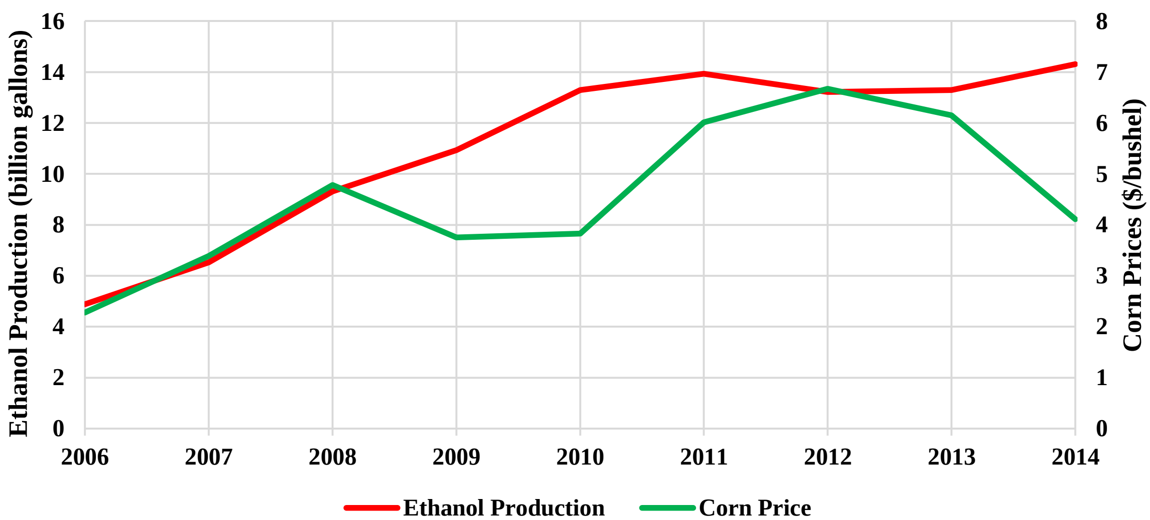


Figure 5. U. S. production of ethanol by year and national corn prices. Production Data Source: USEIA, 2016b. Corn price data source: University of Illinois, 2016.

It seems, when viewing Figure 5, that corn price is, at least to some extent, influenced by ethanol production. It is likely that this increase in corn price has resulted in an increase in corn production. Figure 6 shows the change in national corn prices compared to changes in regional corn production from 2006-2014. Increases in corn prices may have very likely influenced farmers' decisions to produce additional corn. It appears that prices and production are closely related and price may very well drive production.

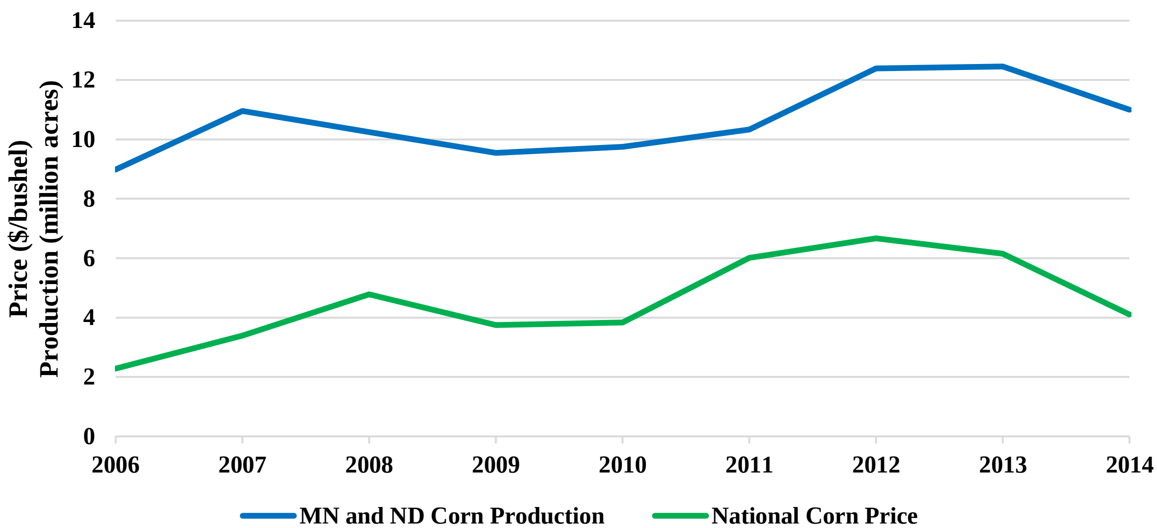


Figure 6. National corn prices and Minnesota and North Dakota corn production, 2006-2014. Corn price data source: University of Illinois, 2016. Corn production data source: USDA, 2015a.

Corn was not the only product that experienced large price increases. Figure 3 shows that the prices in the major crops tend to move in tandem. A simple explanation for this would be that an increase in one crop elicits an increase in production of that crop, resulting in decreases in production of other crops. This creates a short-term shortage of the other crops, driving up their prices. So an increase in the price of any crop can result in more aggressive cultivation of all crops. Between 2001 and 2012 the prices of all major field crops rose 40 percent, indicating there were macroeconomic influences other than ethanol affecting markets (Beckman et al., 2013).

There are certainly other policy and economic drivers of land use change. Two dominant influences are the farm subsidies and the Conservation Reserve Program (CRP). Farm subsidies take a variety of forms, but the two most significant types are direct subsidies and counter-cyclical subsidies (Broussard et al., 2012). Direct subsidies would not be considered to directly influence land use in a given year since they are based on historical land use, not current land use (Broussard et al., 2012).

Likewise, counter-cyclical subsidies are only paid when crop prices fail to reach their target price (Plato et al., 2007), which, given the rapid increase in crop prices (Figure 3), has not been the case in recent years. National counter-cyclical payments for all crops fell from over four billion dollars in 2006 to zero in 2012 (EWG, 2016b). In spite of this decrease in payments, crop production continued to increase. Likely, in recent years farmers have not been incentivized to produce crops with the expectation of receiving a counter-cyclical payment, but the existence of this program reduced the risk of growing crops covered by the program. This would make the cultivation of covered crops such as corn, soybeans and wheat more attractive and discourage the cultivation of crops which are not covered by the program, such as dry beans and alfalfa (Broussard et al., 2012).

The Conservation Reserve Program is a federal program which compensates farmers for removing environmentally sensitive land from crop production (Johnston, 2014). These types of conservation programs have been found to be associated with lower nitrate loss (Booth and Campbell, 2007). However, to incentivize farmers to leave their land in the program, CRP payments must be competitive with expected returns from crop production. With recent increases in crop prices, CRP enrollment has declined despite increases in per acre CRP payments (Figure 7). From 2006 to 2014 per acre CRP payments in Minnesota have increased

35% per acre, yet acreage in enrollment has declined 27% (USDA, usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index). The CRP program is becoming a less significant driver or deterrant of land use change as its payments are not competitive with crop prices (Johnston, 2014).

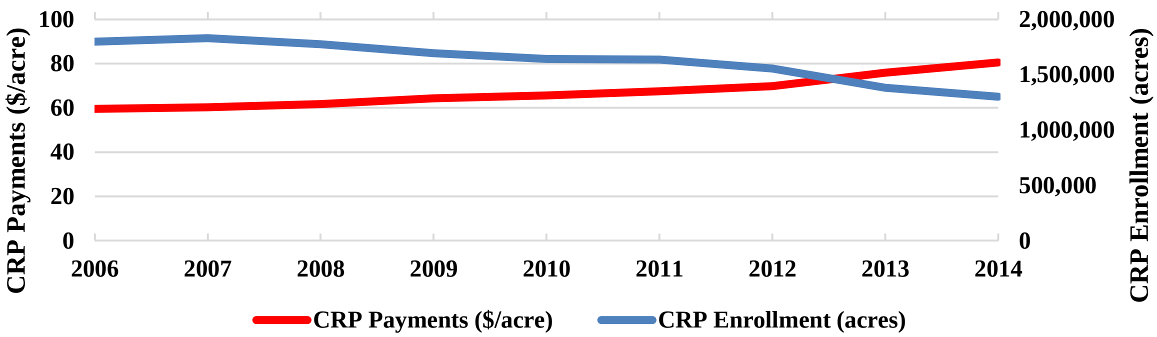


Figure 7. Minnesota CRP payments and enrollment, 2006-2014. Data Source: USDA, 2016a.

It can be seen that there is compelling justification for suspecting that increased production of ethanol, despite a stated purpose of environmental preservation, contributes to aggressive agricultural production, which likely has adverse environmental impacts. Indeed, studies that have attempted to forecast the impact of these mandates have found that these policies will drive land use change in the study area (Li et al., 2012) and increased nitrates in waterways can be expected (Donner and Kucharik, 2008).

Assessing the Influence of Economics on Land Use and Water Quality

It can be seen that policies, such as ethanol production mandates, which incentivize agricultural production by creating demand for agricultural products can influence land use and, consequentially, water quality. This study first assessed how land use has changed during the period of interest, 2006-2014. A model was then developed, identifying the relationships between land use and water quality. Potential crop yields within the study area were identified and, with economic scenarios generated from historical crop prices and direct costs, used as inputs in a simple economic model. The land use-water quality model was used to calculate nitrate loads in surface waters based on the projected land use generated by the economic model under scenario-defined economic conditions. This analysis will provide a better understanding of how changing economic conditions can impact water quality.

CHAPTER II

METHODS

The objectives of this study were to:

- Assess the change in land use in the Red River Basin from 2006-2014.
- Evaluate the influence of economic conditions, such as price increases, on land use, particularly the production of corn.
- Quantify the effect of land use, particularly corn cultivation, on nitrate concentrations in surface waters.

To meet these objectives, it was decided that, first, the area of interest would be delineated. Next, land use within the study area and changes in land use over time would be assessed. Two models would then be developed: a model which identified the relationships between economic conditions and land use and a model which identified the relationships between land use and nitrate concentrations in surface water. Finally, economic scenarios would be created which would be provided as inputs to the economic – land use model, the results of which would be provided as inputs to the land use – water quality model to assess the influence of economics on nitrate concentrations.

A flow chart depicting the steps above is shown in Figure 8. The first step shows that requisite land use and economic data are obtained and a regression analysis of the data is performed to determine the relationships between the variables. The second step shows that historical land use and nitrate observations are obtained and a regression analysis is performed.

The third step shows that economic scenarios are developed and provided as inputs to the economic – land use and land use – water quality models to predict nitrate concentrations due to the defined economic scenario.

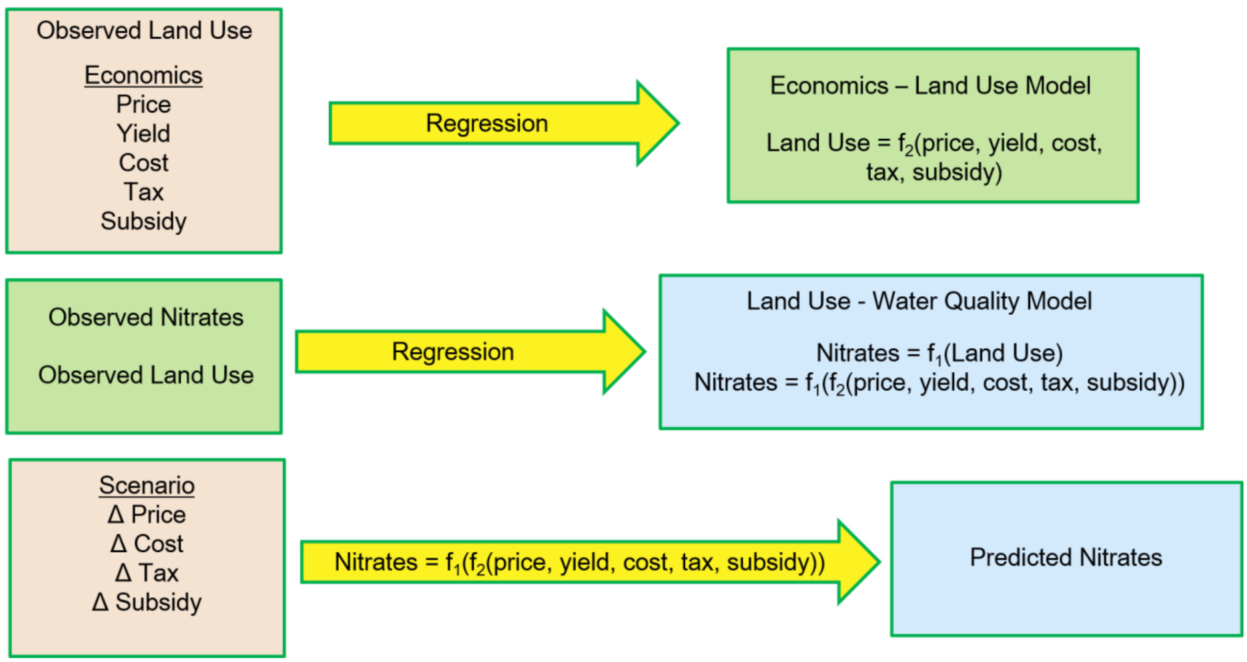


Figure 8. Flow chart of project methodology.

Table 4 identifies the data used in the analysis described above and the data source. Detailed information regarding the sourcing and processing of data is available in the "Data" section of this report.

Detailed methodology is provided below. All geospatial analyses were performed in ESRI ArcMap 10.2, using NAD_1983_UTM_Zone_14N projection and NAD83 datum. Statistical analyses were performed either in R version 3.2.1 or Excel 2013. Variable significance was evaluated at α=0.05.

Table 4. Data and data sources used in this study.

Variable	Source
Crop Price	University of Minnesota FINBIN
Crop Direct Cost	University of Minnesota FINBIN
Land Use	Cropland Data Layer, USDA
Crop Yields	National Agricultural Statistics Service (NASS), USDA
Crop Productivity Index	Soil Survey Geographic Database (SSURGO), USDA
Nitrate Concentrations	STOrage and RETrieval (STORET), EPA
Stream Discharge	National Water Information System (NWIS), USGS
Stream Length	National Hydrography Dataset (NHD), USGS
Basin Area	ArcSWAT delineation
Wetland Area	National Wetland Inventory (NWI), FWS
Point Source Discharge	Discharge Monitoring Report Pollutant Loading Tool, EPA
Tiling Area	USGS

Correlation Analysis

Correlation analyses of variables were performed using the R software package. This was a means of preliminary data exploration, to identify trends and relationships in the data. Some of the correlation analyses performed include comparisons of the area previous year's and current year's land use by crop type, comparisons of nitrate concentrations and area of land use and comparisons of nitrate concentrations and hydrological variables such as stream length and discharge. The relationships of previous and current years' crop areas were evaluated in consideration of the possibility that there was time lag in the influence of land use on water quality. The results of these analyses were then consulted when selecting variables for construction of the land use and water quality model. The results of the correlation analyses were also useful in interpreting the results of the regression analysis.

Regression Analysis of Water Quality and Independent Variables

Multivariate regressions were performed on independent variables and the dependent variable, observed nitrate concentrations in streams. This technique had been used in previous studies including Broussard and Turner (2012), Jordan et al. (1997) and Schilling and Libra (2000). The independent variables included area cultivated in various crop types, stream discharge, stream length, area of drainage basin, area of wetlands, area of subsurface drainage and point source discharge data. An exhaustive series of stepwise multiple linear regressions were performed. This involved progressively adding independent variables to identify the model that produced the best of fit of independent variables to dependent variables. The purpose of this regression analysis was to identify a statistical relationship between land use, particularly the cultivation of corn, and nitrate concentrations and develop a predictive model of water quality, based on various land use scenarios.

The results section provides details about the influence of each additional variable on the model. Since land use, particularly the cultivation of corn, was the focus of this study and the independent variable of greatest interest, land use variables were added to the regression first. The corn variable was first regressed with the nitrate concentrations, followed by the other crop variables in the order of the strength of their correlation with the nitrate variable, from greatest to least. The order in which crops were added to the regression is corn, beets, soybeans, sunflowers, canola, alfalfa, wheat and dry beans.

Next, the discharge variables were added to the regression, since this variable is frequently included in water quality analyses and plays an important role in the export of nitrates. Stream length, basin area and wetland area variables were next added to the regression, because of their expected influence on hydrology and nitrate cycling and/or transport. The last variables to be included in the regression were the point source and tiling variables, because inclusion of these variables resulted in smaller sample sizes; a reduction from 3402 to 2444 in the case of points sources and 3402 to 1211 in the case of tiling. Sample size is the number of observations used in a regression. Larger sample sizes produce more precise results.

As variables were added to the regression, insignificant variables which were detrimental to the overall fit of the model were removed. These variables would be reintroduced to the model with the addition of each new variable to assess if their relationship with the independent variable had changed. The best fit model was identified as that regression which produced the best fit, as measured by the coefficient of determination. For multiple regressions, the adjusted coefficient of determination was assessed.

Assumptions of Regressions and Transformations of Variables

The purpose of the analysis of the dependent nitrate data and independent variables was to identify a relationship between the dependent and independent variables and to develop a predictive model of nitrate concentration based on land use scenarios. For a regression to produce reliable results the residuals must comply with assumptions. Two important assumptions when assessing hydrological data are homoscedasticity (constant variance) and normally distribution (Hirsch et al., 1991).

One of the more important assumptions is that of normality, which is often violated in hydrological data (Hirsch et al., 1991). To avoid distorted results when performing a parametric regression test, the residuals of the results should be assessed for normality by checking for skew or outliers (Osborne and Waters, 2002). Homoscedasticity, a measure of the consistency of variance of an independent variable from its predicted value across the range of independent variable values, is another important assumption of regressions (Osborne and Waters, 2002). Violating homoscedasticity could contribute to a statistical test's incorrect rejection of a null hypothesis (Osborne and Waters, 2002). Homoscedasticity can be checked by viewing the pattern of residuals around the best fit line of the regression. Statistical studies can only produce credible results when the assumptions of the tests used are verified.

Preliminary simple linear regression analyses were performed with the dependent variable, nitrate concentration, and the independent variables. An example of such regression is that of the independent variable corn, expressed as the percent area of each gauge drainage basin planted in corn the previous year, versus the dependent variable, nitrate concentration observed within that gauge drainage basin, which can be expressed as:

*nitrate (mg/L) = m * relative area of previous year's corn + b*

The results of these regressions were assessed to determine if the assumptions of linear regressions, particularly normality, were met using the Breusch–Pagan test. In all cases, the histograms showed a strong right skew. An example of a histogram of the residuals of the regression with previous percent area of corn is shown in Figure 9. It can be seen that the variables and the residuals of the analysis all exhibit strong right skew. The assumption of homoscedasticity is met, as shown in the spread level plot.

Various transformations were attempted and it was found that the assumptions of linear regression were best met with a logarithm base 10 transformation of the crop and nitrate variables. Figure 10 shows an example of a histogram of the residuals of a simple linear regression of transformed nitrate and previous year's percent area of corn. A logarithmic transformation is common when working with hydrological data (Helsel and Hirsch, 2002; Hirsch at al., 1991; Schilling and Lutz, 2004). All variables were logarithm base 10 transformed for analysis in this study.

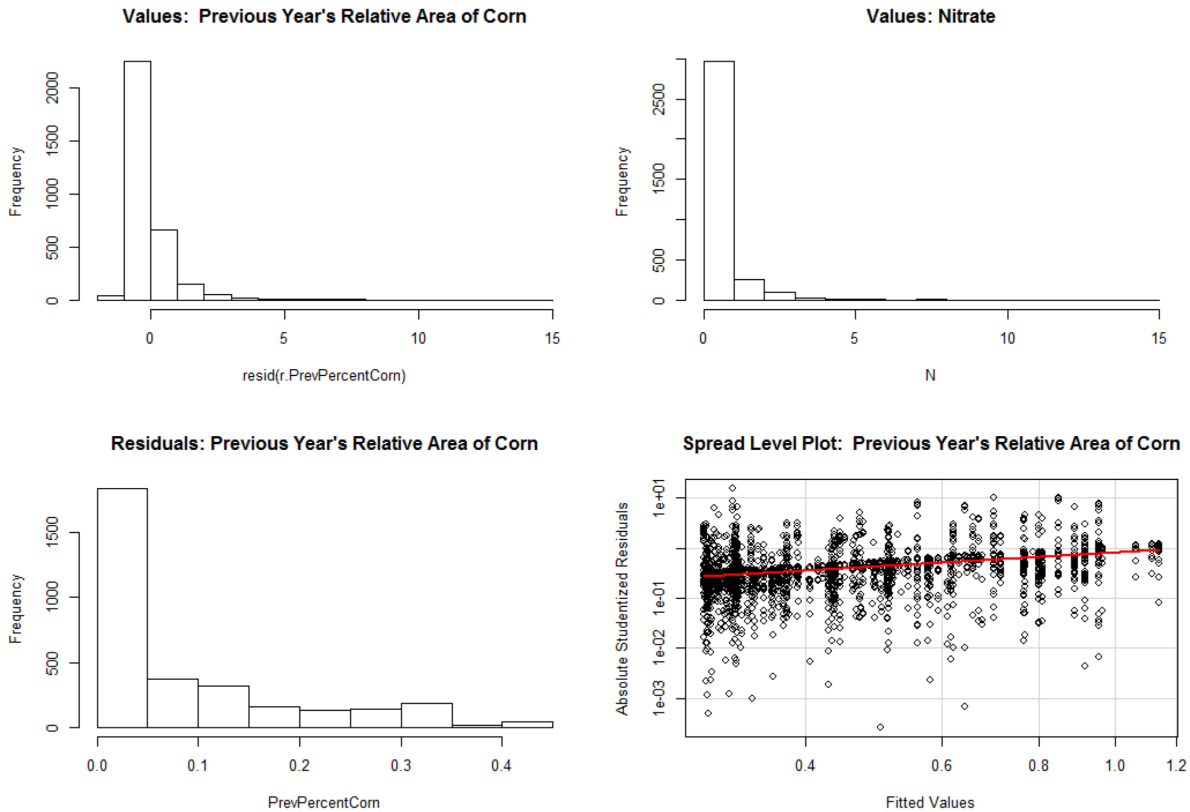


Figure 9. Example of assumption tests of regression results. Histograms display a strong right skew.

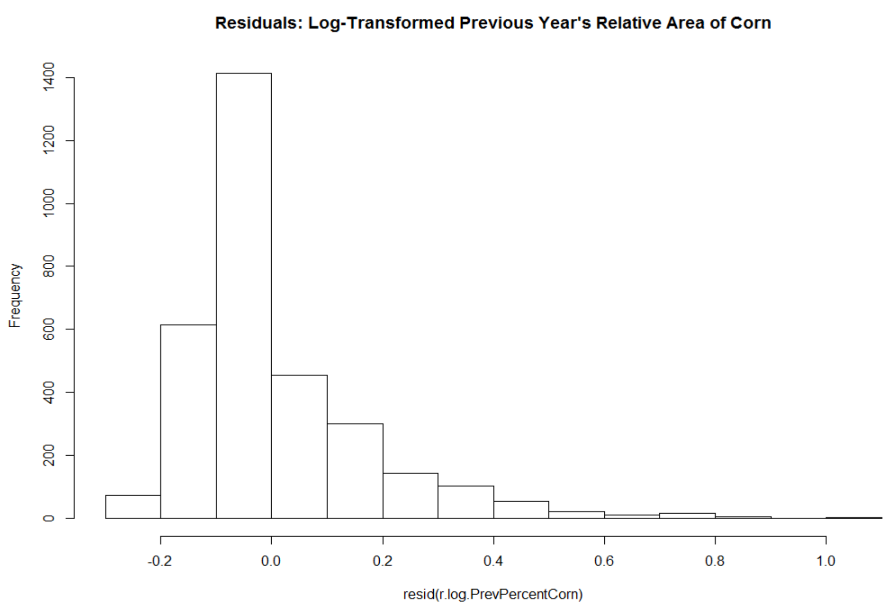


Figure 10. Sample histogram of residuals from regression of log base 10 transformed nitrate and crop area data.

Economic – Land Use Model

One of the objectives of this study was to develop an economic – land use model which could predict land use under different economic scenarios. To accomplish this, the potential yield of each crop had to be determined at each point in the study area. Scenarios of crop price and production expense changes could then be prepared and applied to the economic – land use model to identify the profit-maximizing land use under that scenario. This land use could then be provided as an input to the land use – water quality model to predict the influence of the economic scenarios on water quality.

A script was written for use in the R statistical package which would accept crop price and cost inputs. Using those inputs the program calculated the profit of each crop within each parcel at those prices and costs. This can be expressed as, where i denotes a specific parcel of land and j denotes a particular land use (usually a crop type):

$$Profit_{ij} = Price_{j} * Yield_{ij} - Cost_{j}$$

The sum of the profits of all profitable crops was calculated and the percent of that total profit attributable to land use i was then calculated:

$$Percent_{j\ at\ i} = \frac{Profit_{ij}}{\sum_{j=1}^{j=n} Profit_{ij}}$$

Each parcel was then allocated a percentage area of each crop corresponding to its percent of the total profit.

This provided a distribution of crops based on their relative profitability, a more realistic distribution of crops than that obtained by simply assigning the most profitable crop, which would have resulted in the complete exclusion of some of the minor crops. For the purpose of defining baseline economic and land use conditions within the basin, adjustments were made to the direct cost inputs of the program, within the minimum and maximum range of the costs, until the areas planted in the major crops, as predicted by the model, were comparable to the observed average areas for each crop.

Crop Yields

Historical crop yields for each county within the area of interest (Figure 11) were obtained from the NASS Quick Stats interface (USDA, 2015b; quickstats.nass.usda.gov/), henceforth referred to as “NASS yields”. These data are derived from surveys of farmers. Some counties did not have some crop yield estimates available for some years. Available NASS yields were downloaded for each county in the study area for each of the eight primary RRB crops (alfalfa, canola, corn, dry beans, soybeans, sugar beets, sunflower and wheat) for each year for which there were corresponding CDL data (1997-2014 for North Dakota counties, 2006-2014 for Minnesota and South Dakota counties).

Alternatively, the Soil Survey Geographic (SSURGO) database provides crop yield estimates for some areas (USDA, 2013). SSURGO data were obtained from the National Resources Conservation Service (USDA, 2013; websoilsurvey.sc.egov.usda.gov). These data were raster files of ten meter resolution, delineated by soil property, which can be linked to soil attributes by way of a key (“mukey”) assigned to each cell of the raster. The crop types for which estimated yields were available in SSURGO were limited, and did not include yield estimates for all mukeys and did not include yields for canola or dry beans.

Estimated yields available in SSURGO, henceforth referred to as “SSURGO yields”, are fairly subjective, and are derived by associating estimated yields reported by farmers to all areas with similar soil properties (Beck, 2015). In fact, these yields are no longer available via the online data portal. The SSURGO raster was “clipped” to the area of interest (AOI) using the extract by mask function of ArcGIS. The SSURGO yields were then joined to the raster using the mukey, the key assigned to similar soil types (Beck, 2015).

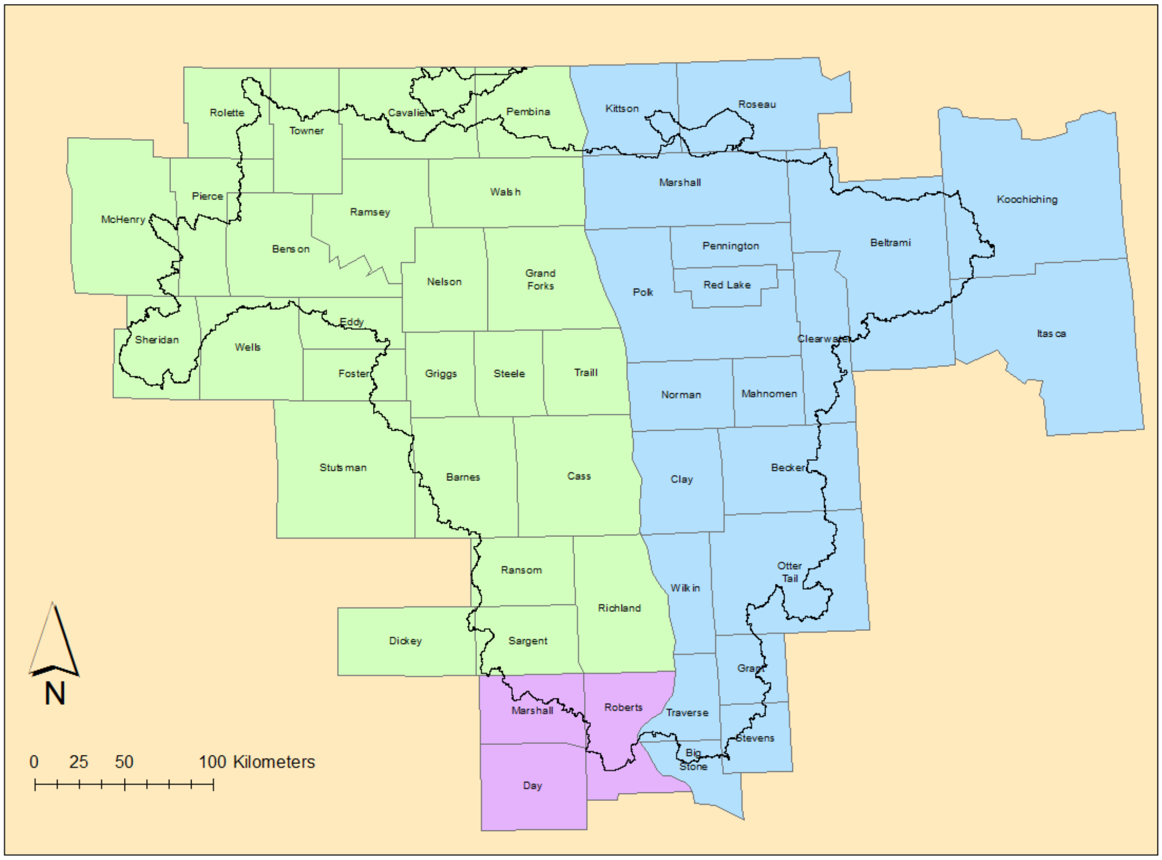


Figure 11. Counties entirely or partially within the delineated Red River Basin. Data source: USDoC, 2015.

SSURGO Crop Productivity Index

Attributes of SSURGO include the National Commodity Crop Productivity Index (NCCPI or CPI) for soybeans and corn and a separate index for small grains. These indices assign a high value to polygons where conditions are favorable for a particular crop and low values where conditions are unfavorable (USDA, 2014b). These indices are derived from soil, climate and landscape properties (Dobos, et al., 2012). However, yield projections for these indices have not yet been determined (Beck, 2015). The small grain CPI raster is shown in Figure 12. Also available is a corn and soybean CPI raster.

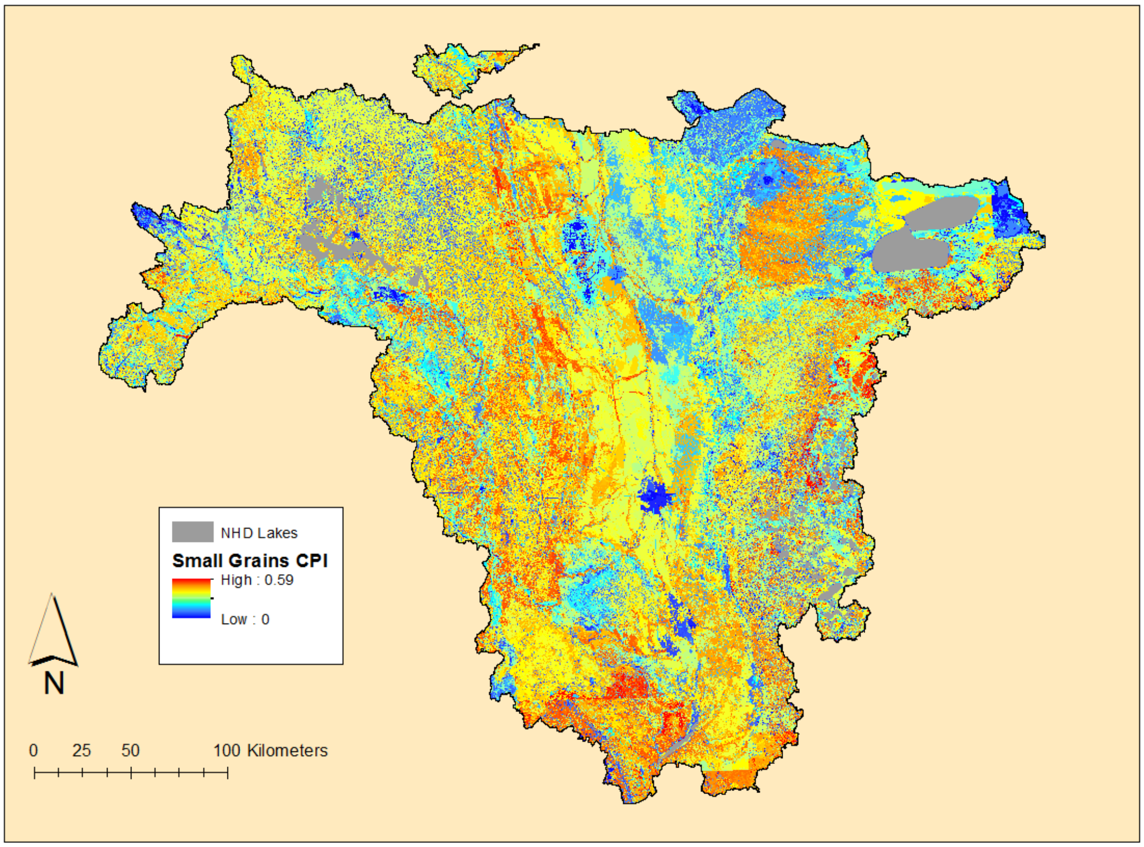


Figure 12. The SSURGO small grain National Commodity Crop Productivity Index for the area of interest. Data source: (USDA, 2013)

Estimating Potential Yields

Since the Crop Productivity Index only assigns a value to the relative productivity of a location and does not provide actual projected yields, it was necessary to establish a relationship between the index value and actual observed yields. This allowed the yield of a particular crop type to be projected at any location within the study area, based on the index value at that location.

To establish a relationship between the CPI and NASS yields, the 48 counties which are entirely or partially within the delineated area of interest were identified (Figure 11). The SSURGO raster, with CPI attributes, and each year's CDL raster, which identified the crop grown in each 30x30 cell each year, were clipped to each of those counties. The Zonal Statistics function of ArcGIS was used to calculate the average CPI (both the corn-soybean and small grains indices) for each of the crop types in each county for each year. To establish a relationship between CPI and SSURGO yields the SSURGO yield values were attached to the clipped SSURGO rasters using the mukey.

Having generated average CPI values for each crop in each county each year and obtained available NASS yields for each crop in each county each year, the correlation of the two variables was assessed. The correlation of the CPI and SSURGO yields was also assessed. Both datasets providing very significant relationships, the NASS yield dataset was chosen to identify potential yields because it included all crop types and provided a higher coefficient of determination when regressed with CPI values. Additional information about the outcome of these analyses are provided in the data section of this report.

It was found that, in almost all cases, the small grains CPI produced a higher coefficient of determination than the corn and soybean CPI when regressions were performed with the county crop area-weighted CPI value as the independent variable and county NASS yield as the dependent variable. Therefore, the small grains CPI was used to generate potential yields for each crop within each cell of the SSURGO raster. This was accomplished by applying the coefficient obtained from the regression of CPI and NASS yield for each crop to the CPI in each cell, as identified by the cell's mukey.

Economic Scenarios

Farm financial information was obtained from University of Minnesota's farm financial database, FINBIN (UMN, 2015; finbin.umn.edu/), as described in the data section of this report. Using those data, a range of potential prices and costs had been identified. From these data, realistic price and expense scenarios were developed for agricultural products within the Red River Basin. The scenarios considered were:

- Increases in the prices of the major crops (corn, soybeans and wheat)
- A conservation incentive, in which farmers were compensated for each hectare set aside from production
- A tax on fertilizer
- A government subsidy on specific crops

Details of the scenarios are provided below.

Increase in Crop Price of Corn, Soybeans and Wheat

This scenario explores the influence of increases in prices of the three major crops: corn, soybeans and wheat. Price increases of 25%, 50% and 100% were arbitrarily chosen. Price increases of 25% and 50% are reasonable changes to the baseline crop price, which is the average crop price observed from 2006-2014 for each crop. To illustrate, the average price of corn during that period was $4.15 per bushel and the maximum was $6.40 per bushel, a 54% increase from the baseline (average). A 100% price increase seems very unlikely, but an interesting scenario nonetheless.

Conservation Programs

Under this scenario, a government program pays farmers for each hectare left out of production. A net profit of $66.50 per hectare was identified as typical within the study area under the Conservation Reserve Program from 2006-2014. This profit was obtained by averaging historical economic data from FINBIN (UMN, 2015).

Fertilizer Tax

The influence on land use and consequent effect on water quality of a fertilizer tax was also considered. This tax would be applied as a tax on fertilizer sales. The average annual fertilizer expense for each crop type within the study area from 2006-2014 was obtained from FINBIN data (UMN, 2015). Fertilizer sales tax scenarios of 5%, 10%, 15% and 20% were considered. Other studies have proposed 100% taxes on fertilizers (O' Shea and Wade, 2009; Berntsen et al., 2003), making the rates suggested by these scenarios appear very conservative, in hindsight.

Subsidies of Corn, Soybeans and Wheat

A crop subsidy scenario in which a payment, similar to that of the former direct subsidy program (White and Hoppe, 2012), was made to farmers to incentivize the cultivation of specific crops was also considered. Reasonable subsidy amounts were obtained by consulting the Environmental Working Group's Farm Subsidy Database (EWG, 2016a; farm.ewg.org/), an accessible source used in other studies (Boody et al., 2005; Booth and Campbell, 2007). Total subsidy payments for corn, soybeans and wheat within the study area from 2006-2014 were considered.

Since subsidy payments, particularly the counter-cyclical subsidy (White and Hoppe, 2012), were often influenced by crop prices, the subsidy used for each of the crops in this scenario was established as the total subsidy paid for that crop in the year in which the baseline crop price (the study area historical average, 2006-2014) and the annual average price for that crop were most similar. The year in which corn prices were closest to baseline was 2010, with a $17.57/ hectare subsidy, 2009 soybean subsidy was $9.76/hectare and 2007 wheat subsidy was $12.71/hectares. Separate scenarios were assessed in which each of the major crop's per-hectare profit was increased by the subsidy amount, and an additional scenario was considered where all the major crops' profits were increased by their respective subsidy amount.

The economic adjustments defined by the above scenarios were then introduced into the economic – land use model, which projected the land use in each mukey. The process by which this land use was assigned is the same as that described in the "Economic – Land Use Model" section of the methods above, where each parcel (mukey) is assigned a relative area corresponding to its profitability relative to the sum of the profits generated by all land uses within that parcel.

Assessing the Impact of Economic Scenarios on Water Quality

The land uses projected by the economic – land use model under each scenario were then provided as inputs to the land use – water quality model. By maintaining the other independent variables of the model at their average, the nitrate concentrations of surface waters under that particular economic scenario were predicted. This could be done for each individual point within the study area for which historical discharge and nitrate observations existed. Using this procedure, the impact of economic scenarios on water quality could be assessed and scenarios which contributed to elevated or reduced nitrate levels were identified.

CHAPTER III

DATA

Data necessary to perform the procedures above were collected obtained from various sources. At times, these data required considerable processing prior to analysis. Summaries of the preparation of potentially significant data and the resulting datasets are detailed below.

Delineation of Gauge Drainage Basins

Since this study is concerned with the influence of land use on the water quality of the streams, it was necessary to identify the land areas which were draining into the monitored points which had been identified. The delineation of these basins was performed with ArcSWAT, the ArcGIS interface for the Soil and Water Assessment Tool. Delineation using Arc Hydro was also attempted, but ArcSWAT produced a stream network which better fit the location of discharge and nitrate monitoring points.

The ArcSWAT delineation required as inputs a 30 meter digital elevation model, obtained from the National Map Viewer (USGS, 2015a), the National Hydrography Dataset (NHD) stream network for “burn-in” and the locations of the USGS stations identified in the previous section. The “burn-in” of the stream network forced the program to generate a more accurate approximation of the true physical stream locations (Almendinger and Alrich, 2010). The location of the USGS stations allowed the program to define the outlet of a basin (Almendinger and Alrich, 2010). This identified the upstream areas contributing drainage to the station, but excluded any areas draining into upstream USGS stations.

For example, in Figure 13, the area in blue drains through USGS 05100000. The area in pink also drains through USGS 05100000, but is not part of the basin delineated by this technique. Since it was necessary to know the land use of all areas draining into a station, the Dissolve function in ArcGIS was used to combine these two areas and identify the resulting basin as the basin contributing drainage to USGS 05100000. The location of these areas within the study area can be seen in Figure 15.

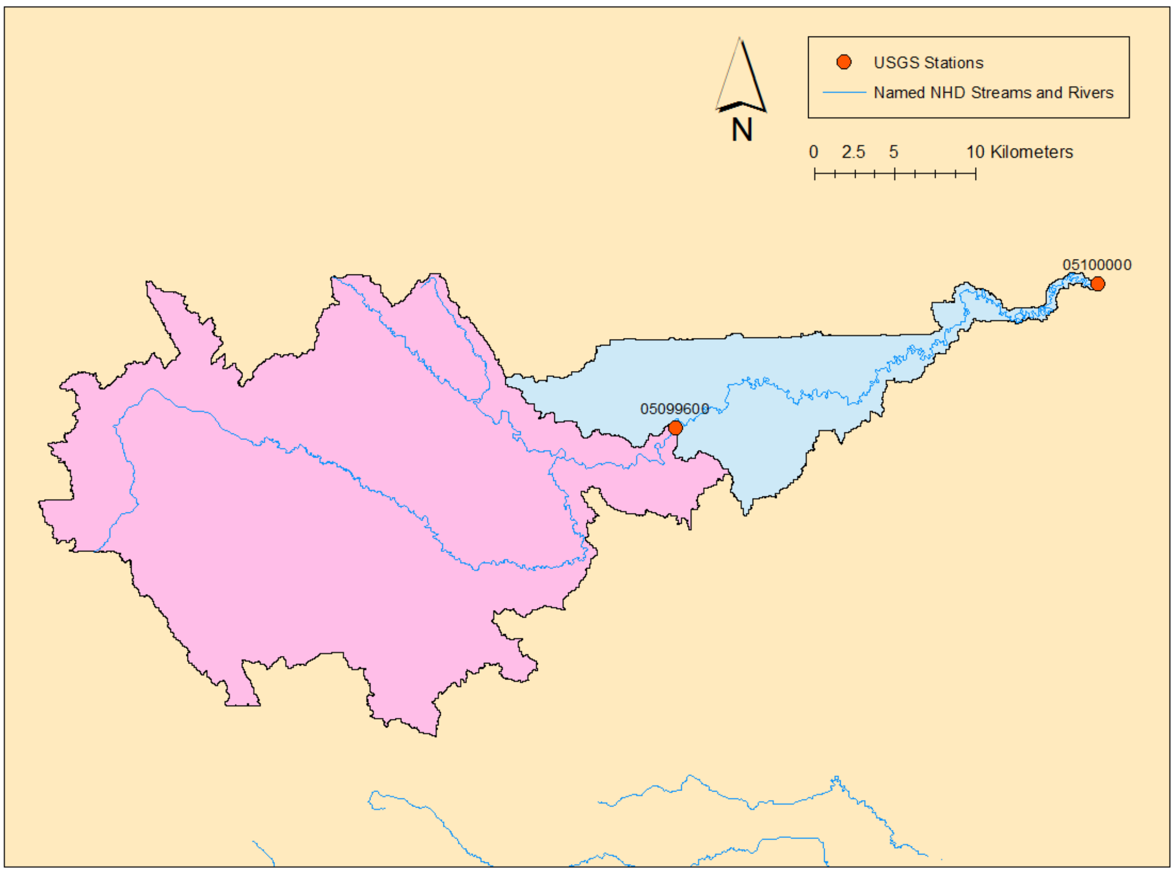


Figure 13. Two drainage areas, as delineated by ArcSWAT. The pink area drains through USGS 05099600. Both the pink and the blue areas drain through USGS 05100000.

The resulting areas identified as draining into a USGS station will henceforth be referred to as a gauge drainage basin. This procedure identified 36 gauge drainage basins, shown in Figure 14. Since smaller basins reside within larger basins, it is difficult to distinguish the actual extent of each basin. USGS gauges, and their delineated basins, which are given particular attention in this study are shown in Figure 15.

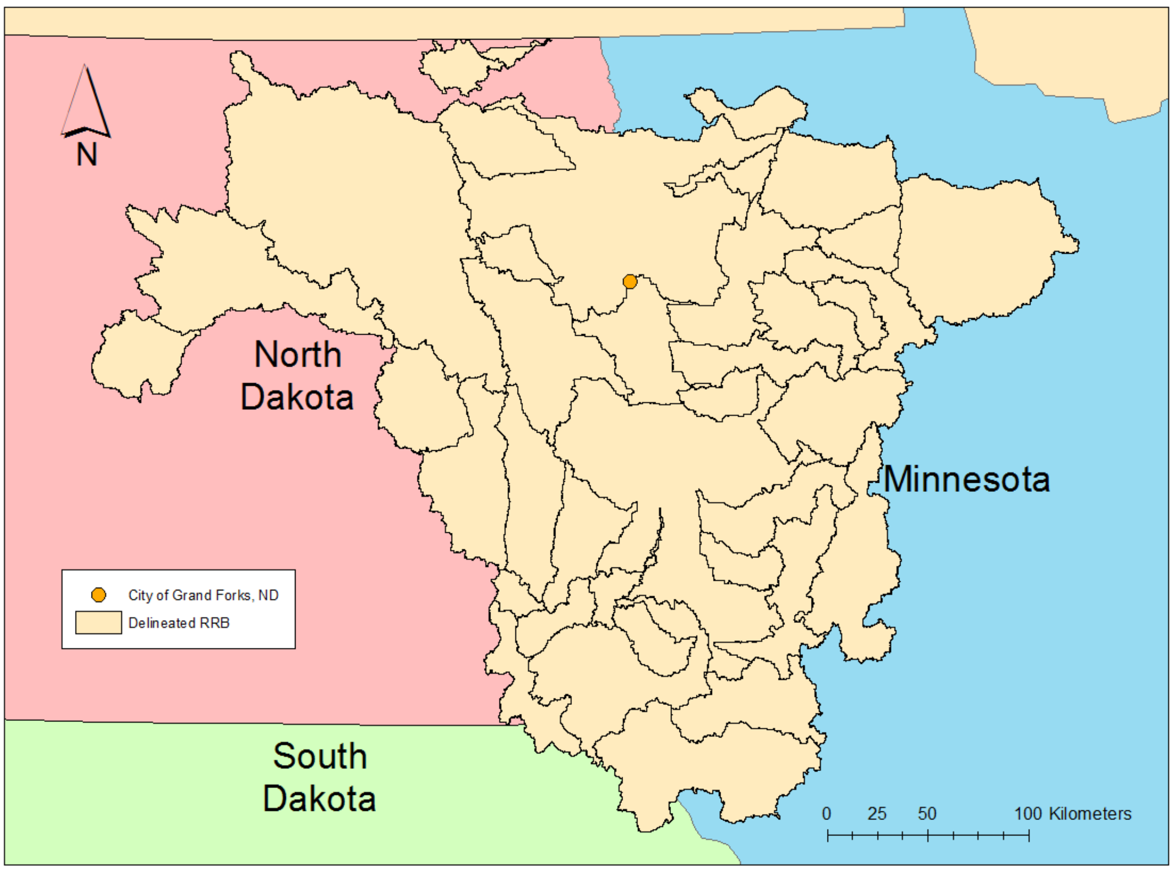


Figure 14. Delineated gauge drainage basins.   Basins were defined by the method described in this report. Note that the full extent of each basin is not obvious, since larger basins overlap smaller basins.

The number of nitrate samples at each drainage point and the size of basins vary greatly, detailed in Table 5. North Dakota basins tend to have more samples than Minnesota and South Dakota basins. This is because the period of land use – water quality analysis in North Dakota extends from 1997-2014, while only the period of 2006-2014 was analyzed in Minnesota and South Dakota, due to the unavailability of spatial crop data prior to 2006. The basin draining through 05080000 has the greatest area, since that station is the most northern station located directly on the Red River near Pembina, ND. However, this basin does not include the areas draining through gauges 05094000, 05099600 and 05100000 which drain into the river north of gauge 05080000.

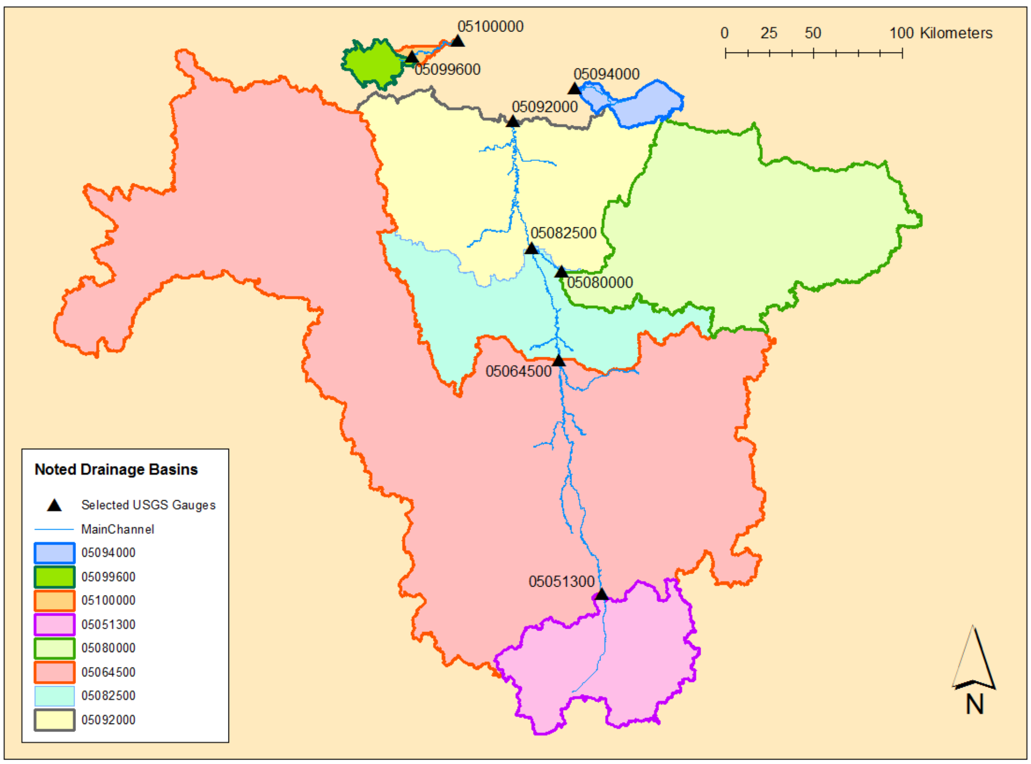


Figure 15. Locations of specific gauges and their delineated basins. Not discernable are areas of overlap. For example, the area draining through USGS 05051300 also drains through USGS 050647500. For reference USGS 05082500 is located at Grand Forks, ND.

Table 5. Gauge drainage basin sizes, as delineated in this study, and the number of nitrate samples available at each gauge.

USGS Station	States	Number of Nitrate Samples	Total Area (ha)
05087500	MN	119	54,349
05078230	MN	30	58,675
05099600	ND	32	64,730
05082625	ND	414	65,626
05067500	MN	51	66,614
05061500	MN	163	68,798
05052500	ND	83	75,905
05100000	ND	76	81,195
05094000	MN	2	83,271
05051600	ND, SD	5	126,165
05069000	MN	186	132,211
05054500	ND	360	143,459
05090000	ND	65	161,356
05057200	ND	25	185,779
05059700	ND	4	217,360
05062000	MN	122	230,443
05062500	MN	47	236,457
05076000	MN	218	254,572
05030500	MN	10	288,184
05066500	ND	28	312,925
05078500	MN	34	356,071
05060100	ND	48	365,485
05074500	MN	95	496,741
05053000	ND, SD	1	553,795
05056000	ND	67	577,604
05051300	MN, ND, SD	412	604,249
05080000	MN	90	1,421,573
05057000	ND	189	1,807,881
05058600	ND	25	2,254,171
05058700	ND	249	2,289,163
05058810	ND	4	2,360,892
05059000	ND	1	2,404,194
05059500	ND	42	2,408,891
05064500	MN, ND, SD	42	5,719,761
05082500	MN, ND, SD	19	7,846,877
05092000	MN, ND, SD	44	9,039,216

Total Discharge, Baseflow and Runoff

Stream discharge, being an important factor in nitrate export, is often included in included in studies of water quality. Some researchers, such as Booth and Campbell (2007), have found that, rather than using a variable of total discharge, the runoff or baseflow contribution to total discharge is a more significant variable. The effect that the variables discharge, baseflow and runoff will have on nitrate loss is difficult to predict. The study by Booth and Campbell (2007) only assessed the runoff component during spring months and found that there was a positive relationship between runoff and nitrate flux. David et al. (2010) concluded that there was a positive relationship between total discharge and nitrogen yield between January and July, the months they assessed in their study. In consideration of these studies, it is expected that months with high total discharge, such as April, will exhibit the highest nitrate concentrations in surface waters.

The "BaseflowSeparation" command of the R package "EcoHydRology" was used to separate the National Water Information System discharge data obtained for each gauge into runoff and baseflow (Fuka et al., 2014). This tool uses the Lyne and Hollick filter, which uses a statistical approach to identify the baseflow and runoff components of total discharge (Ladson, et al., 2014). Although purely a statistical approach with no physical basis (it does not take into account physical characteristics of the study area), it has been used in previous studies (Carlson, et al., 2014) and has been determined to produce an adequate estimate of actual runoff and baseflow (Ladson, et al., 2014).

Figure 16 is a hydrograph of daily discharge at USGS station 05092000. USGS 05092000 lies on the Red River in Pembina county, the northern part of the AOI, as seen in Figure 15. Of the USGS stations in the study area, it drains the largest area, draining 98% of the study area. However, it does not include discharge from two small northern areas of the AOI which do not share a USGS gauge with the rest of the study area. A boxplot of monthly total discharge at USGS station 05092000 is shown in Figure 16.

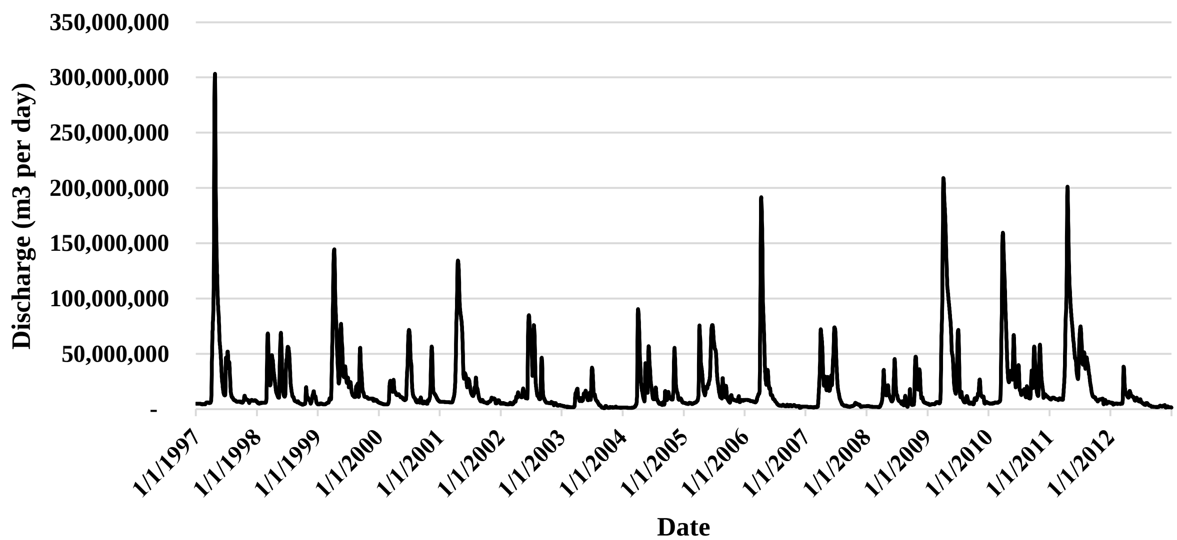


Figure 16. Daily discharge at USGS 05092000 from 1997-2013, cubic meters per day. Data source: (USGS, 2015b; http://waterdata.usgs.gov/nwis).

It can be seen in both Figures 16 and 17 that discharge is highest in the spring, particularly April. The average discharge in April is 64,230,610 cubic meters per day (Table 6). This is due to spring rainfall and snow melt. April also has the most variability in discharge, as shown by the range of the April boxplot. May, June and July also have larger discharge ranges and higher than normal average discharges, all over 25 million cubic meters per day (Table 6). The lowest average discharges are in January and February, with less than five million cubic meters per day (Table 6). March, April and May have the most outliers, indicating isolated extremely high discharge values, as depicted by the circles above the box plots.

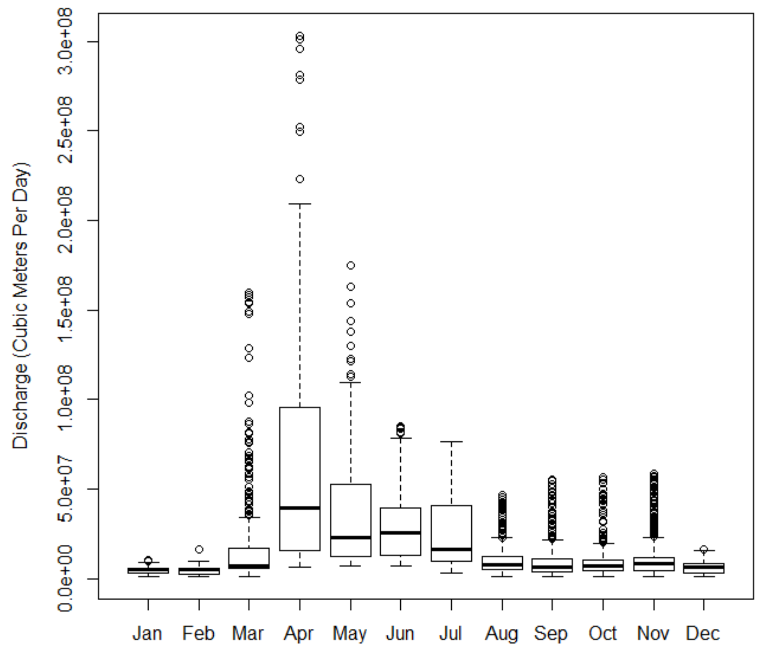


Figure 17. Boxplots of daily discharge by month, 1997-2012, at USGS 05092000, Pembina County, ND.

Table 6. Daily total discharge (cubic meters per day) summary statistics by month, 1997-2012, at USGS 05092000, Pembina County, ND.

month	n	minimum	mean	maximum	std dev
January	497	1,100,959	4,864,688	10,471,343	2,132,479
February	452	1,052,027	4,644,672	16,392,056	2,145,346
March	496	1,333,384	16,890,151	159,516,726	25,607,320
April	480	6,507,891	64,230,610	303,375,368	60,884,386
May	496	6,899,343	35,675,856	174,685,494	30,673,569
June	480	6,752,549	29,626,603	84,896,171	19,852,374
July	496	3,082,685	25,111,681	76,088,499	19,772,724
August	496	1,343,170	10,811,639	46,729,593	9,223,811
September	480	858,748	9,655,614	55,537,265	10,077,359
October	496	1,125,425	8,931,367	56,760,553	8,858,120
November	480	1,225,734	11,894,476	58,473,156	12,174,063
December	496	1,198,822	6,203,929	16,147,399	3,358,995

Figures 18 and 19 show boxplots of baseflow and runoff at USGS 05092000, as calculated by the EcoHydRology tool. Overall, the trends are very similar to those seen in total discharge with high average discharge, high variability and more outliers in summer and late spring. It can be seen when comparing Figures 18 and 19, and more clearly in Tables 7 and 8, that most of the discharge is baseflow in all months except March and April. However, in March and April runoff surpasses baseflow. Tables 7 and 8 show that variability in discharge, as measured by standard deviation, correlates well with the mean discharge; months which experience high volumes of discharge also experience great variability of discharge.

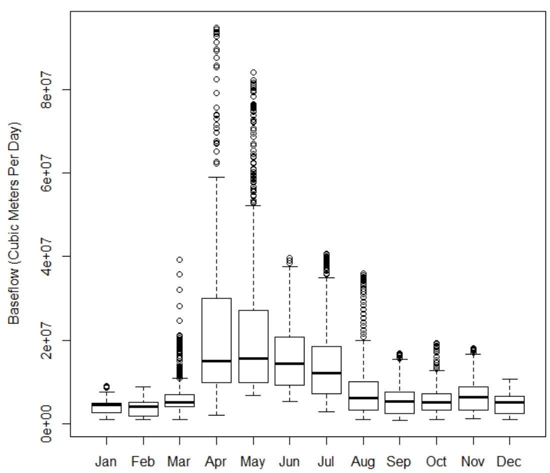


Figure 18. Boxplots of daily baseflow discharge by month, 1997-2012, at USGS 05092000, Pembina County, ND.

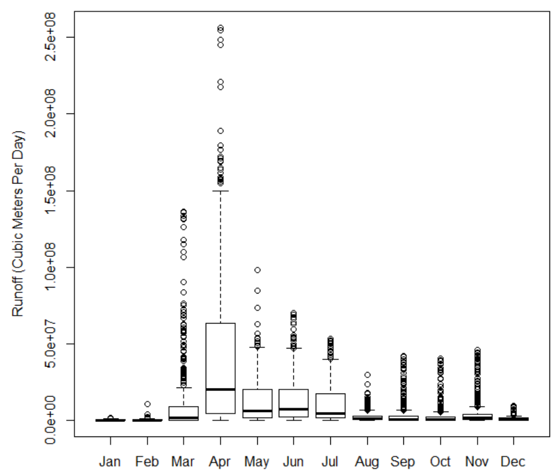


Figure 19. Boxplots of daily runoff discharge by month, 1997-2012, at USGS 05092000, Pembina County, ND.

Table 7. Daily baseflow discharge (cubic meters per day) summary statistics by month, 1997-2012, at USGS 05092000, Pembina County, ND.

month	n	minimum	mean	maximum	std dev
January	497	1,058,211	4,462,017	9,021,729	1,978,189
February	452	1,052,027	4,250,884	8,875,003	1,909,678
March	496	1,107,495	6,169,466	39,341,221	4,743,997
April	480	2,238,943	23,278,034	94,772,398	20,145,510
May	496	6,784,109	23,402,695	83,905,706	19,244,564
June	480	5,487,591	16,165,388	39,705,180	7,851,223
July	496	2,950,859	14,598,280	40,690,501	9,844,787
August	496	1,081,290	7,879,881	36,031,365	6,403,027
September	480	858,748	5,919,912	16,869,170	3,788,614
October	496	1,125,425	5,791,442	19,390,333	3,449,253
November	480	1,225,734	6,640,158	18,194,537	3,991,752
December	496	1,198,822	4,975,074	10,686,829	2,508,807

Table 8. Daily runoff discharge (cubic meters per day) summary statistics by month, 1997-2012, at USGS 05092000, Pembina County, ND.

month	n	minimum	mean	maximum	std dev
January	497	0	402,671	1,579,898	310,806
February	452	0	393,788	10,769,657	649,895
March	496	0	10,720,686	136,298,334	22,568,615
April	480	0	40,952,576	256,601,797	49,009,541
May	496	0	12,273,161	98,432,673	14,247,244
June	480	0	13,461,215	70,129,941	15,661,373
July	496	0	10,513,401	53,679,904	12,272,757
August	496	0	2,931,759	30,137,173	3,878,622
September	480	0	3,735,702	42,143,960	7,387,319
October	496	0	3,139,925	40,384,739	6,787,287
November	480	0	5,254,318	46,037,991	9,422,837
December	496	0	1,228,855	9,498,421	1,381,688

The average monthly individual components of discharge, baseflow and runoff, as measured at Pembina, are shown graphically in Figure 20. Runoff dominates the hydrograph in April and also considerable in months such as March, May, June and July. There are minor volumes of runoff in August, September, October, November and December. Runoff is nearly nonexistent in January and February, as would be expected in a region with very cold winters where all winter precipitation is in the form of snow.

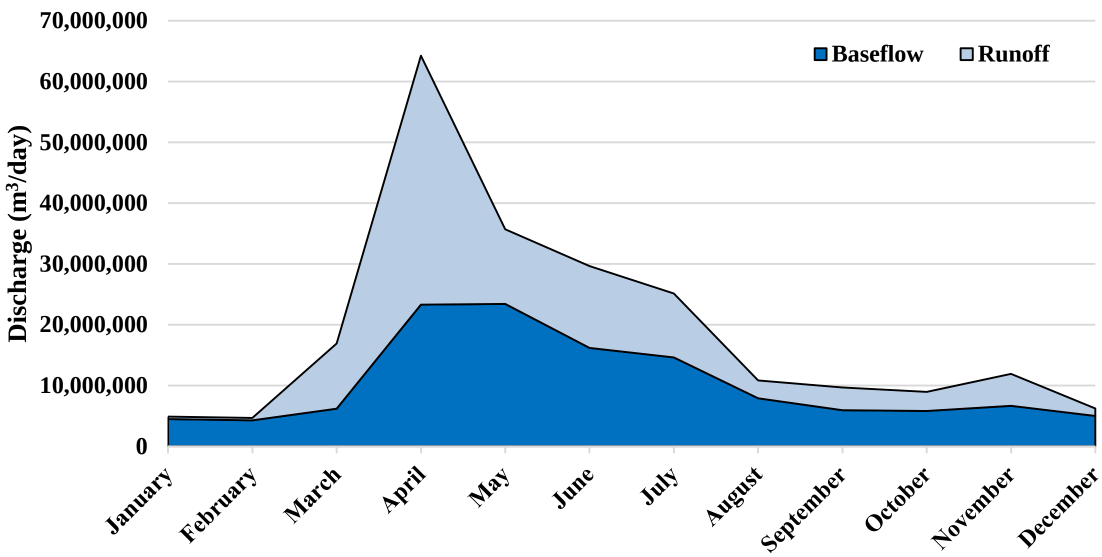


Figure 20. Mean monthly baseflow and runoff components of total discharge at Pembina, ND, USGS 05092000.

Nitrate Concentrations

The water quality parameter of interest is nitrate concentration, measured in milligrams of nitrate per liter of water (mg/L). The USGS seldom monitors nitrates at the stations where discharge is measured. The EPA Storage and Retrieval Data Warehouse (USEPA, 2016b; epa.gov/waterdata/storage-and-retrieval-and-water-quality-exchange#warehouse), or STORET, was used to identify points within the AOI where nitrate concentrations had been monitored. These points were displayed in ArcGIS using the latitude and longitude coordinates of the stations.

To evaluate the effect of discharge on nitrate concentrations, the discharge and nitrate data should be collected at the same point. However, very rarely do discharge and monitoring occur at the same locations and, in fact, this never occurs in this study area. This is likely a challenge that is encountered by other researchers, but it has not been found to be addressed in the literature.

For this study, discharge monitoring points that fell within 0.5 km of a nitrate monitoring station were identified using the ArcGIS Near function. The results of this were manually reviewed and nitrate monitoring points that did not fall on the same stream reach as discharge monitoring stations were removed. Similarly, discharge stations that did not have a nitrate point within 0.5 km were removed. After this process, there remained 36 USGS discharge stations, on stream reaches, that had nitrate concentration data collected within 0.5 km of the station, shown in Figure 21.

Sample size varied over the course of the year, with the lowest being 33 in January and December and the highest being 596 in April (Table 9). There are limited data available during winter months because of the streams are often frozen and samples are not available. Furthermore, during inclement weather, sample collectors may not be inclined to go into the field.

Available nitrate data for points in the study area for which there were USGS discharge observations had been obtained from STORET. The area draining through USGS 05051300 (shown in Figure 15) has the second largest dataset of nitrate samples (n= 412, Table 5) and drains about 7% of the study area. For the purpose of assessing monthly trends in nitrates, summary statistics and boxplots of the monthly nitrate concentrations at this gauge are shown in Figure 22 and Table 10.

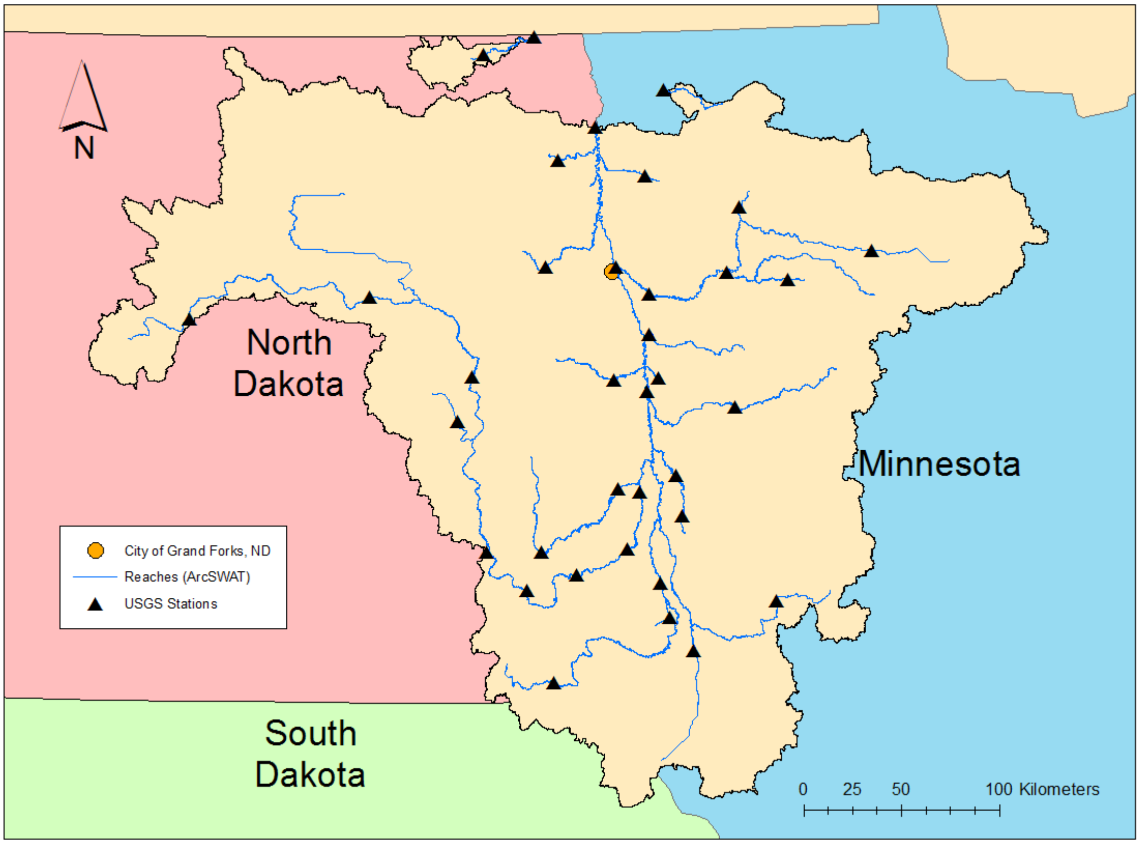


Figure 21. 36 USGS stations within the AOI which were used in this study. Stations were selected using the methodology described in the "Stream Discharge" and "Nitrate Concentration" subsections of the "Data Preparation and Methods" section of this report. Data source: USGS, 2015b.

Table 9. Number of available nitrate concentration observations, by month.

Month	n
January	33
February	65
March	150
April	596
May	566
June	550
July	420
August	335
September	298
October	245
November	110
December	34

Highest nitrate concentrations are in June, April and October; 1.89, 1.71 and 1.02 mg/L respectively. Lowest average concentrations are in August, 0.10 mg/L. June had the largest variability and April had the most outliers, with a maximum concentration over 10 mg/L, the threshold set by the EPA for safe drinking water (USEPA, 2016c). There were fewer samples taken in winter months, less than ten in December and January, with the most samples, 71, being taken in April.

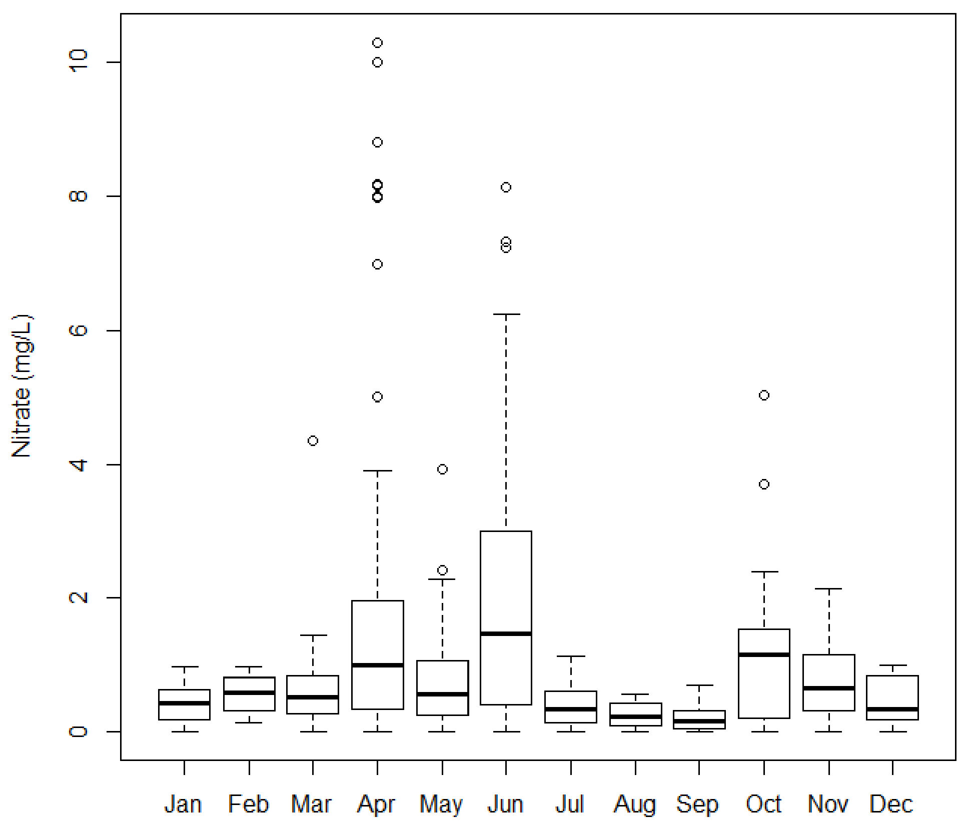


Figure 22. Boxplots of nitrate concentrations samples at USGS 05051300, by month sampled, 2006-2014. Data source: USEPA, 2016b.

Table 10. Summary statistics of the monthly nitrate concentrations (mg/L) at USGS 05051300.

month	n	minimum	mean	maximum	std dev
January	6	0.00	0.45	0.98	0.36
February	18	0.14	0.59	0.98	0.27
March	30	0.00	0.66	4.36	0.80
April	71	0.00	1.71	10.30	2.65
May	58	0.00	0.64	3.92	0.81
June	68	0.00	1.89	8.14	1.90
July	40	0.00	0.27	1.14	0.31
August	31	0.00	0.10	0.56	0.17
September	26	0.00	0.16	0.70	0.20
October	38	0.00	1.02	5.03	1.19
November	18	0.00	0.67	2.15	0.63
December	8	0.00	0.43	1.00	0.41

Crop Areas

USDA's NASS Cropscape (https://nassgeodata.gmu.edu/CropScape/) provides annual spatial crop data for the United States. Using this Cropscape Cropland Data Layer (CDL) online interface, all available crop data for the area of interest were downloaded (USDA, 2015a). Availability of CDL data varies by state. North Dakota data are available for the years 1997-2014 and all data are at 30 meter resolution; Minnesota and South Dakota data are available for the years 2006-2009 at 56 meter resolution, while Minnesota and South Dakota data from 2010-2014 are at 30 meter resolution. Each state's annual data were downloaded independently and later mosaicked. These rasters were in GRID format.

All available rasters for each year were then reprojected and mosaicked within ArcGIS. The resulting rasters were at the lowest resolution of all raster inputs. This process produced spatial crop data for 1997-2005 for the state of North Dakota at 30 meter resolution, data for

2006-2009 for Minnesota, North Dakota and South Dakota at 56 meter resolution and data for 2010-2014 for Minnesota, North Dakota and South Dakota at 30 meter resolution.

For this analysis, it was necessary to obtain the area of each crop grown within each gauge drainage basin in each year. Using Python script generated by Dr. Quiang Zhou, the ArcGIS Zonal Histogram function was used to create tables of land use data for each year and each gauge drainage basin. First, basins that fell entirely within North Dakota were identified visually. These were then used as the input feature zones and 1997-2005 CDL rasters were used as the input value rasters, which calculated the number of 30x30 meter cells grown in each crop type within the basin. Next, the same operation was performed using all basin shapefiles and the 2006-2014 CDL rasters. The output from this operation was at 56 meter resolution for the 2006-2009 data and 30 meter resolution for the 2010-2014 data. All crop area output was then converted to hectares.

This procedure provided a dataset of tabular data showing the area, in hectares, of each gauge drainage basin planted in each crop each year. These data were reformatted to show, for each year and each basin, the area planted with each crop, the area planted with each crop the previous year, the percent of the total area of the basin planted with each crop (referred to henceforth as "relative crop area") and the previous year's relative crop area. It was found that the crops which occupied the greatest area in the Red River Basin are alfalfa, canola, corn, dry beans, soybeans, sugar beets, sunflowers and wheat. Collectively, area planted in these eight crops averaged 89% of the total area planted in crops each year.

There are certainly other land uses which can have a significant impact on water quality, such as conservation areas, wetlands and urban areas. However, these data are not as accessible as the geospatial crop data from CDL. Although the CDL does contain land uses other than crops, these data are obtained from the National Land Cover Database (NLCD) (Hill and Olson, 2013). There is some doubt regarding the accuracy of these data in the study area. A study by Wickham et al. divided the nation into ten regions and evaluated the accuracy of the 2006 NLCD dataset within each region. It was found that the region intersecting the Red River Basin had the poorest accuracy in evaluating changes such as forest loss, shrubland loss and grassland loss, 60%, 4% and 37% respectively (Wickham et al., 2013). Therefore, neither grassland nor woody land data from CDL were used in this study.

Given the relatively low population density in the majority of the Red River Basin, urban land use is not addressed in this study. An attempt is made to evaluate the influence of the extent of wetland areas, as described below. Additional land uses, such as conservation easements due to the Conservation Reserve Program (CRP), are not included here due to the unavailability of spatial data.

The area planted in each crop in each basin had been calculated using CDL rasters and the Zonal Histogram function of ArcGIS. After evaluating land use in the study area by this method, it was found that the dominant crops (most extensively grown) in the study area are alfalfa, canola, corn, soybeans, sugar beets, sunflowers and wheat. As can be seen in Table 11, soybeans are the most widely grown crop, average 1,895,138 hectares per year between 2006 and 2014. On average, sunflowers are the least widely grown, although in 2007 the total area of sunflower reached 142,710 hectares (Table 12) and in 2006 the area of sunflowers surpassed alfalfa, dry beans and canola. From 2006-2014 the average annual percent of total cultivated area planted in soybeans was 38%, wheat 25% and corn 19%, comprising 82% of all crops.

Table 11. Summary statistics of each crop area, in hectares, within the study area, 2006-2014.

crop	minimum	mean	maximum	std dev	total
Corn	601148	928382	1303276	204702	8355435
Soybeans	1424801	1895138	2407235	250118	17056244
Wheat	954260	1286095	1562498	183054	11574858
Alfalfa	49413	112135	187719	52034	1009213
Sugar Beets	125811	162708	191955	18274	1464375
Dry Beans	102711	168136	226797	45461	1513226
Sunflowers	11780	66044	142710	44672	594398
Canola	92663	121161	170732	22222	1090448

Table 12. Total areas, in hectares, of major crops in the study area by year.

crop	2006	2007	2008	2009	2010	2011	2012	2013	2014
Corn	601148	972716	874461	823085	797061	857236	1228856	1303276	897596
Soybeans	1866751	1424801	1681612	1838378	1908983	2041639	1900794	1986051	2407235
Wheat	1562498	1426808	1414931	1347869	1301219	1363747	1083941	954260	1119585
Alfalfa	98061	67276	54210	49413	76241	185615	156791	133887	187719
Sugar beets	125811	160101	152818	154349	161481	160179	191955	185387	172294
Dry Beans	111970	162900	172405	168753	221548	102711	226797	124199	221943
Sunflowers	113338	142710	113100	71906	60110	23221	23805	11780	34428
Canola	107272	116998	103657	106203	140793	126832	170732	92663	125298

Soy covered the largest area in every year except 2007, in which area of wheat was slightly higher. Wheat area was higher than corn all years except 2012 and 2013. In spite of having a smaller average area, corn had a higher standard deviation than wheat (204,702 ha compared to 183,054 ha). There was more variability in the area planted in corn.

Figure 23 shows the change in area devoted to each of the major crops within the delineated RRB from 2006-2014. Area of corn grew from 601,148 ha in 2006 to a high of 1,303,276 ha in 2013, then collapsed to 897,596 ha in 2014. Area of soybean fluctuated through the period but generally grew, increasing from 1,866,751 ha in 2006 to 2,407,235 ha in 2014.

The area of corn lost from 2013 to 2014 seems to have been largely consumed by soybeans, the area of which increased from 1,986,051 ha to 2,407,235 ha from 2013 to 2014. Overall, the area of wheat steadily decline from 1,563,498 ha in 206 to 954,260 ha in 2013, but then rebounded to 1,119,585 in 2014. Area devoted to all crops increased 17% from 2006 to 2014, from 4,705,387 ha to 5,528,806 ha.

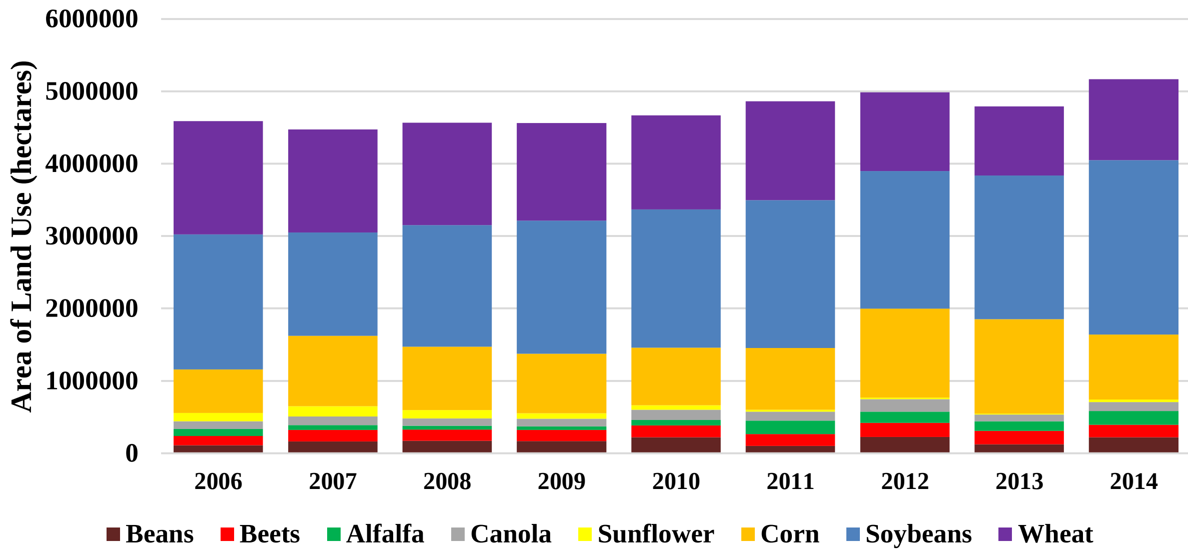


Figure 23. Change in RRB crop areas 2006-2014. Data source: USDA, 2015a.

Stream Length

The length of the streams in each basin was identified as a potentially important variable. Once nitrate has reached a stream, a variety of processes including denitrification occur. Longer streams will likely have greater residence times, allowing these processes to affect the concentration of nitrates (Galloway et al., 2003). Many factors control these processes but, generally, longer stream lengths are expected to allow for greater denitrification (O' Brien et al., 2007). Within ArcGIS the National Hydrography Dataset (USGS, 2015a) stream networks

(Figure 24) were clipped to each gauge drainage basin. The lengths, in kilometers, of all the stream reaches in the clips were then summed. This provided a stream length value for each of the gauge drainage basins, an independent variable which would be included in the land use-water quality analysis.

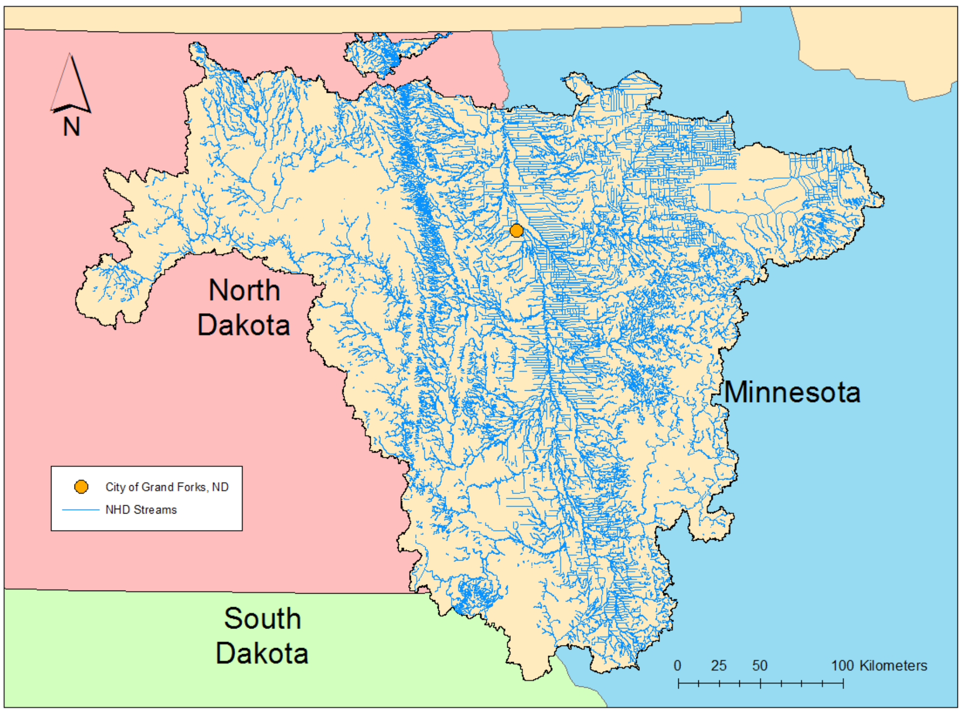


Figure 24. All National Hydrography Dataset (NHD) streams. Data source: USGS, 2015a.

Wetland Areas

A great deal of research has indicated that wetlands provide a variety of ecosystem services, including the remediation of water which has been contaminated with nitrates (Detenbeck et al., 1993; Hanson et al., 1994; Mitsch et al., 2005). With these studies in mind, it is expected that gauge drainage basins with larger areas of wetlands will exhibit less nitrate loss. Therefore, it was desirable to include a variable which quantified the extent of wetlands in each gauge drainage basin to assess whether increased areas of wetlands would be correlated with decreased nitrate concentrations in streams. Unfortunately, the most recent dataset of spatial wetland data is the National Wetland Inventory (NWI). Most of this survey was completed in the 1980s, with some North Dakota portions of the study area being completed in the 1970s (USDOI, 2015; fws.gov/wetlands/Data/Mapper.html). NWI wetlands for the Red River Basin are shown in Figure 25.

Given the extensive land use change and installation of subsurface drainage tiling, there is no assumption that the wetland areas published in the inventory remain accurate for our period of interest. With the data available, the only method identified to estimate the changing wetland extent was to erase the wetland areas which were being used for agriculture in various years, as identified from the CDL. This was accomplished within ArcGIS by converting the various land uses in each year's CDL layer to polygons. The polygons associated with agricultural land use were extracted by attribute, then exported to a new shapefile. For each year in the period of interest, the original NWI shapefile was erased using the agricultural land use polygons, resulting in a shapefile of wetlands areas which had not been identified as converted to agriculture for that particular year. In a fashion similar to that used with the CDL data, zonal histograms were created for each crop drainage basin, producing an area of wetland variable for each basin for use in regressions with nitrate concentrations.

Changes in wetland were assessed by removing areas of the National Wetland Inventory which had been converted to agricultural land use, as detailed above. Total wetland area in the Red River Basin each year is depicted in Figure 26. Wetland areas changed slightly over time, with the smallest area being 1,361,598 ha in 2008 and the largest area being 1,385,951 ha in

2010. Increases in wetland area, as seen from 2008 to 2010, would appear to indicate that areas that had once been designated wetland had been farmed for a period of time, then left unplanted.

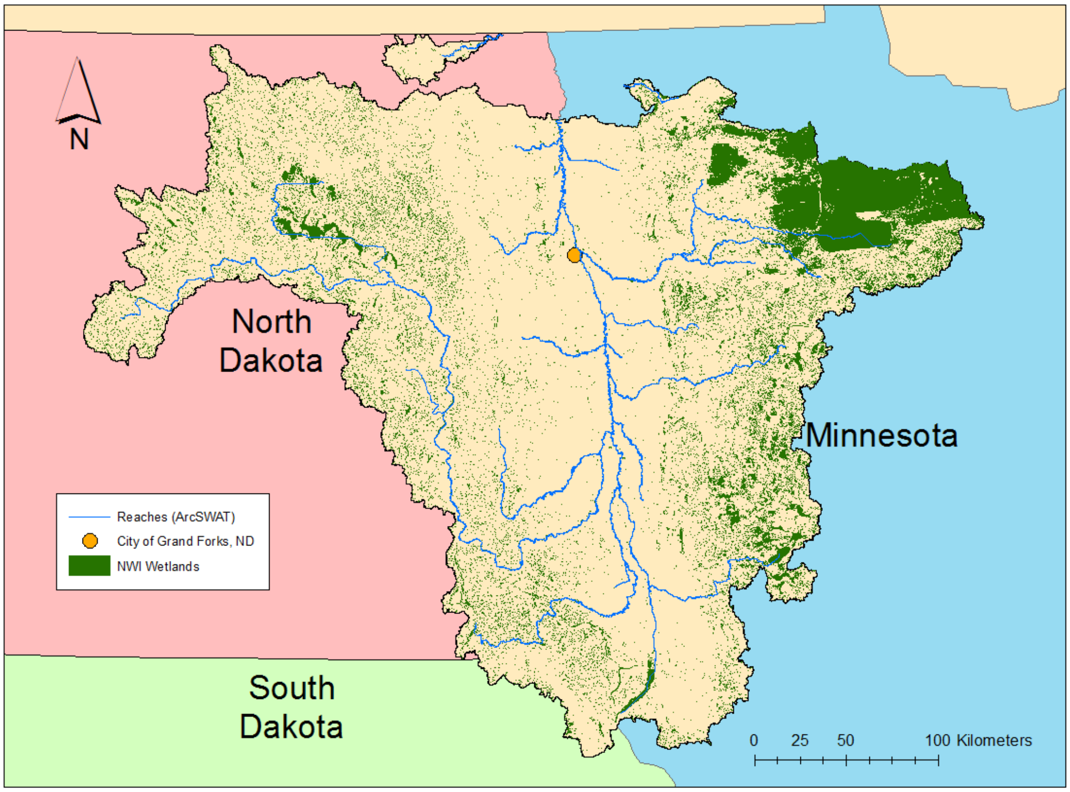


Figure 25. Study area wetlands, as defined by original National Wetland Inventory. Data source: USDOI, 2015.

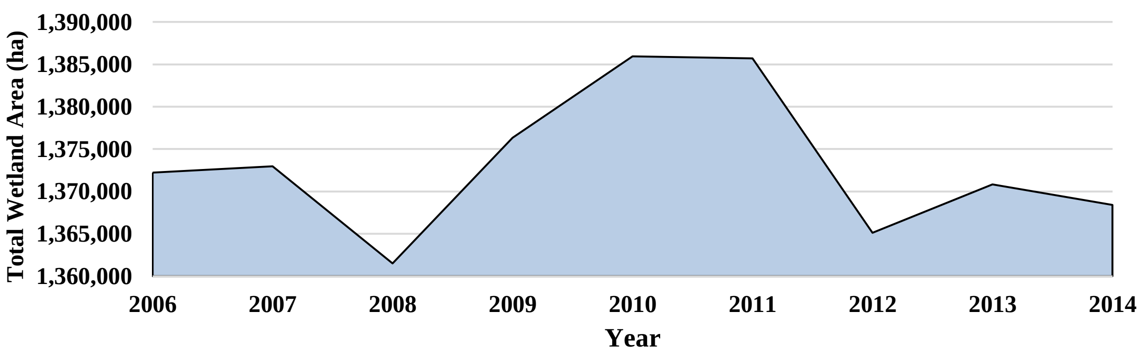


Figure 26. Total wetland areas in the Red River Basin, as calculated by the method described in this study.

Point Sources

In addition to crops, there are numerous anthropogenic sources of nitrates. These include waste water treatment plants, septic tanks, industrial discharges and livestock. The National Pollution Discharge Elimination System (NPDES) regulates municipal wastewater treatment facilities (WWTFs or WWTPs; sometimes referred to as publicly-owned treatment works (POTWs)) and industrial wastewater. Discharges from these types of facilities are likely significant contributors of nitrates to streams (David et al., 2010). By identifying the nitrogen contribution of point sources in this analysis, the nitrate signal of the various crop types should be easier to identify.

A shapefile of all facilities subject to EPA regulation for which the EPA had longitude and latitude data was downloaded from the EPA's Geospatial Data Download Service (USEPA, 2016a; epa.gov/enviro/geospatial-data-download-service). Those facilities identified as "NPDES Majors" were clipped to the study area (Figure 27). Majors are "the largest dischargers" (USEPA, 2010), a subjective classification assigned by an EPA regional director, sometimes in conjunction with a state official, often using a non-codified set of criteria (Johnston, 2015).

Monthly pollutant loading reports were downloaded for each of the facilities using the EPA Discharge Monitoring Report Pollutant Loading Tool (USEPA, 2015a; cfpub.epa.gov/dmr/). Data were available for 2007-2014 for 19 major point sources within the AOI (Figure 27). The only nitrogen species parameter which was available for all facilities was ammonia as nitrogen. This monthly ammonia load was converted to daily load (kg/day) by dividing the monthly value by the number of days in the month. This conversion was performed to account for there being a variable number of days in each month and to moderate the size of the discharges, which were quite large at times.

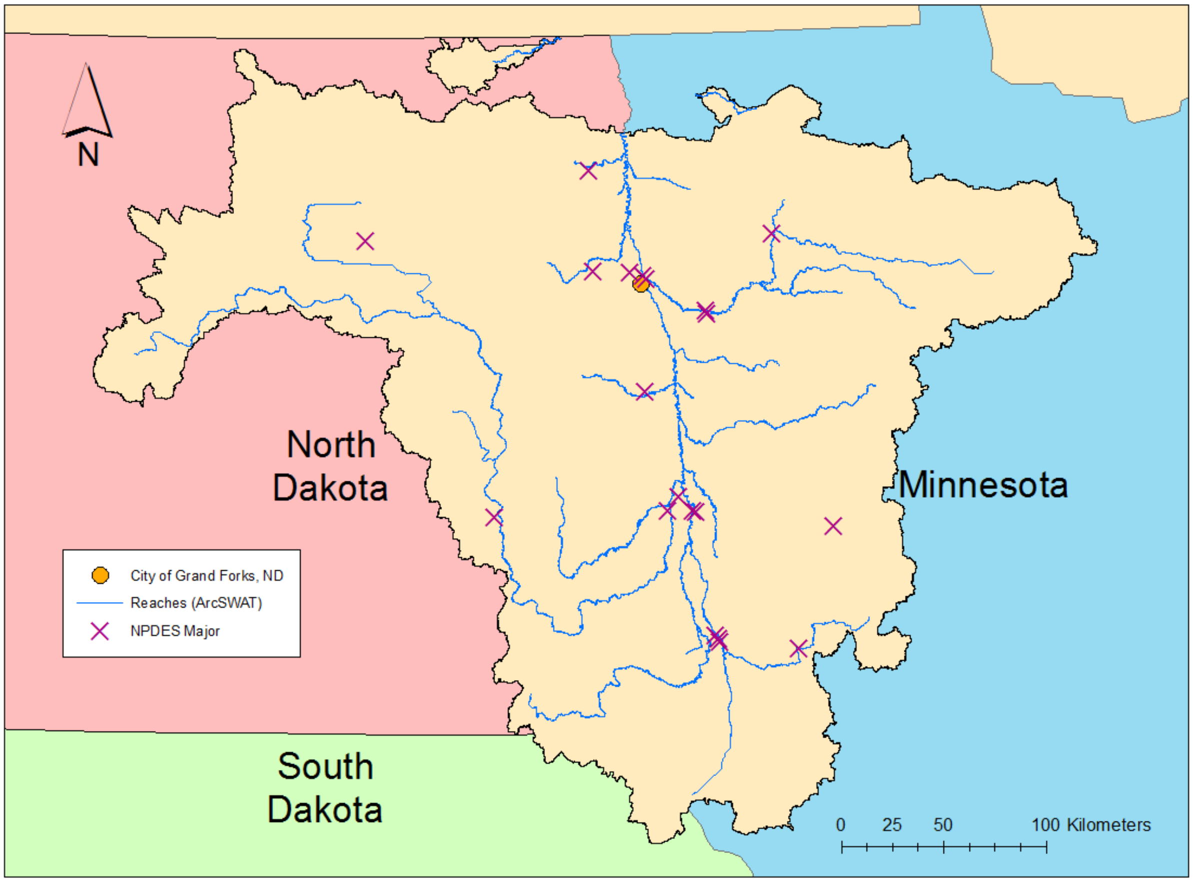


Figure 27. 19 Major NPDES point sources falling within delineated RRB. Data source: USEPA, 2016a.

There were inconsistencies in the point source discharge data. There were periods when some facilities went several months with no reported discharge. The EPA Discharge Monitoring Report Pollutant Loading Tool identified these as months when there were no discharges. For example, the Detroit Lakes, MN municipal wastewater treatment plant has periods of eight or more consecutive months without discharge. Although it is not unusual for WWTPs with some treatment systems to go multiple months without discharge (Johnston, 2015), this same treatment plant was also responsible for the four highest reported discharges, which occurred over the course of four consecutive months. From January 2010 to April 2010 the plant had discharges ranging from 2021 to 3628 kg per day.

The sum of all daily nitrogen point source discharges can be seen in Figure 28. Generally, it appears that there is often a peak discharge in the spring, particularly in 2007 and 2010. The major point sources within each gauge drainage basin were identified. The daily loads for those sources were summed for each basin. Since data were only available for years after 2006, use of this data in a land use – water quality model resulted in a reduced sample size, since data from years prior to 2007 could not be included. A value of 0 kg/day was assigned to any basin from 2007-2014 which did not have point source discharge data.

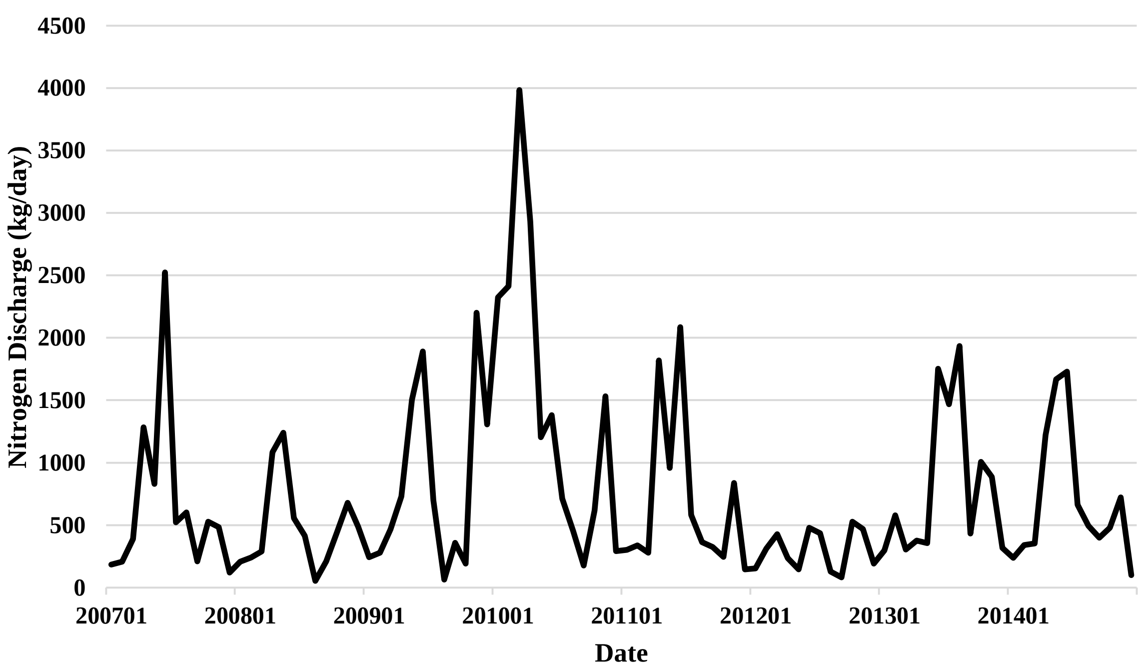


Figure 28. Sum of daily point source discharges for all NPDES Majors in the study area.

Installed Subsurface Drainage

Drainage installation in the study area has been extensive. The 1992 National Resource Inventory estimated 8% of North Dakota and 12% of Minnesota had been drained (Jaynes and James, 2007). This undoubtedly has had an influence on hydrology, nitrification rates and nitrate export. Some studies have determined that areas with larger relative areas of tiling produce greater nitrogen loss (David et al., 2010). It is expected that this study will produce similar results. However, data related to the extent and location of tile installation is scarce and each states regulates tiling differently.

Geospatial tiling data were not available for Minnesota or South Dakota. In North Dakota, large drainage projects currently require permits which are administered by local water resource districts (WRDs) (Sando, 2015). These permits are only required if the area drained is eighty acres or larger (Sando, 2015). The USGS has compiled North Dakota Red River Basin tiling data as of October 2013 into a shapefile using permit records (USGS, 2014a).

Polygons of permitted tiling areas in North Dakota were downloaded from the USGS (USGS, 2014a). This produced a record of 853 permits which had a permit approval date listed. The size of each tiling project was of interest and the most complete related metric was the “tiled area” attribute, of which 840 of the 853 records had a value greater than zero. There were no records of tiling installation completion dates. Therefore, it was decided that if an application was approved prior to April 21 (the earliest planting date for soybeans, the dominant RRB crop (Table 13; Hatchfeld, 2012)), it would be assumed that tiling was installed prior to that year’s crop. If the application was approved on April 21 or later, the tiling would be installed prior to the following year’s crop.

Table 13. Planting dates to be fully eligible for federal crop insurance programs. Data source: Hachfeld, 2012.

Crop	Earliest Planting Date	Latest Planting Date
Corn	April 11	May 31
Soybeans	April 21	June 10
Sugar Beets	April 11	May 31
Wheat	March 21 – April 1	May 15 – June 5

A tiled area shapefile was developed for each year from 2004 to 2013 showing the cumulative area tiled. The record showed only three approved permits prior to 2003, two in 1993 and one in 2002. Within ArcGIS these shapefiles were then clipped to gauge drainage basins which fell entirely within North Dakota. The polygons were merged to eliminate overlap, then areas of permitted drainage areas were summed to determine the total permitted drainage area for each basin each year. This provided a tiling area variable which was converted to hectares for use in this analysis. Using this method, the total area tiled identified within North Dakota in 2013 is shown in Figure 29.

There were no records in the dataset of any tiling projects in the study area prior to 2004. Although there was undoubtedly tiling installed prior to that year, data identifying the extent and locations have not been located. Therefore, all basins were given zero tiling area for 2003, years prior were "NA" and would not be included in analysis. When this variable was included in the land use – water quality analysis, only data from 2003-2014 would be considered and the sample size was reduced to 1176.

Figure 30 shows the cumulative number of approved subsurface drainage (tiling) permits within the North Dakota portion of the study area. It can be seen that the area of tiling and number of permits are correlated, although the number of permits has been growing faster than the area of permitted tiling. Overall, the number of permits and areas tiled per year are

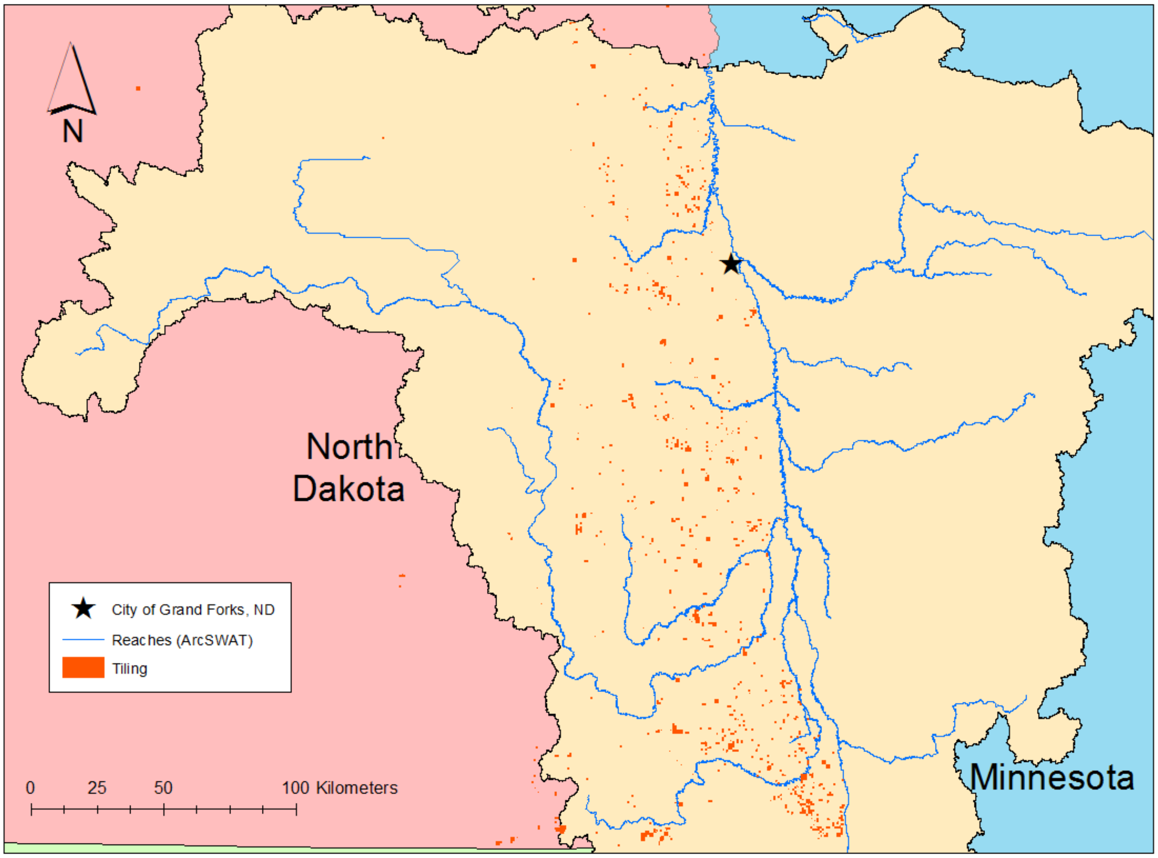


Figure 29. Areas of tiling identified in North Dakota, 2013.

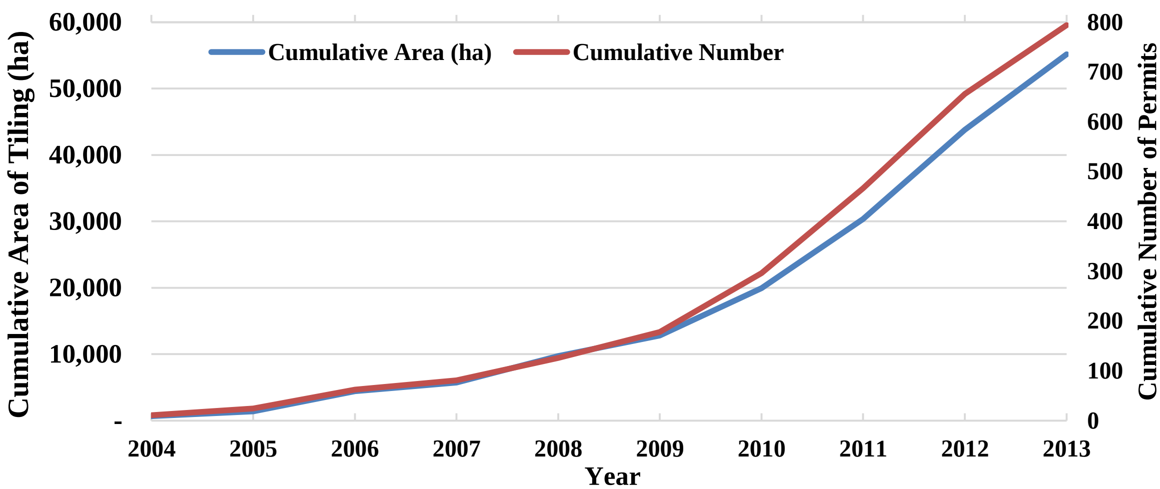


Figure 30. Cumulative number of North Dakota tiling permits and permitted area tiled, 2004-2013. Data source: USGS, 2014b.

increasing, as the lines are not linear and appear exponential. The data shown in Figure 30 represent the extent of tiling installed after 2003, as the dataset did not include any tiling projects prior to 2004. Additionally, since North Dakota only permits larger tiling projects, it is very possible that these tiling data are not representative of total tiling area, since total area of all tiling projects may be considerably higher than total area of permitted projects.

Summary Statistics for Water Quality Analysis

A summary of all the data obtained for the construction of the water quality and land use model is displayed in Table 14. Note that not all variables have the same sample size. For most variables, n=3256. However, point source data n=2326 because data were only available for the period 2007-2014 and tiling data n=1176 because data were only available for the period of 2004-2013 and only for the North Dakota portion of the study area.

Table 14. Summary statistics of variables used in construction of water quality model.

variable	n	minimum	mean	maximum	standard deviation
Area of alfalfa (ha)	3256	0	7,272	182,202	20,447
Area of canola (ha)	3256	0	15,408	142,598	36,321
Area of corn (ha)	3256	0	59,669	1,030,388	150,590
Area of dry beans (ha)	3256	0	12,301	218,027	29,770
Area of soybeans (ha)	3256	281	127,319	2,382,233	323,515
Area of sugar beets (ha)	3256	0	6,539	172,022	22,137
Area of sunflowers (ha)	3256	1	16,026	228,655	39,597
Area of wheat (ha)	3256	374	112,606	1,373,003	207,187
Area of all crops (ha)	3256	2,846	412,957	5,439,488	808,885
Total area of basin (ha)	3256	54,348	785,574	9,039,220	1,441,037
Daily stream discharge (m^3 per day)	3256	0	2,277,535	186,916,608	9,148,269
Daily baseflow discharge (m^3 per day)	3256	0	994,701	89,213,289	3,789,010
Daily runoff (m^3 per day)	3256	0	1,282,834	159,441,924	6,428,638
Stream length (km)	3256	303	2,982	41,595	5,921
Wetland area (ha)	3256	971	122,489	1,360,814	224,525
Daily point source load (kg/day ammonia as nitrogen)	2326	0	38	2,792	190
Area of tiling (ha)	1176	0	675	10,834	1,972
Nitrate concentrations (mg/L)	3256	0.00	0.47	14.40	0.98

Reported County Crop Yields (NASS)

Summaries of reported crop yields used in this analysis, obtained from the National Agricultural Statistics Service (NASS; USDA, 2015b; http://quickstats.nass.usda.gov/), can be seen in Table 15. These are county yields reported in surveys for all counties which fall entirely or partially within the study area (Figure 11). Variance in the number of samples per crop type is due to some counties not having some crop yields published for some years. Data span 1997-2014 for counties within North Dakota and 2006-2014 for counties within Minnesota and South Dakota to match the available CDL data. These yields were used to identify a relationship between the SSURGO crop productivity indices (CPI) and actual observed yields.

Table 15. Summary of reported crop yields (per hectare) used in this analysis, by crop type. Data source: USDA, 2015b

Crop	n	minimum	mean	maximum	standard deviation
Alfalfa (tons)	910	2.47	6.20	11.74	1.67
Canola (pounds)	418	2181.94	3667.56	5016.23	608.69
Corn (bushels)	1142	0.00	278.48	460.36	62.46
Dry Beans (pounds)	800	1452.98	3693.58	5955.23	686.48
Soybeans (bushels)	1206	24.71	76.87	119.10	14.26
Sugar Beets (tons)	452	24.22	56.92	81.30	8.81
Sunflower (pounds)	564	1420.85	3368.36	4830.90	572.31
Wheat (bushels)	482	49.17	87.94	141.10	21.79

Crop Productivity Index

The SSURGO small grains crop productivity index was found to produce the strongest relationship with observed yields, as explained below. A summary of the county SSURGO small grains crop productivity index values used in this analysis is shown in Table 16. These values are the averages of the small grains index values for areas grown in each of the crop types within each county. Data are from all counties falling entirely or partially within the study area. Data span 1997-2014 for counties within North Dakota and 2006-2014 for counties within Minnesota and South Dakota. The variance in the number of samples by crop type are due to some crops in some counties not having yield averages published for some years.

Table 16. Summary of the SSURGO county small grain crop productivity index values used in this analysis, by crop type.

	n	minimum	mean	maximum	standard deviation
Alfalfa	455	0.14	0.27	0.37	0.04
Canola	209	0.17	0.27	0.33	0.02
Corn	571	0.02	0.28	0.40	0.04
Dry Beans	400	0.20	0.29	0.40	0.03
Soybeans	603	0.15	0.29	0.43	0.04
Sugar Beets	226	0.19	0.28	0.37	0.04
Sunflower	282	0.14	0.28	0.35	0.03
Wheat	241	0.15	0.28	0.43	0.03

For each crop, regressions had been performed with each of the CPIs (corn/soybean and small grain) as the independent variable and each of the crop yields (NASS and SSURGO) as the dependent variable. The results can be seen in Table 17. SSURGO does not provided published yield estimates for canola or dry beans.

Table 17. Summary of coefficients of determination and p-values of linear regression of dependent variable yields and dependent variable crop productivity indices.

	SSURGO yields				NASS yields			
	corn/soy CPI		small grain CPI		corn/soy CPI		small grain CPI	
	R^2	p	R^2	p	R^2	p	R^2	p
Alfalfa	0.85	0	0.86	0	0.91	0	**0.94**	0
Canola	NA	NA	NA	NA	0.92	0	**0.96**	0
Corn	0.86	0	0.85	0	0.95	0	**0.96**	0
Dry Beans	NA	NA	NA	NA	0.92	0	**0.96**	0
Soybeans	0.87	0	0.85	0	**0.95**	0	0.94	0
Sugar Beets	0.78	0	0.75	0	**0.97**	0	0.96	0
Sunflower	0.81	0	0.82	0	0.93	0	**0.96**	0
Wheat	0.82	0	0.84	0	0.93	0	**0.94**	0

NASS yields always produced a stronger relationship with CPI values than SSURGO yields. Small grain CPI usually produced a stronger relationship with NASS yields, with the exception of soybeans and sugar beets for which the coefficients of determination from regressions with corn/soy and small grain CPIs were very similar. It was decided to use the NASS yields and small grain CPI to identify potential yields for all crops.

The coefficients of the regressions of the independent small grain CPI variable and the dependent NASS crop yield are displayed in Table 18. Magnitude of the coefficients vary greatly, since the magnitude of the yield data available from NASS vary greatly. For example, canola yields are measured in pounds, while alfalfa yields are measured in tons.   Also shown is the weighted average yield for all mukeys in the study area, calculated by applying the coefficient to the CPI in each mukey, applying weight to each mukey in accordance with its relative total area within the AOI, summing the weighted yields and then dividing by the area of the AOI.

Table 18. Derived crop yield coefficients and projected yields. Coefficients obtained from the regression of independent variable small grain Crop Productivity Index and dependent variable NASS reported yield for each crop and average projected yields for each crop when coefficient is applied to basin mukeys.

Crop	Yield Unit Per Hectare	Coefficient	Projected Yield
Alfalfa	tons	14.5	3.2
Canola	pounds	13353.0	2924.8
Corn	bushels	980.6	214.8
Dry Beans	pounds	12795.9	2802.8
Soybeans	bushels	265.9	58.2
Sugar Beets	tons	203.6	44.6
Sunflower	pounds	12098.0	2650.0
Wheat	bushels	307.0	67.2

Farm Financials

Historical crop prices and farm direct expenses for the period 2006-2014 for all counties falling entirely or partially within the area of interest were collected from University of Minnesota's farm financial database, FINBIN (UMN, 2015; finbin.umn.edu). FINBIN provides summaries of farm data from users of the FINPACK software. All available 2006-2014 historical crop prices (value per bushel, pound or ton) and direct expenses (cost per acre) for the area were obtained. Direct expenses were converted to cost per hectare. The data obtained were used to establish a range of potential prices and expenses for production scenario development. Summaries of direct expense and value data, by crop type, are shown in Tables 19 and 20, respectively.

Although the dry bean yield from NASS had been used to calculate the coefficient of small grain CPI to dry bean yield, financial data for a dry bean crop type were not available in FINBIN. Instead, cost and value data for pinto beans were used. Pinto beans are a prevalent crop in the study area. In 2007, pinto beans comprised 70% of the North Dakota dry bean crop (USDA, 2016b).

Table 19. Summary of direct expenses, by crop, for counties within the study area, 2006-2014. Data source: UMN, 2015.

Crop	minimum expense ($/ha)	average expense ($/ha)	maximum expense ($/ha)
Alfalfa	200.18	255.04	327.99
Canola	346.32	529.33	656.24
Corn	606.26	936.50	1184.84
Dry beans	462.81	672.10	873.17
Soybeans	347.61	498.64	623.07
Sugar Beets	1450.02	1874.21	2415.90
Sunflowers	339.48	547.24	707.29
Wheat	345.79	539.50	674.63
Grassland	24.48	29.52	44.54

Table 20. Summary of crop values, by crop, for counties within the study area, 2006-2014. Data source: UMN, 2015.

	minimum value ($)	average value ($)	maximum value ($)
Alfalfa (ton)	64.69	80.91	104.47
Canola (pound)	0.12	0.19	0.28
Corn (bushel)	2.74	4.15	6.40
Dry Beans (pound)	0.19	0.29	0.42
Soybeans (bushel)	5.91	10.13	13.86
Sugar Beets (tons)	36.76	45.94	65.12
Sunflowers (pound)	0.13	0.21	0.29
Wheat (bushel)	4.40	6.37	8.31
Grassland (hectare)	24.48	31.02	39.72

The average expenses and prices of all crops, as shown in Table 19 and 20, were provided as inputs to the economic-land use model described in the methodology section. It was found that the areas of dry beans and sugar beets predicted by the economic – land use model were very unrealistic. Subsequent research showed that these two crops were generally grown under contracts and, therefore, were not likely to immediately respond to changes in price or cost (American Crystal Sugar Company, 2016; USDA, 2000). For this reason, the areas of beans and beets in each basin were held constant at the basin average.

As described in the methods section, expense and price values were then adjusted until the model produced relative crop areas which were comparable to the average relative crop areas observed in the study area from 2006-2014. This created a baseline from which hypothetical economic scenarios could be constructed. The baseline economic conditions, with a comparison of the modeled land use results and observed land use under the baseline economic conditions, are shown in Table 21.

Table 21. Baseline economic conditions for scenario development and comparison of projected and observed land use. Projected and observed land use is the ratio of the average RRB land use by crop type, 2006-2014, and the land use projected by the economic – land use under baseline economic conditions. *Bean and beet areas were not projected by model and were held at basin average.

Crop	expense ($/ha)	value ($)	projected land use/observed land use
Alfalfa (ton)	327.99	80.91	0.91
Canola (pound)	656.24	0.19	3.18
Corn (bushel)	995.00	4.15	0.91
Dry beans (pound)	*	*	*
Soybeans (bushel)	510.00	10.13	0.92
Sugar Beets (tons)	*	*	*
Sunflowers (pound)	707.29	0.21	3.46
Wheat (bushel)	375.00	6.37	0.92
Grassland (hectare)	31.02	29.52	0.38

In addition to direct costs of crops, fertilizer cost data were required for scenario development. The average annual fertilizer expense for each crop type within the study area from 2006-2014 was obtained from FINBIN data (UMN, 2015), shown in Table 22. Fertilizer tax scenarios were constructed by adding a sales tax, calculated as a percentage of the average fertilizer cost, to the cost.

Table 22. Average fertilizer cost per hectare in the study area, 2006-2014. Data derived from UMN, 2015.

Crop	Average Fertilizer Cost Per Hectare
Alfalfa	$ 53.36
Canola	$ 149.57
Corn	$ 281.56
Soybeans	$ 33.17
Sunflower	$ 105.56
Wheat	$ 175.24

CHAPTER IV

RESULTS

The primary statistical analyses employed in this study are simple linear and multivariate regressions. This is an approach used by other studies investigating the relationships of land use and water quality (Broussard and Turner, 2009; Schilling and Lutz, 2004). Regressions were performed in R 3.2.1. All results were assessed at a significance level of 0.05 (α=0.05). For multiple regressions, the adjusted coefficient of determination is reported.

Correlations

Correlation analyses were performed on variables, the results of which are shown in Figures 30-34. Since the purpose of this study is to identify the relationship between land use (crop type) and surface water nitrate concentrations, it was considered that the previous year's land use may be more significant than the current year's, given the residence time of nitrogen species within the basin. Correlation of the current year's and previous year's crop areas, obtained from the Cropland Data Layer, were assessed for each crop to determine how similar the data were (Figure 31).

It was found, given the strengths of the correlation coefficients, that the area planted in a particular crop within a gauge drainage basin varied little from one year to the following. This relationship was strongest with wheat, which produced a correlation coefficient of 0.9900 and weakest with alfalfa, with a coefficient of 0.7556. In consideration of these results, it is likely that there will not be a large difference in the results of a regression using either current year's or previous year's crop area as an independent variable.

Correlation analyses were also performed on crop area variables and nitrate concentrations (Figure 32). Crop area variables assessed include the absolute area of each crop in the current and previous years (hectares) and the relative area of each crop in the current and previous years (basin hectares planted in the crop / total hectares in the basin). Many studies have found that the relative area of crop is a more significant variable than the total area (Broussard and Turner, 2009; Jordan et al., 1997; Schilling and Lutz, 2004).

Of the three most prevalent crops (corn, soybeans and wheat, which comprise 82% of all crops), relative area of corn and soybean correlations provided a higher correlation coefficient than absolute area correlation. Four of the eight crops (corn, soybeans, alfalfa and sugar beets), or 65% by area, produced higher correlation coefficients when the relative crop area was used, compared to the absolute crop area. Since the total area of these crops comprised the majority of the crop area and because corn was the crop of greatest interest, relative crop areas were selected for use in regression analysis.

For all crops except dry beans, wheat and canola, the previous year's relative crop area produced a higher correlation coefficient than the current year's relative crop area. In all cases the two correlation coefficients were very comparable, with the largest discrepancy occurring with sunflowers, which produced a coefficient of -0.1032 with current year's relative crop area and -0.1757 with previous year's relative crop area. The strongest relationship observed was a 0.2555 correlation coefficient with previous year's relative area of sugar beets, followed closely by 0.2406 coefficient with previous year's relative area of corn. The relationships between nitrate concentrations and relative crop areas were positive for corn, alfalfa, soybeans and sugar

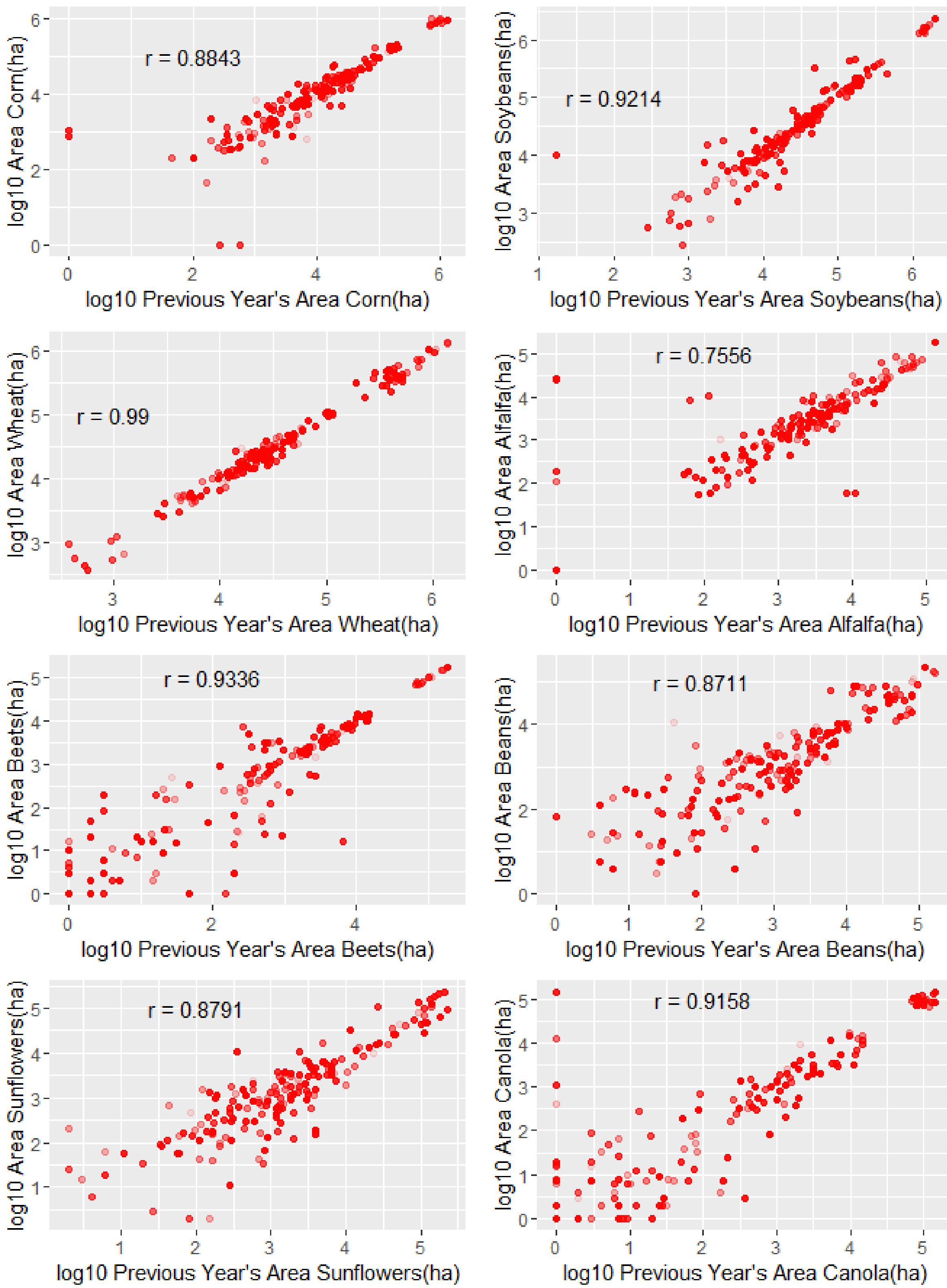


Figure 31. Results of correlation analysis of current year's and previous year's land use.

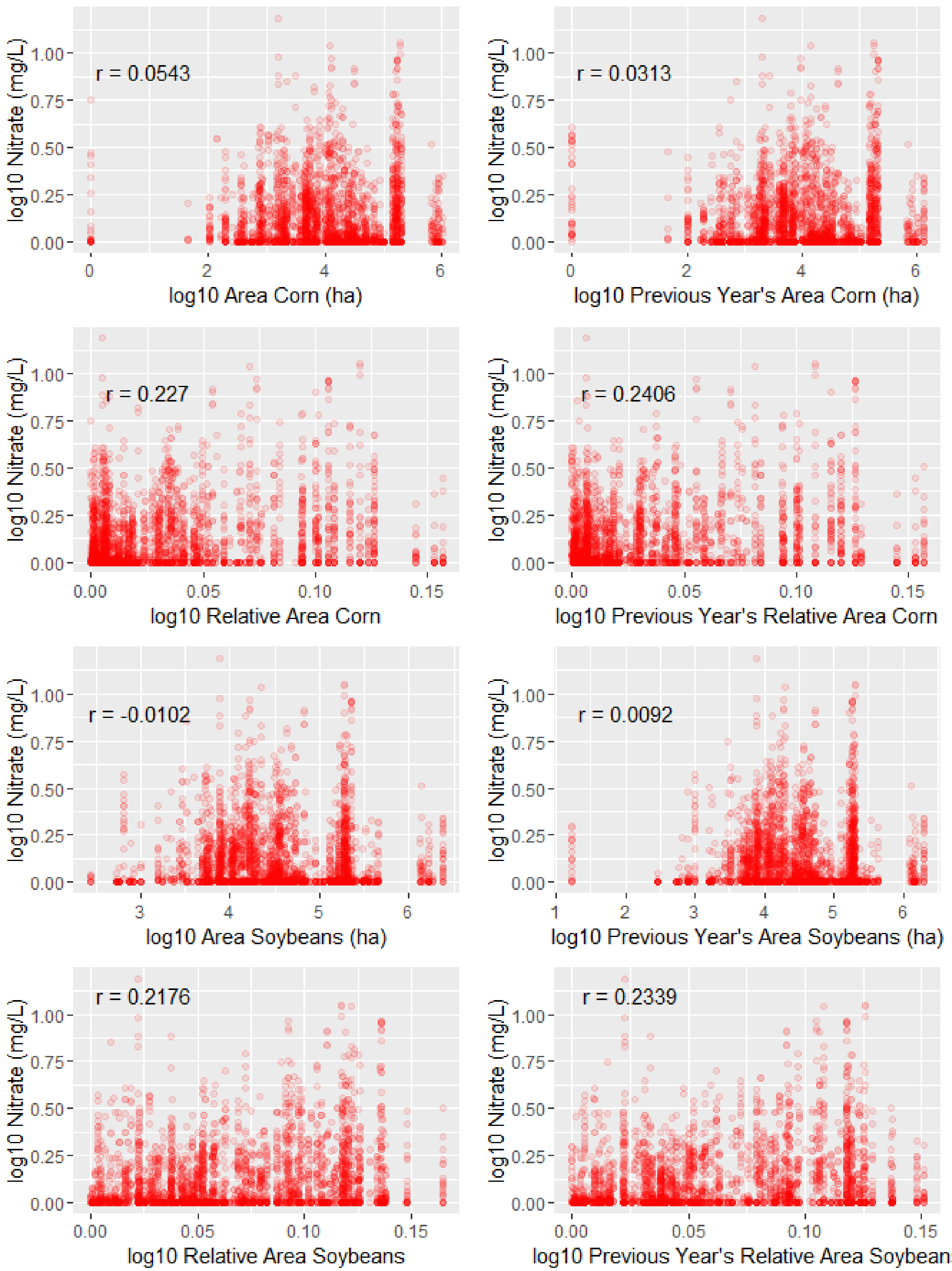


Figure 32. Results of correlation of nitrates and crop areas, by crop type.

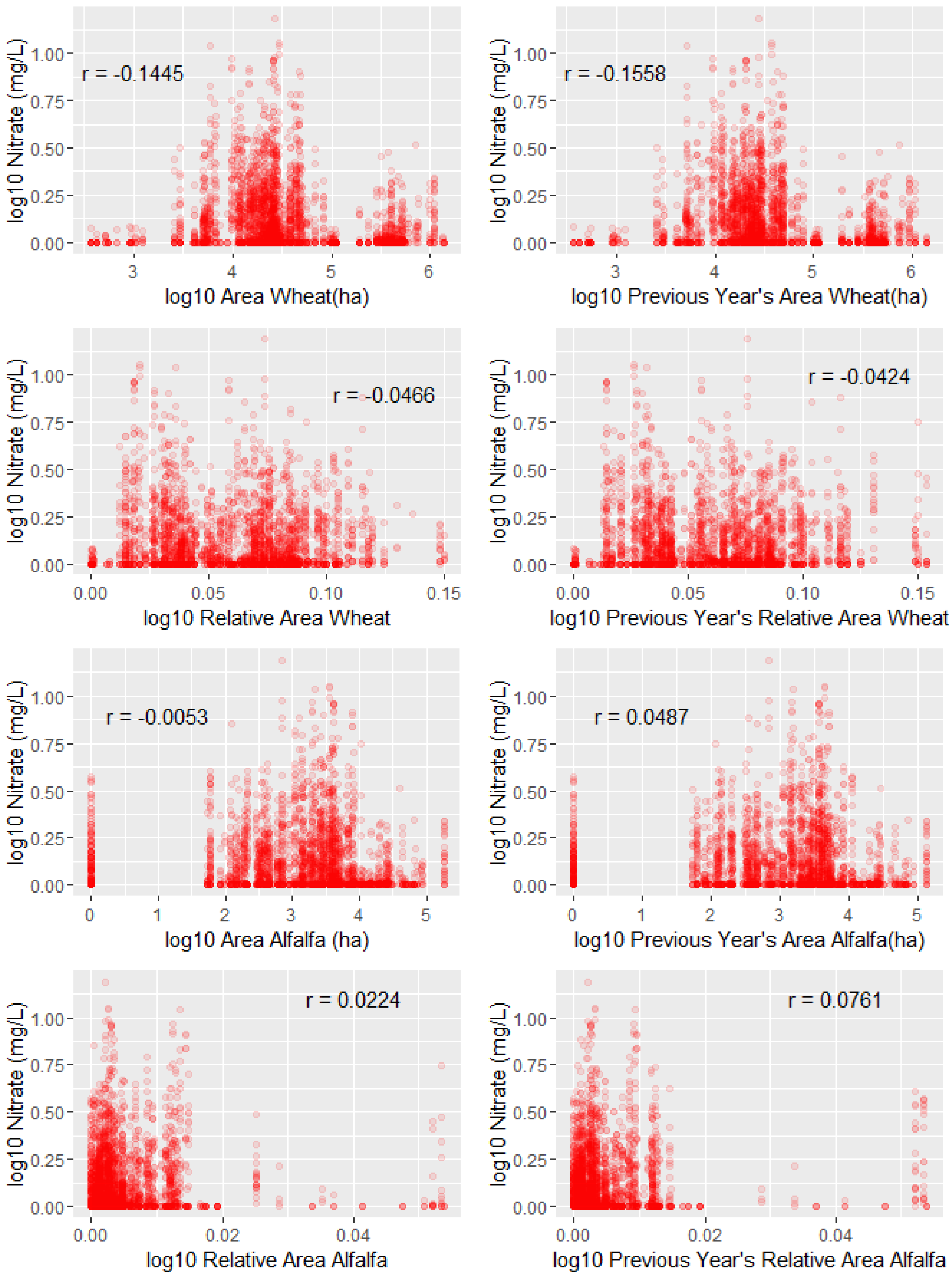


Figure 32 cont. Results of correlation of nitrates and crop areas, by crop type.

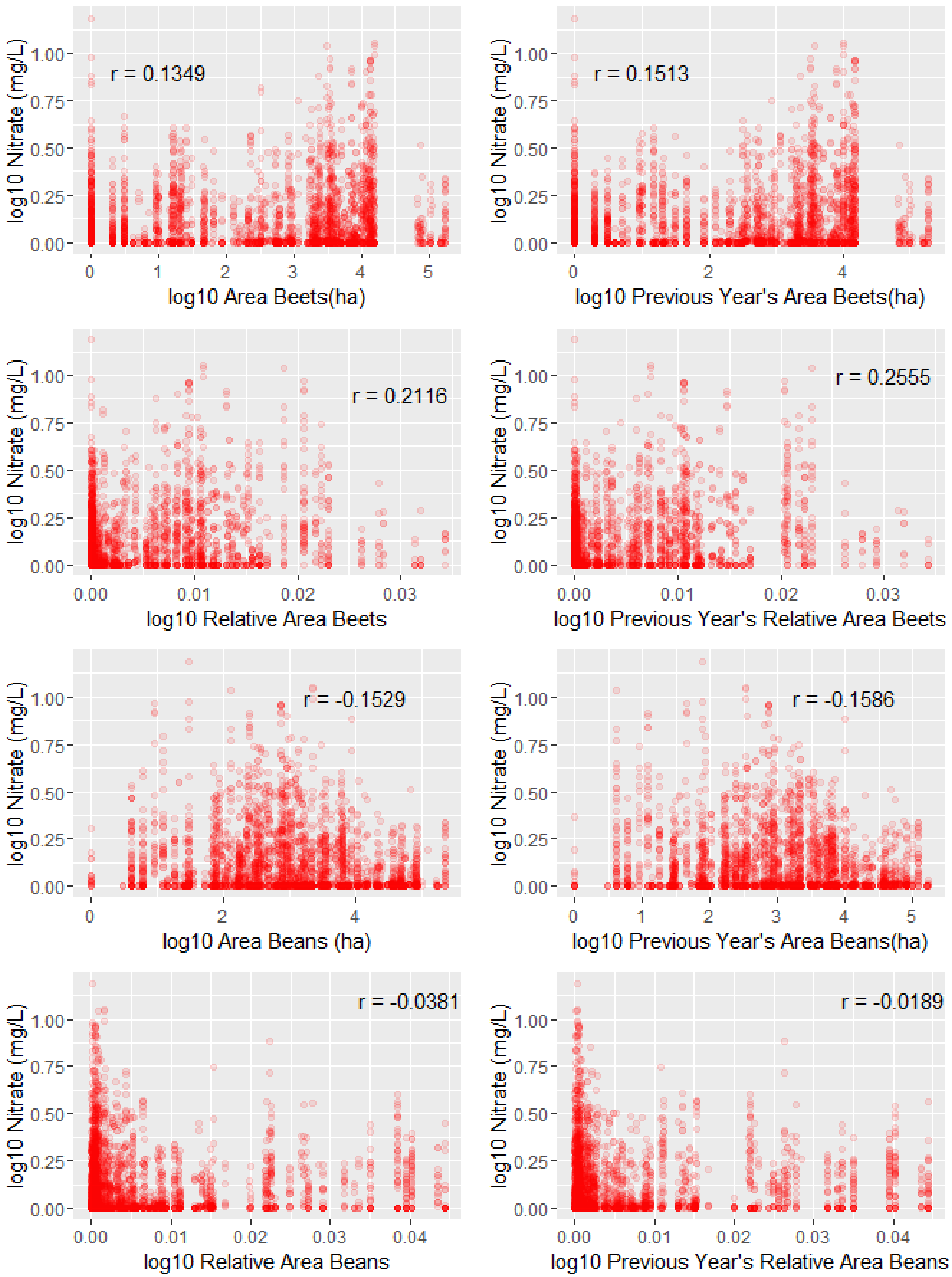


Figure 32 cont. Results of correlation of nitrates and crop areas, by crop type.

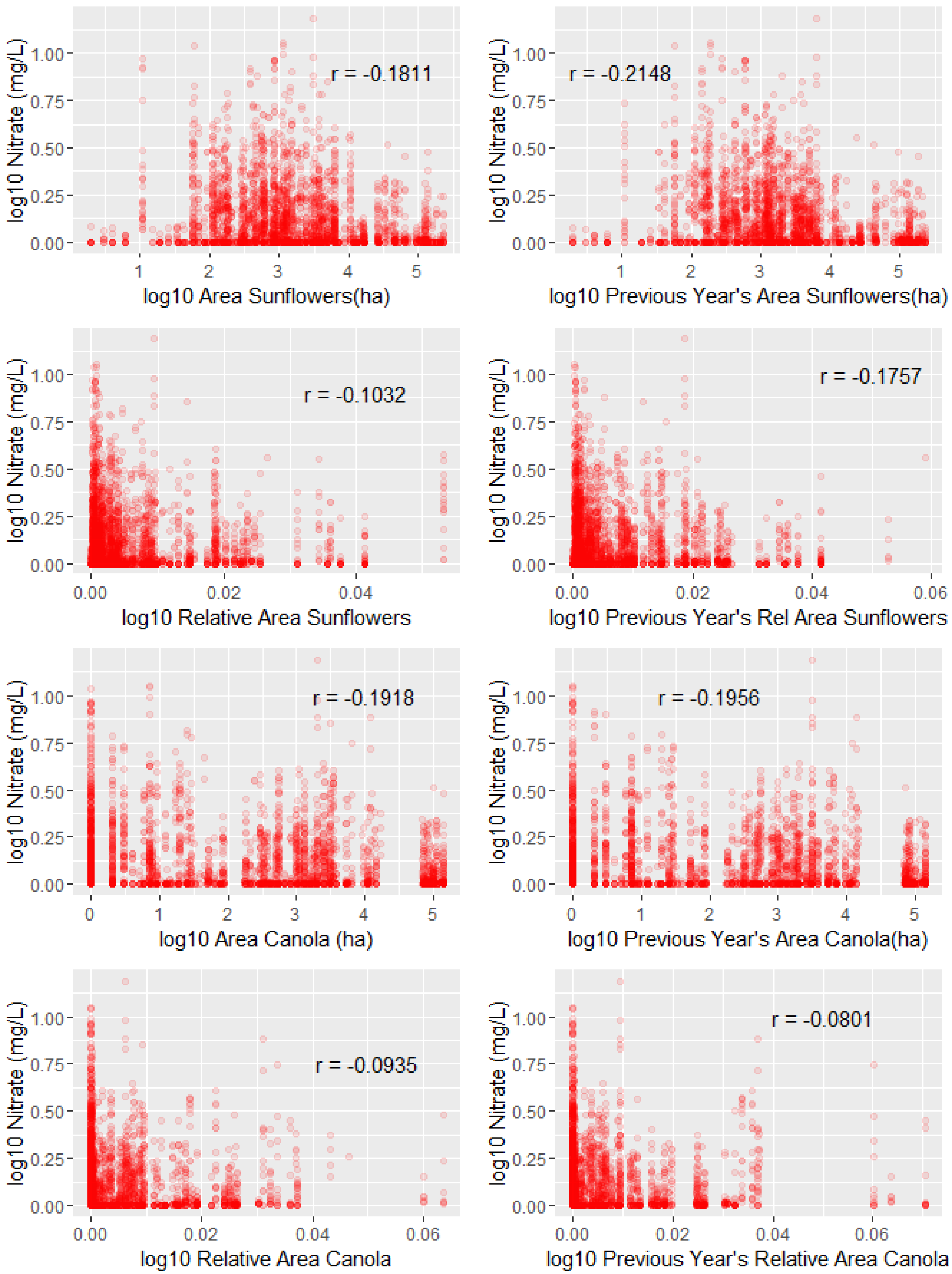


Figure 32 cont. Results of correlation of nitrates and crop areas, by crop type.

beets, indicating that higher relative areas of these crops correlated with higher nitrate concentrations. The coefficients were negative for canola, dry beans, sunflowers and wheat, indicating that higher relative areas of these crops correlated with lower nitrate concentrations.

Having identified that, of the crop variables assessed, the previous year's relative crop areas were most closely related to nitrate concentrations, the correlations of previous year's relative areas of all crops and row crops with nitrate concentrations were evaluated. Row crops were identified as corn, dry beans, soybeans, sugar beets and sunflowers. The "all crop" variable was the total area of all crops (not just the major crops which were individually assessed), as shown in the Cropland Data Layer. The results of these analyses are shown in Figure 33. There was a stronger relationship with row crops than with all crops, 0.2531 compared to 0.197. This correlation coefficient of row crops was higher than any observed among individual crop types, with the exception of that produced by previous year's relative area of beets, which was 0.2555.

Correlation analyses were performed with nitrate concentrations and wetland areas and relative wetland areas (Figure 33). Unlike crops, the area of wetland produced a stronger correlation coefficient ($r = -0.1876$) than the relative area ($r = -0.1348$). The negative coefficient indicates that increased areas of wetland correspond with decreased nitrate concentrations.

Both areas of subsurface drainage (tiling) and relative areas of tiling were used in separate correlation analyses with nitrate concentrations. Both variables produced weak coefficients, the strongest being -0.0542, as shown in Figure 33. The conflicted direction of the coefficients, one being negative and the other being positive, create doubt as to whether the impact of this variable could be accurately determined. Oddly, correlation analysis also indicated that larger point source nitrate emissions coincided with lower nitrate concentrations in surface water ($r = -0.1449$).

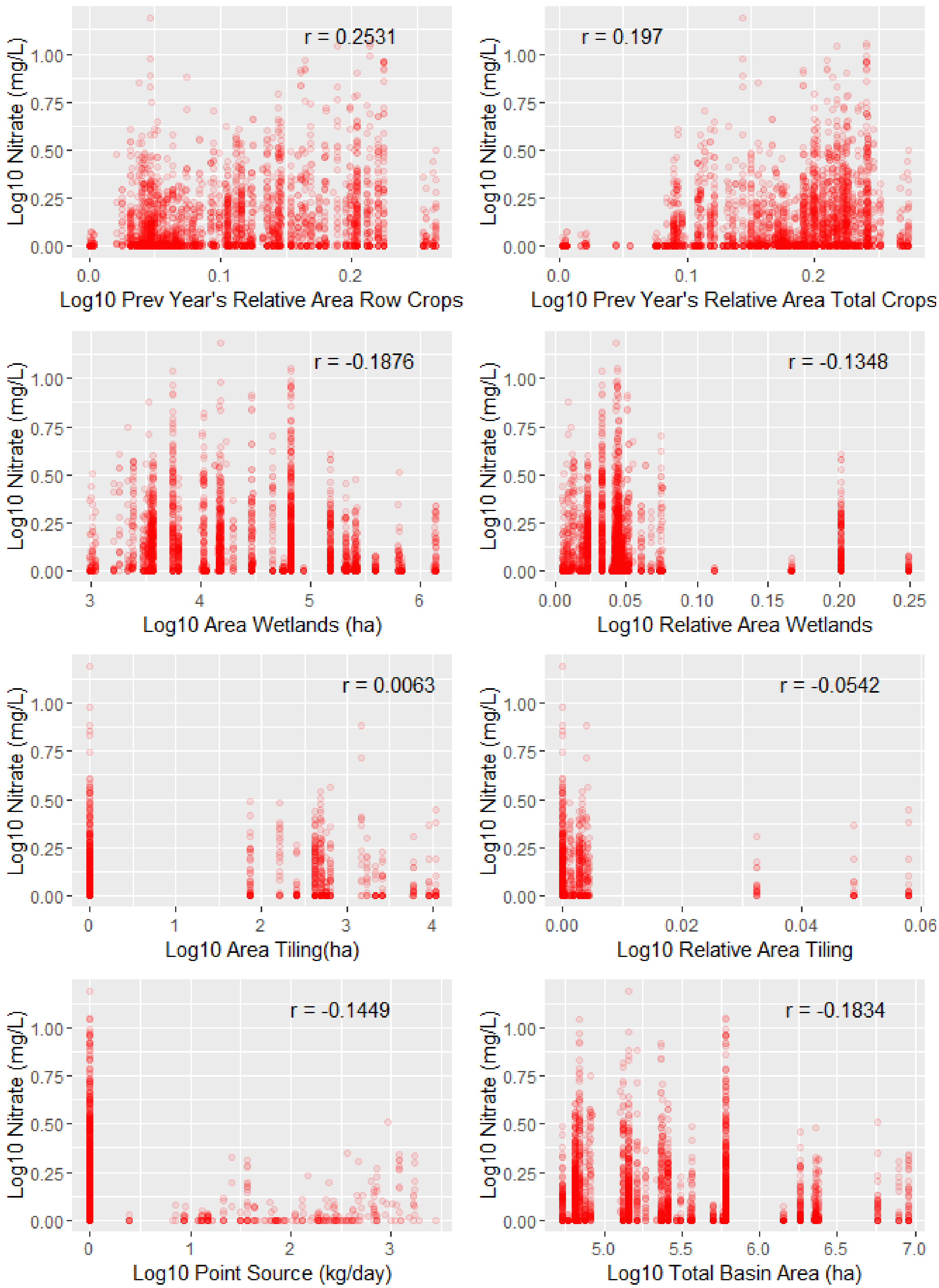


Figure 33. Results of correlation of nitrates and assorted independent variables.

The relationship between total basin area and nitrate concentration was found to be negative (Figure 33), with r = -0.1834. Basins with larger areas appear to have lower nitrate concentrations in their streams.

Relationships were also assessed between stream lengths and discharge variables and nitrate concentrations using correlation analysis (Figure 34). The correlation coefficient of the analysis of stream length and nitrate concentration was negative, showing that basins with more streams had lower nitrate concentrations in those streams.

The three discharge variables (baseflow, runoff and total discharge) were compared to nitrate concentrations using correlation analysis. The results are shown in Figure 34. All produced positive coefficients, indicating that greater discharge correlated with higher nitrate concentrations. Of the three variables, runoff had the strongest relationship, r = 0.3015. The relationship of nitrates with baseflow was quite low, r = 0.0482.

Relationships between the total basin size and other independent variables were also assessed (Figure 35). There was a strong correlation between total stream lengths in a basin and the total size of the basin, r = 0.9252, indicating that larger basins tend to have longer stream networks. There was a similar relationship with total crop areas and basin size (r = 0.8801), indicating that, generally, all basins had a similar percentage of crop area. The correlation of basin size and discharge was moderate, r = 0.5467. Overall, larger basins produce greater discharge. However, the discharge variable used includes observations taken throughout the year, so the correlation may have been stronger if seasonal variations in discharge had been removed.

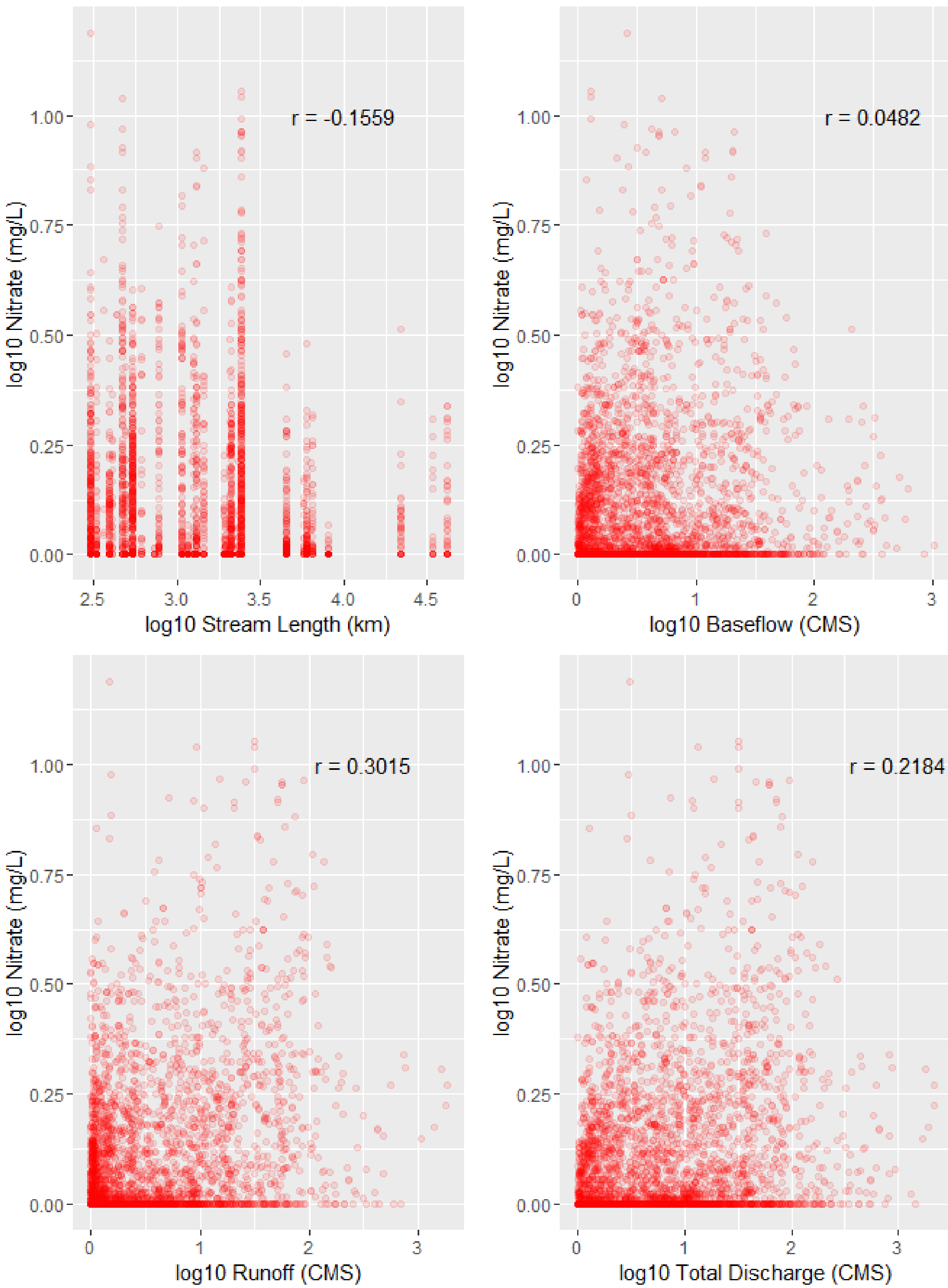


Figure 34. Results of correlation of nitrates and stream length, baseflow, runoff and total discharge variables.

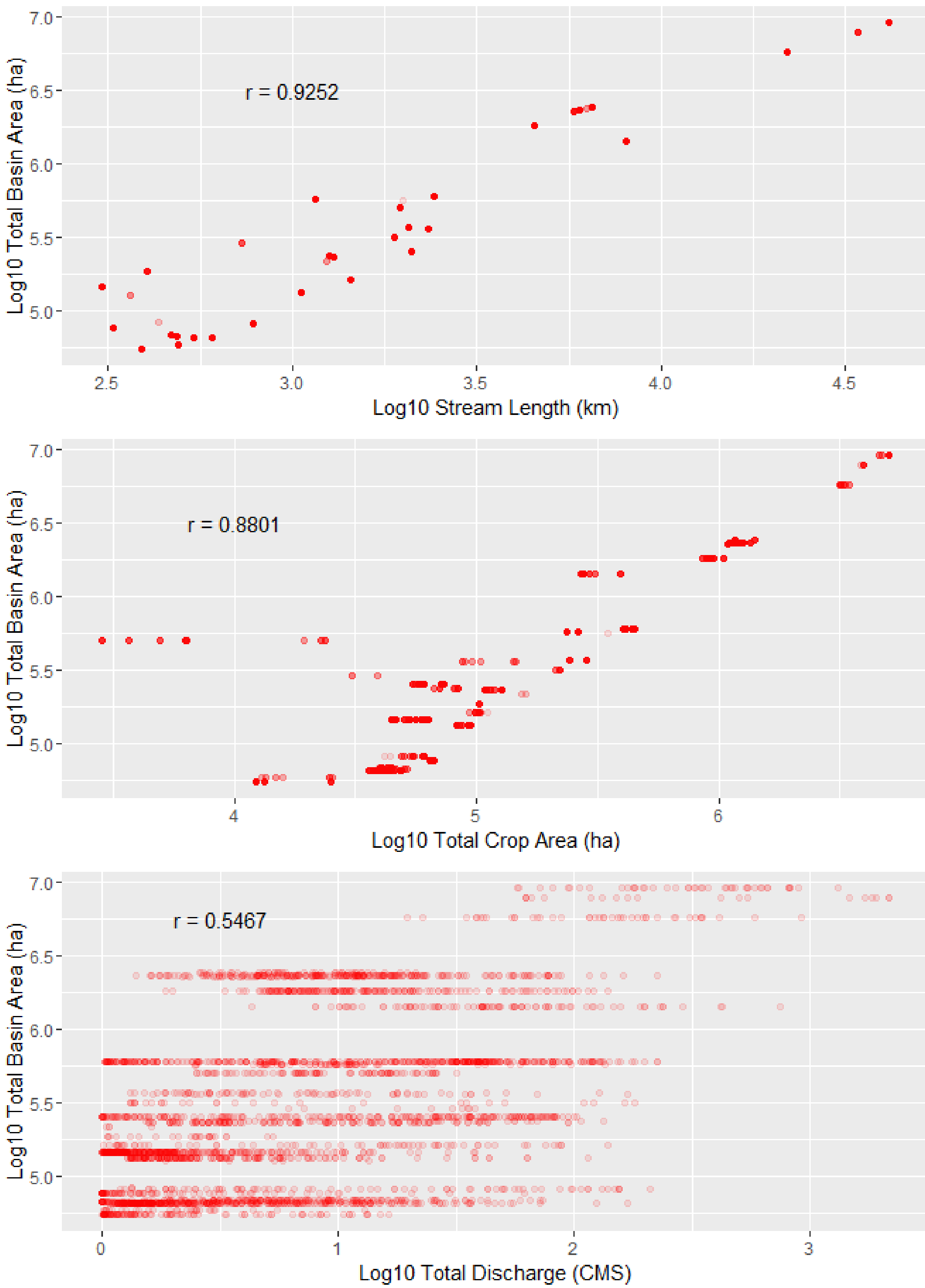


Figure 35. Results of correlation of basin areas and assorted independent variables.

Regression Analysis

Multivariate regression analyses were performed with the nitrate concentration as the dependent variable, and the crop, stream length, discharge, wetland, point source and tiling data as independent variables. In the manner of the study by Jordan et al. (1997), the crop variables were added first since land use is of primary interest to this study. Next, discharge variables were added due to their relatively high correlation with nitrates and the significance of these variables in other studies (Broussard and Turner, 2009; Jordan et al., 1997 and David et al., 2010). Stream length, wetland, point source and tiling variables were then added, in that order, in consideration of their sample size and the strength of their correlation with nitrate concentration.

To avoid multicollinearity, closely related variables were never included in the same regression: total discharge was never included in a regression with baseflow or runoff, area of wetland and relative area of wetland were never included in the same regression and area of tiling and relative area of tiling were never included in the same regression. The final regression specification was chosen based on the significance of coefficient estimates, the overall fit of the statistic model, and the consistency and robustness of each specification. Variables that had been removed from the model were periodically reintroduced into the model to assess if their significance or influence had changed with the addition of other variables.

Regression Analysis – Previous Year's Relative Crop Areas

Regressions using the previous year's relative crop area were performed first. It was expected that these data would provide more trustworthy results, because they had produced higher correlation coefficients when assessed with nitrate concentrations. For example, the coefficient was 0.2406 with previous year's relative corn area, compared to 0.2270 with current year's relative corn area (Figure 32). Other researchers, such as Broussard and Turner (2009), have elected to use the percent crop area, rather than absolute area of crop. Results of the regressions, along with the corresponding correlation results, are summarized in Table 23. The regressions shown in the table are the regression which produced the strongest adjusted coefficient of determination with the addition of each new variable.

Regressions 1-8 show results as relative areas of each crop type were iteratively added to the regression beginning with corn, the crop of greatest interest, and proceeding with crops in order of absolute value of correlation coefficient, from greatest to least. Generally, the adjusted coefficient of determination increased as additional variables were included. Most crops were significant. Soybeans and canola were insignificant until the wheat variable was added. The dry bean variable was insignificant and was never found to be significant in any of the subsequent regression analyses. This is not surprising, given the low correlation coefficient obtained with this variable.

Regressions with relative areas of row crops (corn, dry beans, soybeans, sugar beets and sunflowers) and all crops were then performed (Table 23, Regressions 9 and 10). These variables were significant, but did not produce coefficients of determination as great as those produced by individual crop types.

Additional non-crop variables were then added to the model to identify the model which produced the best fit, as indicated by the adjusted coefficient of determination. Physical and hydrological variables, such as discharge and stream length, are known to influence rate of nitrate loss or surface water concentration through processes such as denitrification. Other non-crop variables, including wetlands, tiling area and point sources, are essentially land use variables, but differ from the land use variables with which this study is primarily concerned,

Table 23. Results of stepwise regressions with previous year’s relative crop area.

log-transformed independent variable	correlation results			regression number 1	2	3	4	5	6	7	8
corn previous year's relative area	r	0.241	coef	1.028	0.573	0.422	0.472	0.487	0.600	1.111	1.122
	p	0.000	p	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
beets previous year's relative area	r	0.256	coef		4.450	4.156	4.125	4.127	3.867	3.417	3.385
	p	0.000	p		0.000	0.000	0.000	0.000	0.000	0.000	0.000
soy previous year's relative area	r	0.234	coef			0.217	0.013	0.032	-0.053	-0.467	-0.473
	p	0.000	p			0.078	0.924	0.820	0.713	0.003	0.004
sunflowers previous year's relative area	r	-0.176	coef				-1.180	-1.240	-1.104	-1.948	-1.953
	p	0.000	p				0.002	0.001	0.003	0.000	0.000
canola previous year's relative area	r	-0.080	coef					0.399	0.288	-0.764	-0.776
	p	0.000	p					0.176	0.335	0.026	0.026
alfalfa previous year's relative area	r	0.076	coef						1.013	1.909	1.918
	p	0.000	p						0.027	0.000	0.000
wheat previous year's relative area	r	-0.042	coef							0.848	0.866
	p	0.016	p							0.000	0.000
dry beans previous year's relative area	r	-0.019	coef								-0.059
	p	0.283	p								0.867
row crops previous year's relative area	r	0.253	coef								
	p	0.000	p								
total crops previous year's relative area	r	0.197	coef								
	p	0.000	p								
runoff	r	0.302	coef								
	p	0.000	p								
baseflow	r	0.048	coef								
	p	0.020	p								
total discharge	r	0.218	coef								
	p	0.000	p								
stream length	r	-0.156	coef								
	p	0.000	p								
basin area	r	-0.183	coef								
	p	0.000	p								
wetland area	r	-0.188	coef								
	p	0.000	p								
wetland relative area	r	-0.135	coef								
	p	0.000	p								
point source	r	-0.145	coef								
	p	0.000	p								
tiling area	r	0.006	coef								
	p	0.825	p								
tiling relative area	r	-0.542	coef								
	p	0.059	p								
dummy				no	no	no	no	no	no	no	no
n				3207	3207	3207	3207	3207	3207	3207	3207
R^2				0.058	0.076	0.076	0.079	0.079	0.081	0.092	0.091

Table 23 cont. Results of stepwise regressions with previous year's relative crop area.

log-transformed independent variable	correlation results			regression number 9	10	11	12	13	14	15	16
corn previous year's relative area	r	0.241	coef			1.109	0.838	1.205	0.510	0.529	**0.992**
	p	0.000	p			0.000	0.000	0.000	0.000	0.000	**0.000**
beets previous year's relative area	r	0.256	coef			3.548	3.887	3.368	3.248	2.663	**2.975**
	p	0.000	p			0.000	0.000	0.000	0.000	0.000	**0.000**
soy previous year's relative area	r	0.234	coef			-0.560	-0.488	-0.561			**0.242**
	p	0.000	p			0.000	0.001	0.000			**0.090**
sunflowers previous year's relative area	r	-0.176	coef			-1.679	-1.477	-1.837			**1.109**
	p	0.000	p			0.000	0.000	0.000			**0.011**
canola previous year's relative area	r	-0.080	coef			-1.221	-0.774	-1.259			**0.874**
	p	0.000	p			0.000	0.015	0.000			**0.008**
alfalfa previous year's relative area	r	0.076	coef			1.718	1.555	1.833			
	p	0.000	p			0.000	0.001	0.000			
wheat previous year's relative area	r	-0.042	coef			1.216	0.900	1.231	0.347	0.284	**0.887**
	p	0.016	p			0.000	0.000	0.000	0.001	0.005	**0.000**
dry beans previous year's relative area	r	-0.019	coef								
	p	0.283	p								
row crops previous year's relative area	r	0.253	coef	0.659							
	p	0.000	p	0.000							
total crops previous year's relative area	r	0.197	coef		0.605						
	p	0.000	p		0.000						
runoff	r	0.302	coef			0.083	0.159		0.156	0.153	**0.152**
	p	0.000	p			0.000	0.000		0.000	0.000	**0.000**
baseflow	r	0.048	coef				-0.115		-0.055	-0.064	**-0.045**
	p	0.020	p				0.000		0.000	0.000	**0.000**
total discharge	r	0.218	coef					0.058			
	p	0.000	p					0.000			
stream length	r	-0.156	coef						-0.095		**-0.094**
	p	0.000	p						0.000		**0.000**
basin area	r	-0.183	coef							-0.073	**-0.116**
	p	0.000	p							0.000	**0.000**
wetland area	r	-0.188	coef								**0.091**
	p	0.000	p								**0.000**
wetland relative area	r	-0.135	coef								
	p	0.000	p								
point source	r	-0.145	coef								
	p	0.000	p								
tiling area	r	0.006	coef								
	p	0.825	p								
tiling relative area	r	-0.542	coef								
	p	0.059	p								
dummy				no	no	no	no	no	no	no	**no**
n				3207	3207	3207	3207	3207	3207	3207	**3207**
R^2				0.064	0.039	0.171	0.225	0.136	0.258	0.253	**0.265**

Table 23 cont. Results of stepwise regressions with previous year's relative crop area.

log-transformed independent variable	correlation results			regression number 17	18	19	20	21	22	23
corn previous year's relative area	r	0.241	coef	0.413	1.692	-0.877	-1.288			0.404
	p	0.000	p	0.001	0.000	0.001	0.002			0.222
beets previous year's relative area	r	0.256	coef	2.919	2.319	9.998	8.869			3.037
	p	0.000	p	0.000	0.000	0.000	0.011			0.068
soy previous year's relative area	r	0.234	coef	0.437	0.438	0.295	0.362			0.064
	p	0.000	p	0.003	0.045	0.071	0.039			0.812
sunflowers previous year's relative area	r	-0.176	coef	2.070	-1.671					-0.450
	p	0.000	p	0.000	0.104					0.476
canola previous year's relative area	r	-0.080	coef	1.140	3.359					-0.557
	p	0.000	p	0.001	0.000					0.215
alfalfa previous year's relative area	r	0.076	coef							
	p	0.000	p							
wheat previous year's relative area	r	-0.042	coef	0.143	1.768					-0.191
	p	0.016	p	0.384	0.000					0.485
dry beans previous year's relative area	r	-0.019	coef							
	p	0.283	p							
row crops previous year's relative area	r	0.253	coef					0.415		
	p	0.000	p					0.000		
total crops previous year's relative area	r	0.197	coef						1.130	
	p	0.000	p						0.000	
runoff	r	0.302	coef	0.155	0.146	0.147	0.146	0.154	0.150	0.147
	p	0.000	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000
baseflow	r	0.048	coef	-0.055	-0.031	-0.083	-0.082	-0.048	-0.037	-0.049
	p	0.020	p	0.000	0.007	0.000	0.000	0.000	0.000	0.000
total discharge	r	0.218	coef							
	p	0.000	p							
stream length	r	-0.156	coef	-0.063	-0.171	0.118	0.100	-0.073	-0.114	-180.632
	p	0.000	p	0.000	0.000	0.005	0.008	0.000	0.000	0.527
basin area	r	-0.183	coef	-0.029	-0.197	-0.218	-0.200	-0.027	-0.151	-11.295
	p	0.000	p	0.036	0.000	0.000	0.000	0.029	0.000	0.480
wetland area	r	-0.188	coef		0.194				0.127	0.261
	p	0.000	p		0.000				0.000	0.531
wetland relative area	r	-0.135	coef	-0.116		4.012	3.819	-0.113		
	p	0.000	p	0.174		0.000	0.001	0.044		
point source	r	-0.145	coef		0.003					
	p	0.000	p		0.659					
tiling area	r	0.006	coef			-0.006				
	p	0.825	p			0.248				
tiling relative area	r	-0.542	coef				0.805			
	p	0.059	p				0.545			
dummy				no	no	no	no	no	no	yes
n				3207	2443	1210	1210	3207	3207	3207
R^2				0.259	0.261	0.226	0.226	0.252	0.263	0.315

crop production or, more specifically, corn production. These non-crop land use variables are also known to influence nitrate concentrations.

The runoff variable always produced a positive coefficient and the baseflow coefficient was always negative. Both coefficient estimates were always statistically significant. However, the inclusion of the runoff variable (Regression 10) greatly improved the model, increasing R^2 to 0.171. The inclusion of both of these variables (Regression 12) further improved the adjusted coefficient of determination to 0.225.

Regressions which included the separate baseflow and runoff variables accounted for more of the variance in nitrates than when a single variable of total discharge was used. The two components of discharge appear to have different effects on nitrates and it is better to assess them independently. The total discharge variable and either of its component parts, baseflow and discharge, were never included in the same regression because these variables are not independent of each other.

When added, the stream length variable was found to be significant and the adjusted coefficient of determination improved (Regression 14). However, the soybean, sunflower, canola and alfalfa variables all became insignificant. Removal of those insignificant factors did not change the adjusted coefficient of determination or coefficients or significance of other variables. Addition of the basin area variable created a slightly better fitting model (Regression 15). However, the basin area variable did not become significant until the stream length variable was removed, which resulted in a lower adjusted coefficient of determination.

The addition of the area of wetland variable further increased the adjusted coefficient of determination and the addition of some previously removed crop variables in Regression 16 produced the best model obtained with previous year's relative crop area data. The adjusted coefficient of determination for this model was found to be 0.265, indicating that the variables present in this model account for just over one quarter of the variation in nitrate concentrations. With the addition of the wetland area variable, the sunflower and canola variables, which had been insignificant in some earlier models, regained significance. The runoff and baseflow variables were removed from the model and the total discharge model was reintroduced, but this produced a weaker model.

The coefficients of all crop variables in the best-fit model (Regression 16) were found to be positive, as well as the runoff and wetland variables. The direction and magnitude of the corn, beet and wheat variables and all non-crop independent variables were fairly consistent in all regressions. The sunflower and canola coefficients were consistently negative, then found to be positive in the best-fit model.

The inclusion of the relative wetland area, point source, tiling area and relative tiling area in subsequent models (Regressions 17-20) did not produce coefficients of determination that were as strong as that which was produced in Regression 16, although it was found that relative wetland area did sometimes provide a better model fit than that obtained with wetland area (Regressions 19 and 20). Point source and tiling data were never found to be significant in any subsequent regressions and they were never found to contribute to the fit of a model. The inclusion of point source and tiling data also reduces the sample size, since these data were not available for the entire period of interest.

The relative row crop area and total row crop area variables were now reassessed using all the independent variables except individual crop variables. The best respective models are Regressions 21 and 22. Although these did not result in models that were as reliable as the best fitting model, the regression with total relative crop area (Regression 22) produced an R^2 of

0.263, comparable to R^2 = 0.265 in the best-fit model. Given the similarity in significance and coefficients of the non-crop variables in the two regressions, it appears that total crop area and the significant crops in the best-fit model (corn, beets, sunflowers, canola and wheat; Regression 16) may be interchangeable in these models.

Finally, a dummy variable was included in the regression with all factors listed in the best fit model. A categorical variable was included which created a factor identifying the gauge drainage basin which each observation belonged to. The results of this regression are shown in Regression 23. Although producing a relatively high adjusted coefficient of determination, 0.315, the inclusion of this variable rendered all other independent variables except runoff and baseflow insignificant.

Regression Analysis – Current Year's Relative Crop Areas

Using a method similar to that which was used with the previous year's crops, regressions were performed with the relative area of the current year's crops. The results are shown in Table 24. The use of current year's crop data allows for a slightly larger total sample size, 3402 compared to 3207.

Unlike the results found with previous year's crop data, the soybean and sunflower variables were insignificant prior to the addition of non-crop independent variables (see Regressions 6-8). Again, addition of the discharge variables improved the model (Regressions 12-15) with the regression that included both the independent runoff and baseflow variables (Regression 14) producing the highest adjusted coefficient of determination (0.205). The addition of stream length and basin area variables further improved the model (Regressions 16 and 17). As was seen in the regressions with the previous year's relative crop areas, the best model was produced when the wetland area variable was included (Regression 18), with R^2 = 0.262.

Table 24. Results of stepwise regressions with current year's relative crop area.

log-transformed independent variable		correlation results		regression number 1	2	3	4	5	6	7	8
corn current year's relative area	r	0.227	coef	0.991	0.681	0.508	0.505	0.503	0.519	0.850	0.898
	p	0.000	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
beets current year's relative area	r	0.212	coef		2.967	2.646	2.646	2.642	2.607	2.269	2.064
	p	0.000	p		0.000	0.000	0.000	0.000	0.000	0.000	0.001
soy current year's relative area	r	0.218	coef			0.242	0.257	0.256	0.246	-0.001	-0.016
	p	0.000	p			0.044	0.048	0.050	0.069	0.997	0.912
sunflowers current year's relative area	r	-0.103	coef				0.108	0.110	0.129	-0.406	-0.433
	p	0.000	p				0.761	0.759	0.722	0.291	0.261
canola current year's relative area	r	-0.094	coef					-0.036	-0.042	-0.831	-0.853
	p	0.000	p					0.913	0.900	0.030	0.026
alfalfa current year's relative area	r	0.022	coef						0.148	0.824	0.847
	p	0.192	p						0.746	0.089	0.080
wheat current year's relative area	r	-0.047	coef							0.567	0.668
	p	0.007	p							0.000	0.000
dry beans current year's relative area	r	0.038	coef								-0.396
	p	0.026	p								0.243
row crops current year's relative area	r	0.237	coef								
	p	0.000	p								
total crops current year's relative area	r	0.193	coef								
	p	0.000	p								
runoff	r	0.301	coef								
	p	0.000	p								
baseflow	r	0.048	coef								
	p	0.005	p								
total discharge	r	0.218	coef								
	p	0.000	p								
stream length	r	-0.156	coef								
	p	0.000	p								
basin area	r	-0.183	coef								
	p	0.000	p								
wetland area	r	-0.188	coef								
	p	0.000	p								
wetland relative area	r	-0.135	coef								
	p	0.000	p								
point source	r	-0.145	coef								
	p	0.000	p								
tiling area	r	0.006	coef								
	p	0.825	p								
tiling relative area	r	-0.054	coef								
	p	0.059	p								
dummy				no	no	no	no	no	no	no	no
n				3402	3402	3402	3402	3402	3402	3402	3402
R^2				0.051	0.060	0.060	0.060	0.060	0.060	0.064	0.064

Table 24 cont. Results of stepwise regressions with current year's relative crop area.

log-transformed independent variable		correlation results		regression number 9	10	11	12	13	14	15	16
corn current year's relative area	r	0.227	coef	0.873			0.803	0.907	0.541	0.901	0.363
	p	0.000	p	0.000			0.000	0.000	0.000	0.000	0.003
beets current year's relative area	r	0.212	coef	2.318			2.478	2.283	3.031	2.297	1.908
	p	0.000	p	0.000			0.000	0.000	0.000	0.000	0.000
soy current year's relative area	r	0.218	coef								0.285
	p	0.000	p								0.010
sunflowers current year's relative area	r	-0.103	coef								
	p	0.000	p								
canola current year's relative area	r	-0.094	coef	-0.819			1.433	-1.085	-0.634	-1.582	
	p	0.000	p	0.026			0.000	0.004	0.062	0.000	
alfalfa current year's relative area	r	0.022	coef	0.927			1.030	1.030		1.157	
	p	0.192	p	0.037			0.992	0.021		0.008	
wheat current year's relative area	r	-0.047	coef	0.536			0.992	0.693	0.589	1.017	0.299
	p	0.007	p	0.000			0.000	0.000	0.000	0.000	0.003
dry beans current year's relative area	r	0.038	coef								
	p	0.026	p								
row crops current year's relative area	r	0.237	coef		0.616						
	p	0.000	p		0.000						
total crops current year's relative area	r	0.193	coef			0.589					
	p	0.000	p			0.000					
runoff	r	0.301	coef				0.088		0.162		0.157
	p	0.000	p				0.000		0.000		0.000
baseflow	r	0.048	coef					0.024	-0.113		-0.046
	p	0.005	p					0.000	0.000		0.000
total discharge	r	0.218	coef							0.064	
	p	0.000	p							0.000	
stream length	r	-0.156	coef								-0.105
	p	0.000	p								0.000
basin area	r	-0.183	coef								
	p	0.000	p								
wetland area	r	-0.188	coef								
	p	0.000	p								
wetland relative area	r	-0.135	coef								
	p	0.000	p								
point source	r	-0.145	coef								
	p	0.000	p								
tiling area	r	0.006	coef								
	p	0.825	p								
tiling relative area	r	-0.054	coef								
	p	0.059	p								
dummy				no	no	no	no	no	no	no	no
n				3402	3402	3402	3402	3402	3402	3402	3402
R^2				0.064	0.056	0.037	0.155	0.069	0.205	0.119	0.253

Table 24 cont. Results of stepwise regressions with current year's relative crop area.

log-transformed independent variable		correlation results		regression number					
				17	18	19	20	21	22
corn current year's relative area	r	0.227	coef	0.262	**0.775**	0.411	1.008	-0.643	-1.034
	p	0.000	p	0.074	**0.000**	0.000	0.000	0.104	0.000
beets current year's relative area	r	0.212	coef	1.882	**1.917**	1.888	1.818	-1.752	
	p	0.000	p	0.000	**0.000**	0.000	0.005	0.590	
soy current year's relative area	r	0.218	coef	0.444	**0.629**		1.328	0.108	
	p	0.000	p	0.002	**0.000**		0.000	0.713	
sunflowers current year's relative area	r	-0.103	coef	0.885	**1.857**		1.132	1.167	
	p	0.000	p	0.016	**0.000**		0.299	0.203	
canola current year's relative area	r	-0.094	coef	0.739	**1.677**		3.998	0.842	
	p	0.000	p	0.049	**0.000**		0.000	0.299	
alfalfa current year's relative area	r	0.022	coef	-0.569	**-0.625**		-0.577	-1.372	
	p	0.192	p	0.207	**0.163**		0.370	0.079	
wheat current year's relative area	r	-0.047	coef	0.017	**0.652**		1.284	-0.554	
	p	0.007	p	0.907	**0.000**		0.000	0.166	
dry beans current year's relative area	r	0.038	coef						
	p	0.026	p						
row crops current year's relative area	r	0.237	coef						
	p	0.000	p						
total crops current year's relative area	r	0.193	coef						
	p	0.000	p						
runoff	r	0.301	coef	0.156	**0.153**	0.157	0.148	0.146	0.146
	p	0.000	p	0.000	**0.000**	0.000	0.000	0.000	0.000
baseflow	r	0.048	coef	-0.044	**-0.036**	-0.049	-0.030	-0.076	-0.077
	p	0.005	p	0.000	**0.000**	0.000	0.008	0.000	0.000
total discharge	r	0.218	coef						
	p	0.000	p						
stream length	r	-0.156	coef	-0.081	**-0.097**	-0.062	-0.172	0.061	
	p	0.000	p	0.000	**0.000**	0.000	0.000	0.171	
basin area	r	-0.183	coef	-0.028	**-0.131**	-0.034	-0.203	-0.131	-0.082
	p	0.000	p	0.042	**0.000**	0.005	0.000	0.122	0.000
wetland area	r	-0.188	coef		**0.094**		0.196	-0.011	
	p	0.000	p		**0.000**		0.000	0.832	
wetland relative area	r	-0.135	coef			-0.182			
	p	0.000	p			0.000			
point source	r	-0.145	coef				0.001		
	p	0.000	p				0.905		
tiling area	r	0.006	coef					-0.011	
	p	0.825	p					0.037	
tiling relative area	r	-0.054	coef						1.057
	p	0.059	p						0.189
dummy				no	**no**	no	no	no	no
n				3402	**3402**	3402	2444	1211	1211
R^2				0.254	**0.262**	0.253	0.255	0.216	0.216

Table 24 cont. Results of stepwise regressions with current year's relative crop area.

log-transformed independent variable		correlation results		regression number 23	24	25
corn current year's relative area	r	0.227	coef			-0.522
	p	0.000	p			0.134
beets current year's relative area	r	0.212	coef			-1.577
	p	0.000	p			0.3
soy current year's relative area	r	0.218	coef			0.704
	p	0.000	p			0.011
sunflowers current year's relative area	r	-0.103	coef			0.4
	p	0.000	p			0.547
canola current year's relative area	r	-0.094	coef			-0.216
	p	0.000	p			0.652
alfalfa current year's relative area	r	0.022	coef			-0.172
	p	0.192	p			0.779
wheat current year's relative area	r	-0.047	coef			-0.298
	p	0.007	p			0.317
dry beans current year's relative area	r	0.038	coef			
	p	0.026	p			
row crops current year's relative area	r	0.237	coef	0.505		
	p	0.000	p	0.000		
total crops current year's relative area	r	0.193	coef		1.096	
	p	0.000	p		0.000	
runoff	r	0.301	coef	0.154	0.151	0.149
	p	0.000	p	0.000	0.000	0
baseflow	r	0.048	coef	-0.042	-0.031	-0.047
	p	0.005	p	0.000	0.000	0
total discharge	r	0.218	coef			
	p	0.000	p			
stream length	r	-0.156	coef	-0.100	-0.121	-292.627
	p	0.000	p	0.000	0.000	0.29
basin area	r	-0.183	coef	0.031	-0.144	-18.201
	p	0.000	p	0.028	0.000	0.233
wetland area	r	-0.188	coef	0.016	0.120	0.492
	p	0.000	p	0.060	0.000	0.245
wetland relative area	r	-0.135	coef			
	p	0.000	p			
point source	r	-0.145	coef			
	p	0.000	p			
tiling area	r	0.006	coef			
	p	0.825	p			
tiling relative area	r	-0.054	coef			
	p	0.059	p			
dummy				no	no	yes
n				3402	3402	3402
R^2				0.252	0.263	0.319

Addition of relative wetland area, point source, tiling area and relative tiling area variables did not improve the model (Regressions 19-22). It was again observed that total crop relative area produced an adjusted coefficient of determination similar to that obtained with the best-fit model of individual crop types, as can be seen when comparing the results of Regressions 24 and 18. In fact, the R^2 of the regression with total crops was a bit higher than that with the individual crops, 0.263 compared to 0.262.

Again, the inclusion of the dummy basin factor produced a higher adjusted coefficient of determination, 0.319, but rendered most independent variables insignificant as shown in Regression 25. Surprisingly, in addition to runoff and baseflow retaining their significance, the soybean variable remained significant when the dummy variable was included.

Overall, the stepwise addition of independent variables produced similar results in respect to the significance and coefficients of the independent variables regardless of whether the current or previous year's crop data were used. However, regressions using the previous year's crop data tended to account for more of the nitrate variability. To illustrate, the best fit model for current year's data (Table 24, Regression 18) had an R^2 of 0.262 and the best model for previous year's data had an R^2 of 0.265 (Table 23, Regression 16).

Comparing the two best-fit models (Table 24, Regression 18 and Table 23, Regression 16), the most notable difference is that, although the soybean variable had been insignificant with the previous year's data, it was significant and positive when analyzing the current year's data. When further comparing the two models, it can be seen that the variables other than soybeans generated comparable results in the two models. The coefficients of all other variables remained similar in respect to whether they were positive or negative; all crop variables retained their positive coefficients along with wetland area and runoff. However, the magnitude of the coefficients of the variables changed, with the current year's corn, beets and wheat relative areas having a smaller contribution to nitrates than the previous year's and sunflower and canola having a greater contribution than the previous year's. The coefficients and significance of the non-crop independent variables were basically the same for both analyses.

Regression Analysis – Spatial Subsets

Two spatial data subsets were developed for further analysis. The first excluded observations from gauge drainage basins which overlapped the Devils Lake Basin from the dataset. The second subset excluded areas which overlapped the Otter Tail watershed. The third included observations only from basins which did not overlap.

Basins Independent of Devils Lake Basin

The Devils Lake Basin is terminal and only rarely do surface waters from the basin drain into the Red River's tributaries (Kharel and Kirilenko, 2015). In spite of this, the delineation method used here, as detailed in the methods section of this report, identified the Devils Lake Basin as a contributor to larger order basins and, ultimately, the Red River. The total area of the Red River Basin occupied by the Devils Lake Basin was about 11%, as delineated by this study (see Figure 36). It was decided to develop a subset of data which included only basins which did not include the Devils Lake Basin. If the Devils Lake Basin was hydrologically separate from the Red River Basin, its removal from the dataset should allow for a model with less variability.

The 23 Basins which do not overlap areas of the Devils Lake Basin are shown in Figure 36. Regression analysis of nitrate concentrations and independent variables from these basins was performed. Considering that current year's and previous year's relative crop area variables had produced such similar significant variables and coefficients in previous models, current year's relative crop data were used in this analysis, which provided a slightly larger sample size. The model which produced the best fit with these data is shown in Table 25.

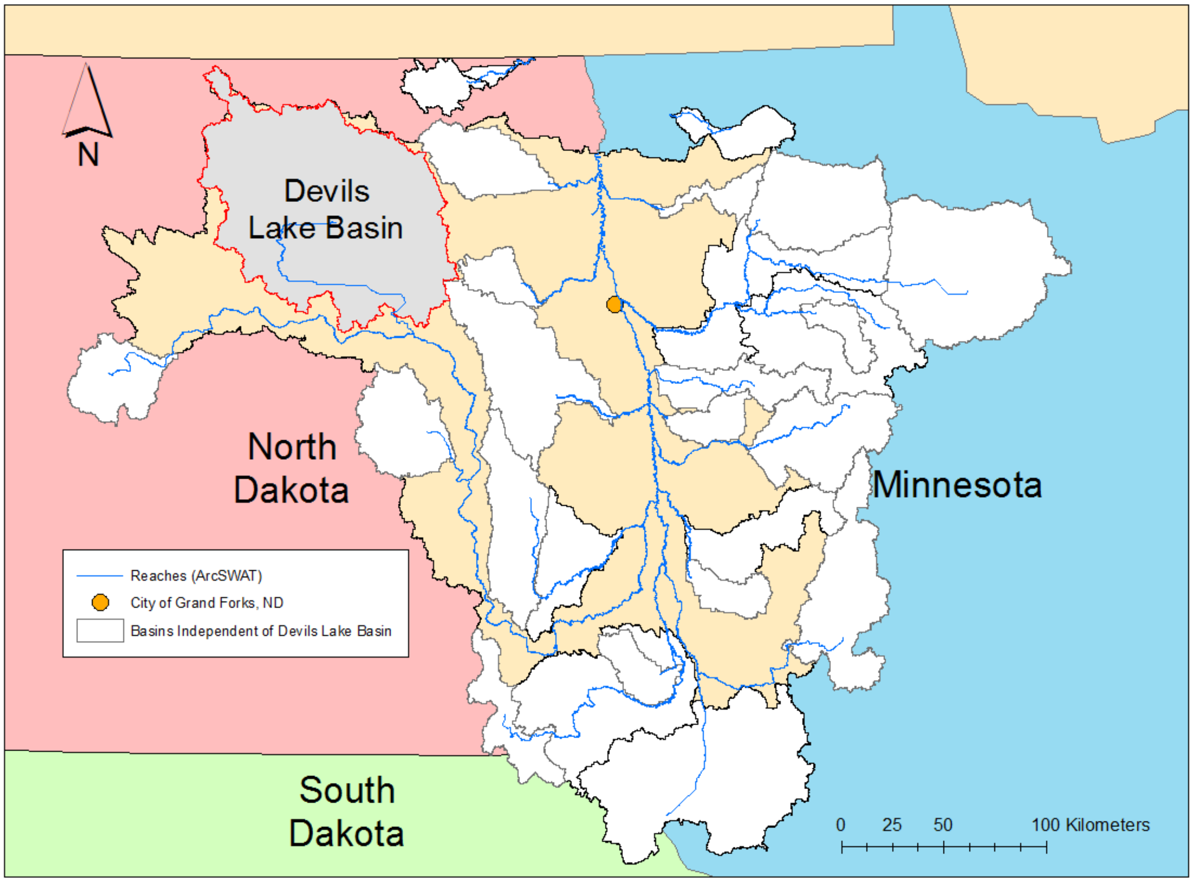


Figure 36. Gauge drainage basins which do not include area of Devils Lake Basin.

By eliminating basins which are influenced by the Devils Lake Basin the sample size was reduced to 2331. The adjusted coefficient of determination of the best-fit model, 0.296, was higher than that produced the dataset which included the Devils Lake Basin area, 0.262 (Table 24). The same variables were included in both best-fit models but the basin area variable was not significant in the model without Devils Lake areas. The direction of the variable coefficients

Table 25. Results of regressions with spatial subsets of data.

		Spatial Subsets		
log-transformed independent variable		Independent of Devils Lake	Independent of Otter Tail	Independent Basins
corn previous year's relative area	coef	0.621	1.028	0.669
	p	0.004	0.000	0.001
beets previous year's relative area	coef	1.851	2.957	0.054
	p	0.001	0.000	0.934
soy previous year's relative area	coef	0.825	0.164	0.979
	p	0.000	0.294	0.000
sunflowers previous year's relative area	coef	2.552	0.967	3.196
	p	0.000	0.033	0.000
canola previous year's relative area	coef	1.894	0.714	2.411
	p	0.002	0.043	0.000
alfalfa previous year's relative area	coef	-0.562	0.280	-0.481
	p	0.252	0.535	0.497
wheat previous year's relative area	coef	0.951	0.922	0.307
	p	0.000	0.000	0.181
dry beans previous year's relative area	coef			
	p			
row crops previous year's relative area	coef			
	p			
total crops previous year's relative area	coef			
	p			
runoff	coef	0.184	0.156	0.180
	p	0.000	0.000	0.000
baseflow	coef	-0.033	-0.044	-0.049
	p	0.003	0.000	0.000
total discharge	coef			
	p			
stream length	coef	-0.211	-0.096	-0.003
	p	0.000	0.000	0.950
basin area	coef	-0.060	-0.108	-0.258
	p	0.252	0.000	0.000
wetland area	coef	0.110	0.087	0.133
	p	0.000	0.000	0.000
wetland relative area	coef			
	p			
point source	coef			
	p			
tiling area	coef			
	p			
tiling relative area	coef			
	p			
dummy		no	no	no
n		2331	3092	2007
R^2		0.296	0.266	0.281

remained unchanged with the removal of the Devils Lake areas, although there were small changes in the magnitude. To illustrate, in the model without Devils Lake areas the contribution of crop areas to nitrate was greatest from sunflowers, followed by canola, beets, wheat, soybeans and corn. In the model which included Devils Lake, the order crop contribution was beets, sunflowers, canola, corn, wheat and soybeans. The influence of soybean, sunflowers, canola, wheat, runoff, stream length and wetland area were all greater when Devils Lake was removed and the basin area became insignificant. The unexplained variance of the model was reduced when Devils Lake was removed (R^2=0.296, compared to R^2=0.262), but not to the extent expected.

Basins Independent of Otter Tail Watershed

It has been observed by Dr. Zhulu Lin (2016) that the hydrology of the Otter Tail watershed within the Red River Basin may be significantly different than that of the other watersheds. Because of this, it was suspected that removing basins overlapping the Otter Tail watershed may produce a land use – water quality model which is able to account for more of the variation in nitrate concentrations. In a manner similar to that used with the Devils Basin above, basins which do not intersect Otter Tail watershed were identified, as shown in Figure 37.

Regressions were performed with the subset of data produced by excluding Otter Tail watershed data. The results area shown in Table 25. These results were very similar to those found when then entire dataset was used.

Independent Basins

Some gauge drainage basins identified in this study overlap. Smaller basins drain into larger basins and the attributes of those smaller basins, such as area of land use, then influence the attributes of the larger basin. There were concerns that this may give extra weight to the attributes of smaller basins.

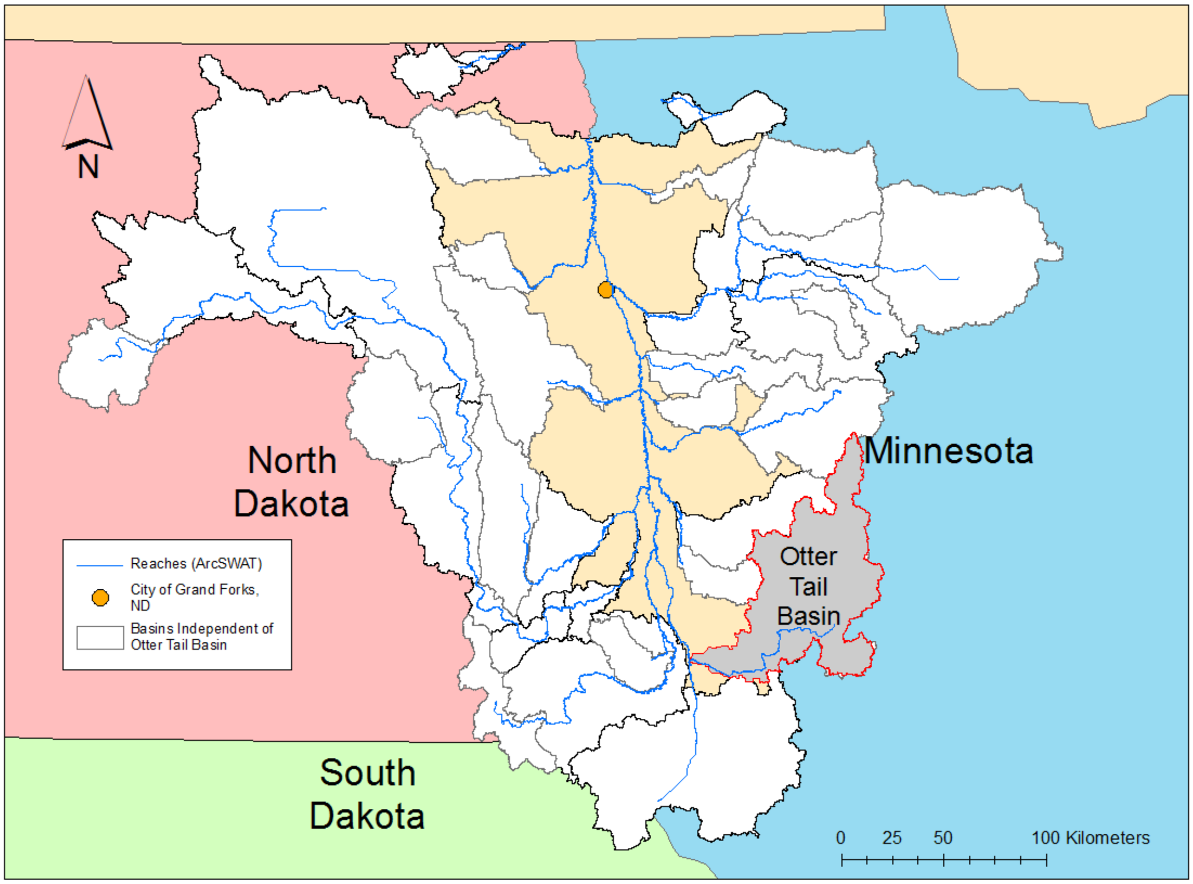


Figure 37. Gauge drainage basins which do not include area of Otter Tail Basin.

A subset of the data, the largest independent drainage basins, was identified. This is an approach similar to that used in the study by Broussard and Turner (2009), in which only data from non-overlapping watersheds were used. These are essentially the areas draining into the gauges located farthest downstream in the tributaries of the Red River, henceforth referred to as largest independent basins. When used in regression analysis, no data from smaller basins within the largest independent basins were included in the analysis. There was a subjective component to developing this dataset. When a slightly smaller basin nested within a larger basin provided a substantially larger dataset, data from the smaller basin rather than the larger basin were included in the data subset. The 17 basins selected for inclusion in this subset are shown in Figure 38.

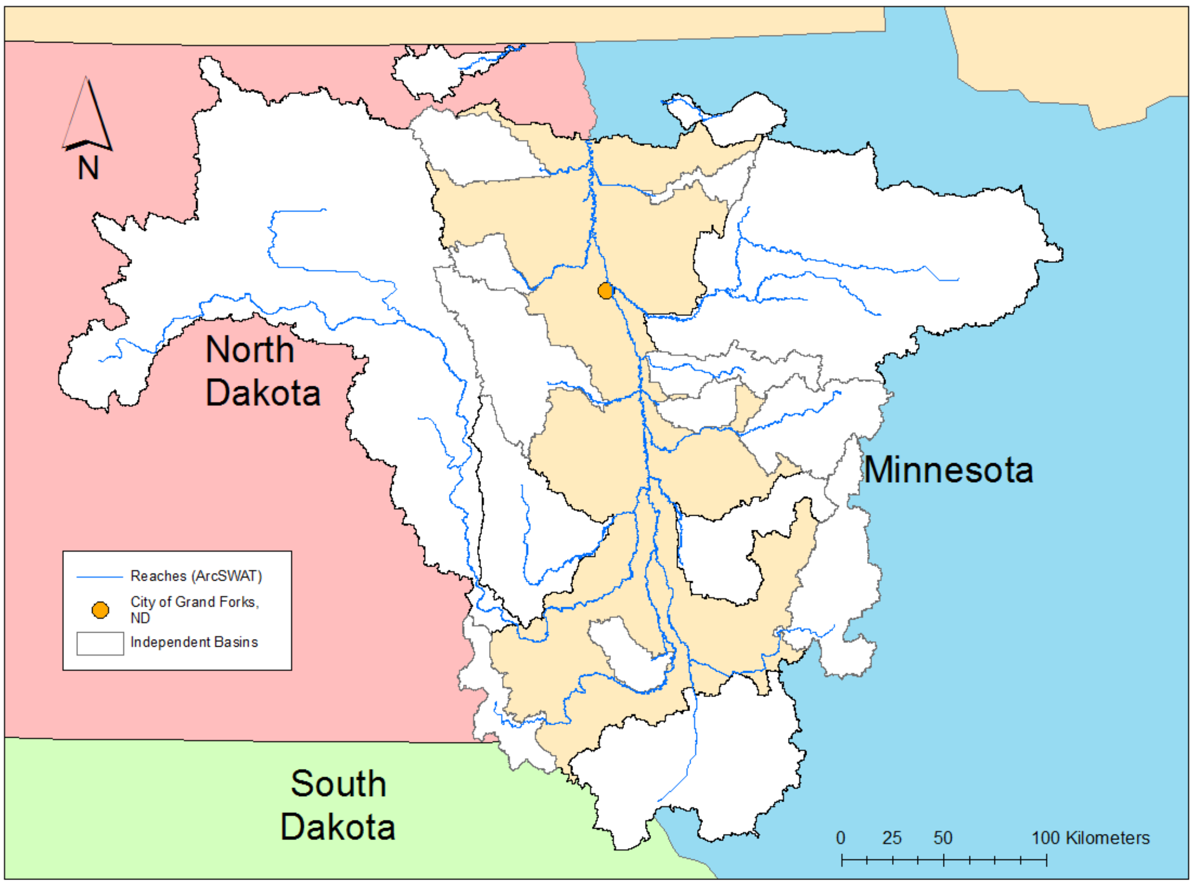


Figure 38. Selected non-overlapping gauge drainage basins.

Current year's relative crop areas and other independent variable data from this data subset were regressed with nitrate concentrations. The model produced by this analysis is shown in Table 24. Removing the overlapping basins reduced the sample size to 2007. The adjusted coefficient of determination was again higher than when the entire dataset was used (Table 25), 0.281 compared to 0.262, and the coefficient of corn decreased. However, the influences of soybean, sunflowers and canola increased when compared to the results in Table 24, and the influence of soybeans on nitrates became greater than that of corn. Sugar beets and wheat became insignificant. Basin area became insignificant and the coefficients of stream length and wetland area increased.

Regression Analysis – Monthly Subsets

The data were subset temporally by sorting the data and identifying observations which occurred in specific months. It was expected that there would be less variability in monthly subsets of data. The months of May, June and October were chosen for additional analysis. May was chosen because it is the month when farmers would be expected to plant (Table 13) and apply spring fertilizer, June is the month with the most precipitation (MNDNR, 2016) and a study in southwest Minnesota found that 70% of nitrate loss occurs in April, May and June (Oquist et al., 2007). October would be expected to capture some of the effects of harvest and fall fertilizer application and previous analyses in this study area by this author had shown that October data tended to produce the best model. Subsetting the data by month resulted in smaller sample sizes.

The results of the regressions with previous year’s relative crop area and current year’s relative crop data are shown in Table 26. In regards to both the previous and current years’ data, October provided the best model and May the poorest. However, in all cases the adjusted coefficient of determination was improved compared to models derived using the entire dataset. The higher adjusted coefficient of determination with the monthly subsets indicate that a greater amount of the variability of nitrates is accounted for. This was expected as, within a given

Table 26. Results of regressions with temporal subsets of data.

log-transformed independent variable		Monthly Subsets: Previous year's relative crop area			Monthly Subsets: Current year's relative crop area		
		May	June	October	May	June	October
corn relative area	coef	0.881	3.09	3.192	0.013	0.032	0.055
	p	0.006	0.000	0.000	0.164	0.038	0.003
beets relative area	coef						
	p						
soy relative area	coef	0.030	0.716	-0.732	0.019	0.069	-0.014
	p	0.912	0.103	0.101	0.207	0.008	0.680
sunflowers relative area	coef	0.769	3.112	2.102	-0.017	-0.054	0.039
	p	0.381	0.032	0.124	0.149	0.005	0.062
canola relative area	coef						
	p						
alfalfa relative area	coef						
	p						
wheat relative area	coef	0.473	2.716	1.053	0.013	0.041	-0.145
	p	0.163	0.000	0.510	0.528	0.225	0.002
dry beans relative area	coef						
	p						
row crops relative area	coef						
	p						
total crops relative area	coef						
	p						
runoff	coef	0.143	0.159	0.160	0.137	0.175	0.206
	p	0.000	0.000	0.000	0.000	0.000	0.000
baseflow	coef	-0.023	0.040	-0.038	-0.024	-0.016	-0.101
	p	0.229	0.164	0.287	0.219	0.574	0.004
total discharge	coef						
	p						
stream length	coef	-0.038	-0.355	-0.060	-0.064	-0.344	-0.006
	p	0.284	0.000	0.298	0.060	0.000	0.919
basin area	coef	-0.136	-0.153	-0.143	-0.074	0.085	0.117
	p	0.001	0.018	0.063	0.115	0.247	0.219
wetland area	coef	0.042	0.255	0.103	-0.101	-0.008	-0.090
	p	0.170	0.000	0.108	0.643	0.803	0.057
wetland relative area	coef						
	p						
point source	coef						
	p						
tiling area	coef						
	p						
tiling relative area	coef						
	p						
dummy		no	no	no	no	no	no
n		524	527	224	566	550	245
R^2		0.287	0.350	0.430	0.272	0.308	0.353

month, there will be less variation in factors such as weather and land management than when all twelve months are assessed.

Regressions with the previous year's crop data provided better results. In every month, the previous year's relative crop area accounted for more variability in the model, as measured by the adjusted coefficient of determination. To illustrate, the regression of October previous year's crop data produced $R^2 = 0.430$, accounting for nearly half the variability of nitrates, compared to a coefficient of 0.353 with current year's data. Surprisingly, the October previous year's data regression only contained two significant terms, compared to four significant terms when regressing the current year's data.

It can be seen that the significance and coefficients of variables varied widely when comparing monthly results. The coefficient of corn was much higher when assessing previous year's crop data and always higher in June and October, compared to May. In fact, when analyzing the current year's crop data, corn was not significant in May and the coefficients for June and October were the lowest corn coefficients observed in any of the analyses.

Soybeans, sunflowers and wheat were sometimes significant. The intermittent significance and conflicted direction of these variables made them difficult to interpret. Overall, like corn, these crops' significance and coefficients were greater when assessing previous year's data.

The runoff variable remained the most reliable and consistent independent variable, always significant and producing a positive coefficient. When analyzing May's current year's crops, runoff was the only significant variable, and accounted for 27% of the variability in nitrates. Baseflow, however, was only found to be significant in the regression of October current year's crops, in which it produced its typical negative coefficient.

The other non-crop variables were seldom significant except in the regression of June's previous year's crops, in which stream length, basin area and wetland area were all significant. Analyzing monthly subsets produced varied results and resulted in a better explanation of the variability of nitrate concentrations. Most surprising was the much stronger relationships identified with the previous year's crop dataset, compared to the current year's. However, smaller sample sizes due to subsetting produce less robust results.

Land Use – Water Quality Model Specification

The results of the multivariate regressions (Tables 23 and 24) were reviewed and the model shown in Regression 16 of Table 23 was selected as the most reliable model, providing consistent and robust coefficient estimates and best fit of the data. This model uses previous year's relative crop area. The soybean variable, an insignificant term in the specification, is not included in the model.

The land use – water quality model is expressed as:

$$
\begin{aligned}
\log_{10}(\text{nitrate concentration}) = {} & 0.992 * \log_{10}(\text{relative area of corn}) \\
& + 2.975 * \log_{10}(\text{relative area beets}) \\
& + 1.109 * \log_{10}(\text{relative area sunflowers}) \\
& + 0.874 * \log_{10}(\text{relative area canola}) \\
& + 0.887 * \log_{10}(\text{relative area wheat}) \\
& + 0.152 * \log_{10}(\text{runoff}) \\
& - 0.045 * \log_{10}(\text{baseflow}) \\
& - 0.094 * \log_{10}(\text{stream length}) \\
& - 0.116 * \log_{10}(\text{basin area}) \\
& + 0.091 * \log_{10}(\text{wetland area}) \\
& + 0.450
\end{aligned}
$$

When using this model, all independent variables must be log10-transformed prior to insertion into the model. Since the logarithm of zero is undefined, prior to transformation a value of one is added to the variable. After solving for log10(nitrate concentration), that value must then be back-transformed to obtain the nitrate concentration in mg/L.

For example:

$$\log10\,(\textit{nitrate concentration} + 1) = 0.10$$

$$10^{0.10} = 1.26$$

$$\textit{nitrate concentration} = 1.26 - 1 = 0.26\ mg/L$$

Economic – Land Use Model

The economic – land use model had been developed and adjustments had been made to calibrate its baseline results with observed land use, as described in the methodology. The baseline relative crop areas identified by the calibrated model are shown in Table 27. This shows the relative area of each crop within each basin (area of crop/total area of basin) under the baseline economic conditions, shown in Table 21. The baseline relative areas of the major crops (corn, soybeans and wheat) are comparable to the average relative areas observed within the study area from 2006-2014, as indicated by the ratio comparing the two values, also shown in Table 21.

The economic – land use model predicted the land areas of alfalfa, corn, soybeans and wheat at about 90% of their observed areas and predicted the areas of canola and sunflower at over 300% their observed area. Although the model performed poorly when projecting areas of canola and sunflower, the resulting areas of these crops would still be negligible. For example, in 2014 area planted in sunflower was only 4% that of corn and area planted in canola was less than 2% of area planted in corn.

The areas of dry beans and sugar beets are fixed at their historical average within each basin, due to conditions that preclude their immediate response to economic conditions, such as contracts. Dry beans and sugar beets are often grown under contract, and do not respond well in

Table 27. Economic – land use model baseline relative crop areas in each basin. Identified by the calibrated economic – land use model under baseline economic conditions.

	Relative area of the basin, by crop type								
Basin	Corn	Alfalfa	Canola	Dry Beans	Soybeans	Sugar Beets	Sunflowers	Wheat	Grassland
05030500	0.10	0.01	0.04	0.01	0.24	0.00	0.02	0.16	0.41
05051300	0.19	0.03	0.09	0.00	0.26	0.02	0.07	0.18	0.15
05051600	0.14	0.02	0.07	0.01	0.22	0.00	0.04	0.15	0.34
05052500	0.10	0.01	0.04	0.01	0.24	0.02	0.03	0.17	0.37
05053000	0.14	0.02	0.07	0.00	0.26	0.01	0.04	0.17	0.29
05054500	0.09	0.01	0.03	0.00	0.31	0.00	0.02	0.21	0.33
05056000	0.11	0.01	0.04	0.01	0.26	0.00	0.02	0.18	0.36
05057000	0.10	0.01	0.04	0.02	0.25	0.00	0.02	0.17	0.39
05057200	0.12	0.01	0.05	0.02	0.22	0.00	0.03	0.15	0.39
05058600	0.10	0.01	0.04	0.02	0.24	0.00	0.02	0.17	0.39
05058700	0.10	0.01	0.04	0.02	0.24	0.00	0.02	0.17	0.39
05058810	0.10	0.01	0.05	0.02	0.24	0.00	0.02	0.17	0.39
05059000	0.10	0.01	0.04	0.02	0.24	0.00	0.02	0.17	0.39
05059500	0.10	0.01	0.04	0.02	0.24	0.00	0.02	0.17	0.39
05059700	0.14	0.02	0.07	0.02	0.20	0.00	0.04	0.14	0.37
05060100	0.14	0.02	0.07	0.02	0.20	0.00	0.04	0.14	0.37
05061500	0.14	0.02	0.06	0.00	0.31	0.05	0.04	0.21	0.17
05062000	0.13	0.02	0.06	0.00	0.28	0.03	0.04	0.19	0.25
05062500	0.14	0.02	0.06	0.00	0.30	0.01	0.04	0.21	0.21
05066500	0.15	0.02	0.07	0.06	0.26	0.01	0.04	0.18	0.22
05067500	0.08	0.01	0.03	0.01	0.24	0.07	0.03	0.17	0.35
05069000	0.03	0.00	0.01	0.01	0.14	0.03	0.01	0.09	0.67
05074500	0.09	0.01	0.04	0.00	0.21	0.00	0.02	0.12	0.51
05076000	0.04	0.00	0.02	0.00	0.23	0.00	0.01	0.12	0.58
05078230	0.15	0.03	0.07	0.00	0.28	0.00	0.06	0.19	0.22
05078500	0.09	0.01	0.04	0.00	0.21	0.00	0.03	0.13	0.49
05080000	0.08	0.01	0.04	0.00	0.20	0.00	0.02	0.12	0.51
05082500	0.11	0.01	0.05	0.01	0.24	0.01	0.03	0.16	0.37
05082625	0.16	0.02	0.07	0.07	0.26	0.00	0.05	0.18	0.19
05087500	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.05	0.84
05090000	0.14	0.02	0.06	0.05	0.23	0.02	0.03	0.16	0.29
05092000	0.11	0.01	0.05	0.02	0.23	0.02	0.03	0.16	0.36
05094000	0.01	0.00	0.00	0.00	0.21	0.00	0.00	0.11	0.67
05099600	0.13	0.01	0.06	0.02	0.21	0.00	0.03	0.14	0.40
05100000	0.13	0.01	0.06	0.03	0.22	0.01	0.03	0.15	0.36

the short term to changes in economic conditions, as explained in the Farm Financials Data section of this report.

Impact of Economic Scenarios on Land Use

The economic scenarios developed were provided as inputs to the economic – land use model. It was expected that economic conditions which favored crop production, such as increases in crop prices, would result in greater cultivation of crops. Conversely, economic conditions which were prohibitive to crop production, such as fertilizer taxes, were anticipated to result in less land use devoted to crops. The following scenarios were explored:

- 25%, 50% and 100% increases in the prices of corn, soybeans and wheat
- A conservation program which compensates farmers $65.50 per hectare for retiring land from cultivation
- 5%, 10%, 15% and 20% tax on fertilizer sales
- Subsidy payments of $17.57/hectare for corn, $9.76/hectare for soybeans and $12.71/hectare for wheat

An enumeration of the resulting areas of each land use type in each basin under each scenario would be extensive. To provide an overview of how the scenarios influence land use, the percent area of land use by each type under each scenario within the basin draining through USGS 05092000 is shown in Figure 39. 98% of the study area drains through this gauge, as can be seen in Figure 15. All non-crop land uses, including conservation program enlistment, are referred to as “grassland”.

It can be seen that increases in prices of the major crops have limited impact on the area grown in soybeans and wheat, but considerably increase the area grown in corn, mostly at the expense of grassland acreage. Under the 100% price increase scenario, relative area grown in soybeans only increased from 23% to 27% and wheat increased from 16% to 19%, compared to the baseline (Table 27). However, the area grown in corn increased from 11% to 28%. Grassland (all non-crop land uses) covered 36% of the study area in the baseline scenario and was reduced to 20% of the study area when crop prices increased 100%.

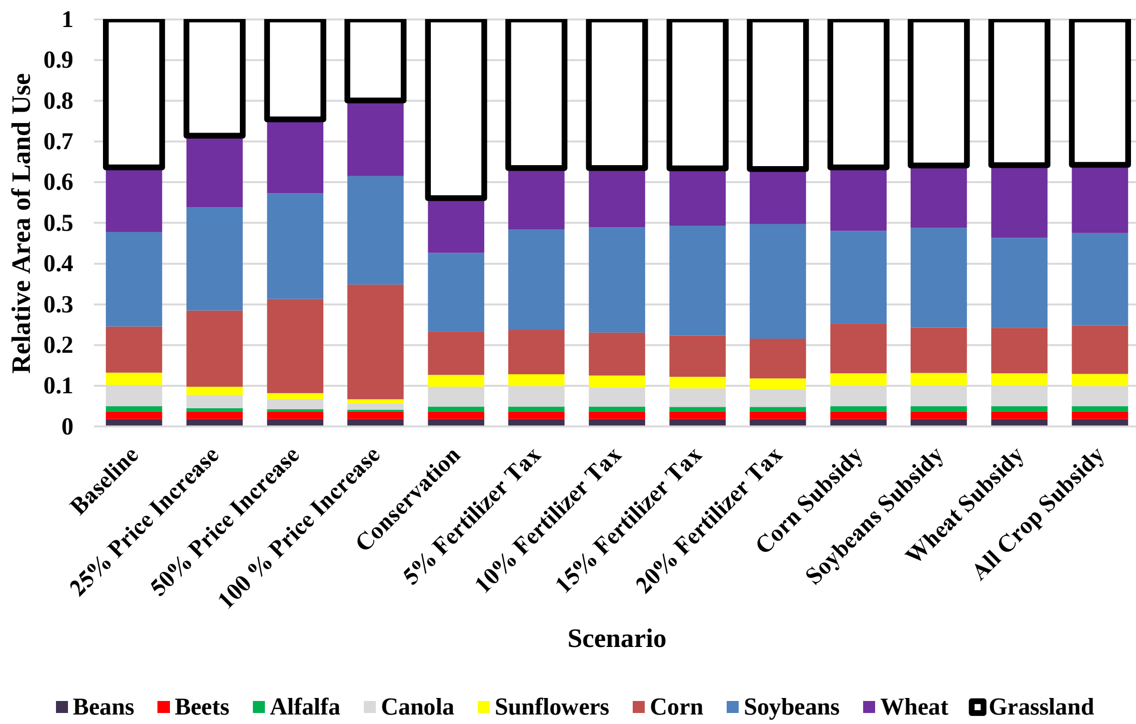


Figure 39. Projected land use in basin draining through USGS 05092000 under various economic scenarios.

The conservation program was successful in producing a larger area of grassland. Relative area in grassland increased from 36% to 44% when conservation payments were offered. However, the area of corn remained relatively unchanged at about 11%, with total area planted in wheat and soybeans decreasing from 39% to 33%.

Fertilizer taxes impacted area of wheat the greatest. The largest tax, a 20% sales tax, reduced the area in wheat from 16% to 14%. This tax resulted in very small reductions in areas planted in corn and the minor crops, a slight increase in grassland and an increase in soybean areas from about 23% to 28%.

A subsidy that targeted an individual crop had the anticipated effect of producing additional acreage of that crop but, when subsidies were applied to all crops, area of soybean actually decreased. The increase in relative crop area from each targeted subsidy was an approximate 1% addition to relative corn area, a 1% addition to soybean area and a 2% addition to soybean area. When all three subsidies were offered, relative area of corn increased slightly, wheat increased from about 16% of the study area to about 17% and soybean relative areas decreased slightly.

Subsidies resulted in a slight decrease in grassland (the greatest was 36.4% to 35.7%). The reduction in grassland was greater under soybean and wheat subsidy scenarios than the corn subsidy scenario. Usually an increase in area of a major crop resulted in a decrease in area of a different major crop.

Impact of Economic Scenarios on Water Quality

Next, the land uses defined by the economic scenarios were used to predict nitrate concentrations. When a scenario predicted that a basin would experience greater cultivation of a crop which had a positive coefficient in the land use – water quality regression, such as corn, that land use would be expected to result in increased nitrate concentrations in that basin. If the economic – land use model predicted land use that was not associated with increased nitrates, such as grassland or soybean cultivation, nitrate reductions were anticipated.

The land use within each basin resulting from each scenario was provided as inputs to the land use – water quality model. The other significant independent variables, such as discharge and runoff, were held at the basin average, calculated from the entire study period, 2006-2014. The resulting nitrate concentrations under the scenario-defined land use were calculated. Under baseline economic and crop production conditions, the expected nitrate concentrations within each basin are shown in Figure 40. These concentrations are also listed in Table 28.

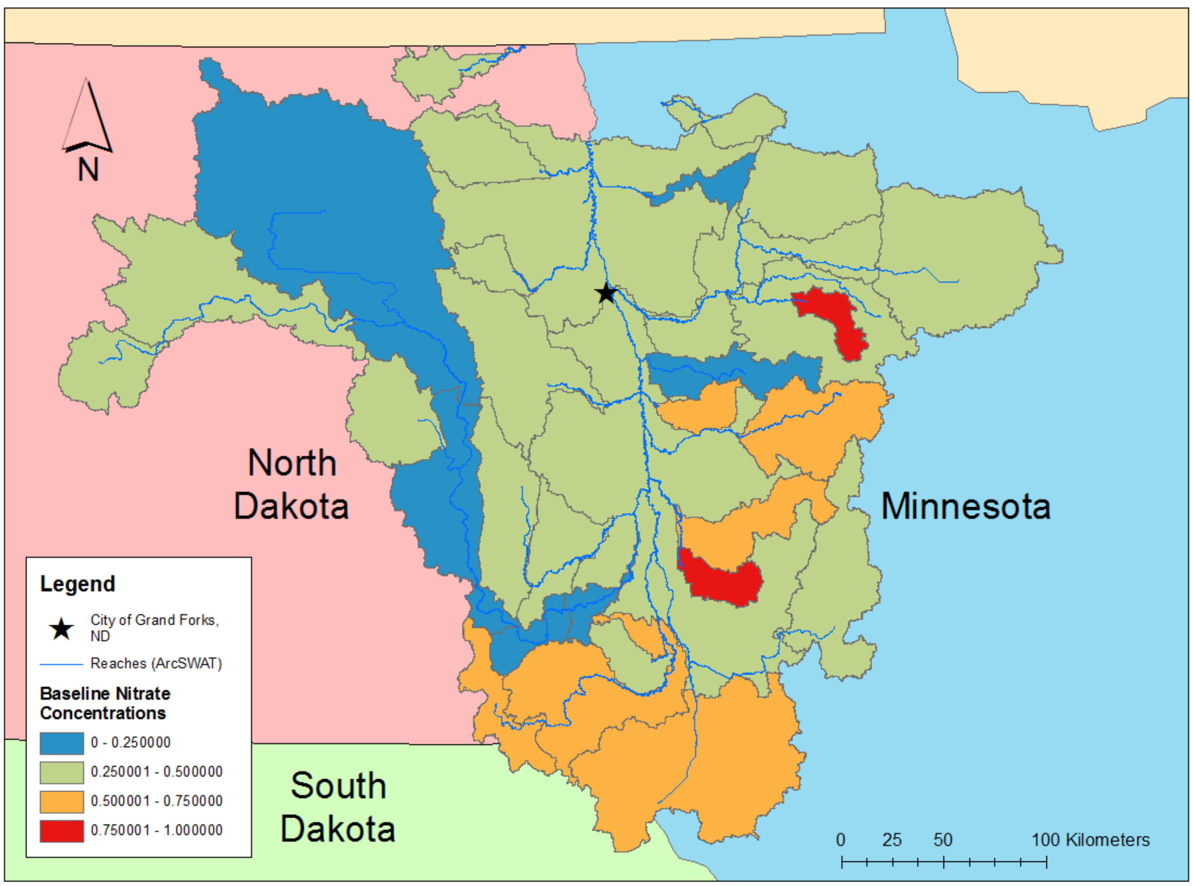


Figure 40. Modeled gauge drainage basin nitrate concentrations under the baseline economic scenario.

Table 28. Percent change in nitrates from baseline under various economic scenarios.

Basin	Baseline (mg/L)	25% Price Increase	50% Price Increase	100% Price Increase	Conservation	5% N Tax	10% N Tax
05030500	0.42	19%	28%	43%	-11%	-5%	-9%
05051300	0.72	4%	5%	6%	-6%	-2%	-4%
05051600	0.62	9%	15%	19%	-7%	-3%	-5%
05052500	0.49	13%	18%	28%	-8%	-3%	-7%
05053000	0.52	11%	17%	22%	-8%	-3%	-6%
05054500	0.40	27%	44%	62%	-13%	-6%	-13%
05056000	0.33	25%	42%	58%	-13%	-6%	-12%
05057000	0.17	40%	73%	102%	-22%	-8%	-17%
05057200	0.46	23%	36%	55%	-8%	-3%	-7%
05058600	0.06	99%	172%	243%	-50%	-18%	-37%
05058700	0.19	38%	67%	94%	-19%	-7%	-14%
05058810	0.05	119%	206%	290%	-59%	-21%	-43%
05059000	0.16	44%	76%	107%	-21%	-8%	-16%
05059500	0.16	43%	75%	106%	-21%	-8%	-15%
05059700	0.36	31%	42%	58%	-8%	-3%	-5%
05060100	0.32	27%	36%	52%	-9%	-3%	-6%
05061500	0.92	10%	14%	17%	-7%	-3%	-6%
05062000	0.74	10%	13%	19%	-7%	-3%	-6%
05062500	0.66	13%	18%	24%	-9%	-4%	-7%
05066500	0.41	17%	23%	31%	-11%	-4%	-8%
05067500	0.75	14%	19%	26%	-7%	-3%	-7%
05069000	0.24	18%	24%	52%	-9%	-3%	-7%
05074500	0.39	18%	31%	43%	-11%	-8%	-12%
05076000	0.40	50%	84%	125%	-14%	-12%	-17%
05078230	0.75	10%	15%	18%	-8%	-4%	-7%
05078500	0.39	15%	23%	36%	-11%	-6%	-10%
05080000	0.39	18%	31%	48%	-11%	-7%	-11%
05082500	0.38	18%	29%	41%	-10%	-4%	-8%
05082625	0.47	9%	15%	19%	-9%	-3%	-6%
05087500	0.22	83%	117%	206%	-12%	-8%	-13%
05090000	0.30	15%	29%	42%	-11%	-4%	-7%
05092000	0.37	19%	29%	42%	-10%	-4%	-8%
05094000	0.37	38%	69%	98%	-18%	-20%	-23%
05099600	0.44	9%	38%	56%	-8%	-2%	-5%
05100000	0.46	9%	33%	47%	-8%	-2%	-5%
Average	0.42	28%	46%	67%	-14%	-6%	-11%

Table 28 cont. Percent change in nitrates from baseline under various economic scenarios.

Basin	Baseline (mg/L)	15% N Tax	20% N Tax	Corn Subsidy	Soybeans Subsidy	Wheat Subsidy	All Crop Subsidy
05030500	0.42	-13%	-16%	2%	-2%	6%	4%
05051300	0.72	-6%	-8%	1%	-1%	1%	1%
05051600	0.62	-7%	-9%	1%	-1%	5%	3%
05052500	0.49	-9%	-12%	2%	-2%	4%	4%
05053000	0.52	-9%	-12%	1%	-2%	4%	3%
05054500	0.40	-17%	-21%	3%	-3%	5%	5%
05056000	0.33	-16%	-21%	3%	-3%	7%	6%
05057000	0.17	-24%	-32%	3%	-4%	10%	7%
05057200	0.46	-10%	-13%	1%	-2%	3%	2%
05058600	0.06	-54%	-72%	7%	-9%	21%	15%
05058700	0.19	-21%	-28%	3%	-4%	8%	6%
05058810	0.05	-64%	-85%	9%	-11%	25%	19%
05059000	0.16	-23%	-31%	3%	-4%	9%	7%
05059500	0.16	-23%	-30%	3%	-4%	9%	7%
05059700	0.36	-8%	-10%	1%	-1%	2%	2%
05060100	0.32	-8%	-11%	1%	-2%	2%	2%
05061500	0.92	-9%	-12%	1%	-1%	4%	3%
05062000	0.74	-8%	-11%	1%	-1%	4%	3%
05062500	0.66	-11%	-14%	1%	-2%	5%	3%
05066500	0.41	-12%	-16%	2%	-2%	3%	2%
05067500	0.75	-10%	-11%	2%	-1%	6%	4%
05069000	0.24	-10%	-13%	2%	-2%	5%	4%
05074500	0.39	-14%	-16%	1%	-3%	9%	6%
05076000	0.40	-19%	-21%	1%	-5%	22%	13%
05078230	0.75	-10%	-12%	1%	-2%	4%	2%
05078500	0.39	-14%	-16%	1%	-3%	7%	4%
05080000	0.39	-14%	-16%	1%	-3%	9%	5%
05082500	0.38	-12%	-15%	2%	-2%	5%	4%
05082625	0.47	-9%	-11%	2%	-2%	2%	2%
05087500	0.22	-21%	-22%	0%	-4%	48%	25%
05090000	0.30	-11%	-16%	2%	-2%	2%	2%
05092000	0.37	-12%	-15%	2%	-2%	5%	4%
05094000	0.37	-25%	-26%	0%	-6%	20%	11%
05099600	0.44	-7%	-10%	1%	-1%	3%	2%
05100000	0.46	-8%	-10%	1%	-1%	3%	2%
Average	0.42	-16%	-20%	2%	-3%	8%	6%

Modeled nitrate concentrations were not consistent across basins due to unique properties of the basin. These unique properties include variations in the Crop Productivity Index, which was used to predict land use under the various economic scenarios. These land uses were then inputs to the land use – water quality model, which contained other independent variables unique to basins such as discharge and stream length. The result is a projected baseline nitrate concentration that is unique to each basin.

The changes in nitrates from baseline in each basin under each scenario are shown in Table 28. It can be seen that, under any scenario, nitrate changes were not consistent across all basins. Since all independent variables except land use are held at their average, these variations in changes of nitrate concentrations were driven by variations in projected yields, due to soil productivity, across the basins.

Nitrate concentrations change as would be expected, given the projected changes in land use (Figure 39) and the coefficients of the various land use types in the land use – water quality model. For example, the 50% price increase, which caused an increase of relative corn area from 11% to 23% (Figure 40), caused an increase in nitrates in all basins (Table 28). These increases ranged from 5% to 206%. These variations in change can be more easily observed in Figure 41, which depicts the nitrate changes from baseline due to a 50% price increase. The 50% price increase scenario is featured because it provides a more realistic scenario than a 100% price increase, which will be discussed below.

The change in nitrate under the 50% price increase scenario can be compared to that of the corn subsidy scenario, shown in Figure 42. Both scenarios result in increases in nitrates. However, nitrate changes under the corn subsidy scenario are much more subtle, never exceeding 9%. Although both scenarios produced different nitrate increases in different basins,

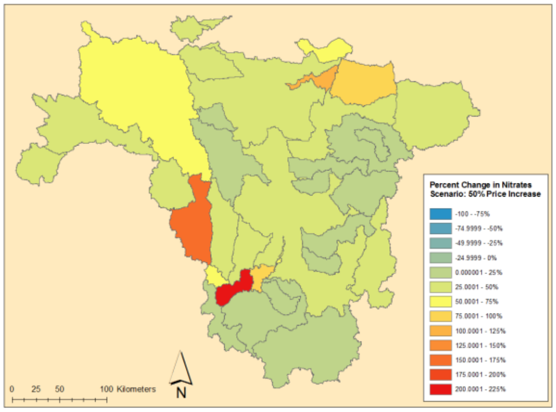


Figure 41. Modeled changes in nitrates from baseline under 50% price increase economic scenario.

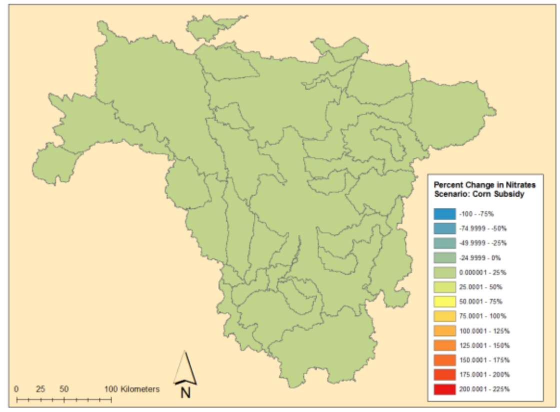


Figure 42. Modeled changes in nitrates from baseline under corn subsidy economic scenario.

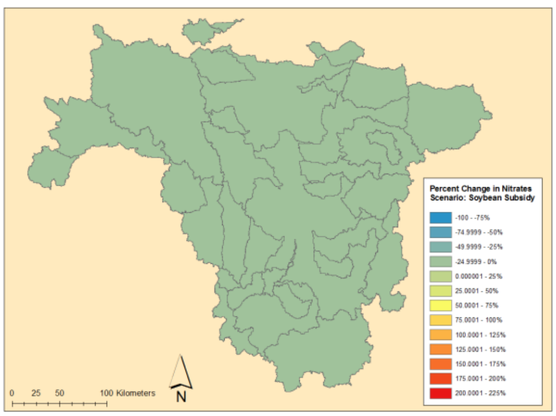


Figure 43. Modeled changes in nitrates from baseline under soybean subsidy economic scenario.

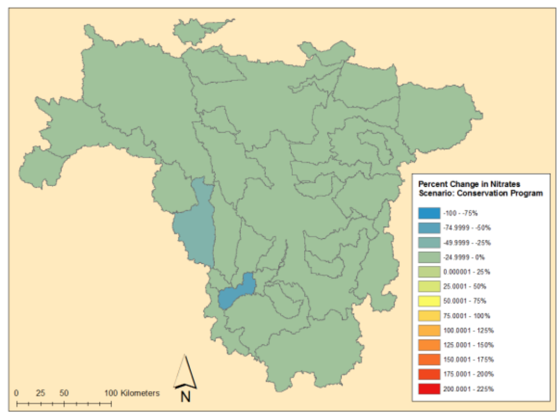


Figure 44. Modeled changes in nitrates from baseline under conservation program economic scenario.

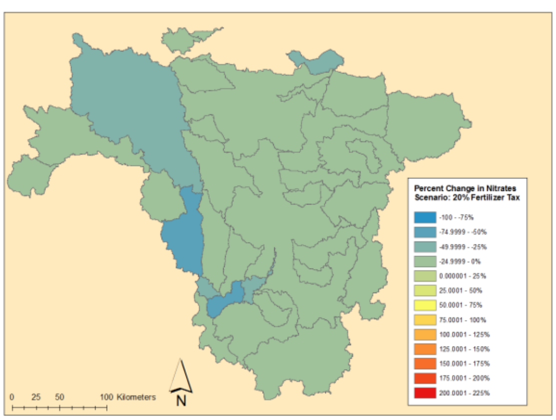
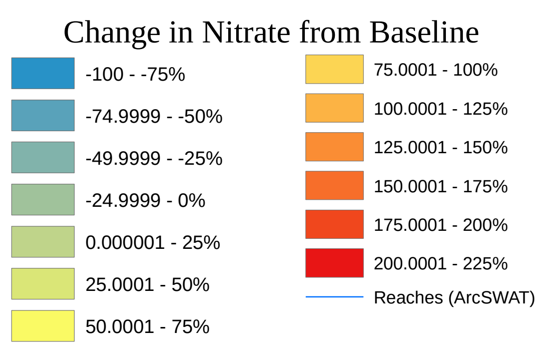


Figure 45. Modeled changes in nitrates from baseline under 20% fertilizer tax economic scenario.



the extent of that effect was not consistent between the scenarios. For example, when the price increased the nitrates in basin 05087500 increased 117%, but when the subsidy was offered nitrates did not change in that basin. The economic scenarios, one providing a per-production unit revenue increase and the other providing a per-hectare revenue increase, affect the nitrate concentrations in different ways.

Soybean subsidies, conservation programs and fertilizer taxes all resulted in lower than baseline nitrate concentrations. Changes due to the soybean subsidy, shown in Figure 43, are slight. The subsidy produced a reduction in nitrate concentrations in all basins, but the greatest reduction was only 11%. The conservation program produced larger nitrate reductions, ranging from 7% to 59% reductions (Figure 44). The 20% fertilizer sales tax resulted in the largest nitrate reductions, ranging from 8% to 85% reductions (Figure 45).

The effect of an economic scenario varied among basins. However, each scenario produced the same trend among basins, either increasing or decreasing the nitrate concentrations. As expected, scenarios which were expected to result in increased nitrate loss, such as crop price increases, did produce increased nitrate concentrations. Scenarios expected to reduce nitrate export, such as fertilizer taxes, did result in decreased nitrate concentrations.

CHAPTER V

DISCUSSION

As expected, land use changed considerably in the Red River Basin from 2006-2014, with a large increase in corn, corresponding to the increase in corn price. Areas of soybean remained fairly consistent and, overall, areas of wheat decreased in spite of increases in the price of both these crops.

Regressions of crop areas and nitrate concentrations were performed and it was found that relative areas of crops produced better results, similar to other studies. Also the previous year's crop data produced better models than current year's data, possibly indicating a time lag. Corn, canola, sunflowers and wheat contributed similar amounts of nitrates, which would be expected considering their similar nitrate requirements. Beets had a much larger influence on nitrates, possibly due to their location in close proximity to the main river channels. Soybeans, alfalfa and dry beans were not identified as significantly contributing nitrates, corresponding to their low fertilizer requirements. The relationships identified within the land use – water quality model will be explored in more depth below.

The economic – land use model produced expected results when provided the various economic scenarios. As predicted, economic conditions which impel increased production of crops, such as increases in crop prices or the establishment of crop subsidies, resulted in projections of increased area devoted to crops. Conditions which discourage the production of crops, such as increases in the costs of growing crops or financial incentives to remove land from production, result in decreases in cropland.

When applied to the land use – water quality model, scenarios which impelled production of corn and wheat resulted in greater nitrate export. Scenarios which discouraged corn and wheat cultivation, such as a fertilizer tax, or scenarios which were conducive to other land use, such as soybean production of conservation enrollment, produced lower projected nitrate concentrations in surface waters.

Land Use Change

The changes in corn production within the Red River Basin has followed the changes in corn prices. Prices of the three major crops, (corn, soybeans and wheat) moved in tandem during the study period (Figure 3). Generally, the prices of crops moved upwards, with a slight decline in 2009 and another decline in 2013-2014. Corn cultivation in the study area seemed to mirror these changes in crop price, as can be seen in Figure 6 or when viewing the gradual increase in area of soybeans and corn in Figure 23.

National corn prices experienced the most rapid growth, increasing 193% from 2006-2012 (University of Illinois, 2016), contributing to a 104% increase in corn area planted, as identified in this study from the Cropland Data Layer. Another, less quantifiable, driver of corn production may be reduced risk offered by producing corn. The ethanol mandates provided an assured market for corn, protected from other market forces and guaranteed to grow until at least the mandated 2015 conventional ethanol production was achieved.

National soybean prices increased 149% from 2006-2013 (University of Illinois, 2016). In consideration of this, increases in soybean acreage within the study area seem quite conservative, only increasing 29%. Again, this may be attributable to greater sense of risk associated with soybean demand, compared to that of corn.

National wheat prices increased 88% from 2006-2014 (University of Illinois, 2016). Surprisingly, area planted in wheat within the study area declined considerably, by 31%. The decrease in wheat area planted, in spite of steady price increases, might be explained a couple of ways. First, corn remained considerably more profitable than wheat. Although the wheat price per bushel was, at times, nearly double the corn price per bushel (Figure 3), corn yields are much higher than wheat. National Agricultural Statistics Service data show that, within counties within the study area between 2006 and 2012, corn yields averaged 115 bushels per acre and wheat yields averaged 37 bushels per acre (USDA, 2015b). It is reasonable to speculate that many of the 478,557 hectares of wheat lost from 2006-2012 were consumed by the additional 627,708 hectares of corn planted.

All the major crops in the study area increased in acreage from 2006-2014 except wheat and sunflowers. Total area planted with the seven major crops within the study area increased 25% during that period. Overall, the agricultural trends observed in the study area from 2006-2012 tend to indicate clear relationships between economics, policies and crop production.

Land Use – Water Quality Model

Using land use data and available hydrological and physical variables multivariate, regressions were performed with the dependent variable nitrate concentration. It was found that the best fit model utilized log base 10-transformed variables. The crop variable which produced the best result was the relative area of each crop type (area planted in a crop divided by the total area) which had been planted the previous year, regressed with the current year's nitrate observations.

The land use-water quality model specified had an adjusted coefficient of determination of 0.265. This indicates that the variables used account for 26.5% of the variation in nitrate concentrations. The net effect of the 73.5% unaccounted for variation can be seen in the 0.45 intercept, which is likely due to variables which were not addressed in this study, of which there are many. A few examples of possibly significant variables include soil permeability, depth of groundwater, slope and land uses not quantified here, such as urban and grassland areas.

Use of Previous Year's Crop Data

The best-fit models obtained with the previous and current year's crop data were similar. It was found that nitrate concentrations were slightly more strongly correlated with previous year's crops than current year's crops for all crop types except wheat, dry beans and canola. The selected model using previous year's relative crop areas (Table 23) had $R^2 = 0.265$, compared to $R^2 = 0.262$ when current year's relative crop areas were used (Table 24). The coefficients of determination varied little and the significant factors and their coefficients were comparable. For example, the coefficient of the previous year's corn variable was 0.992, the current year's was 0.775. The variables which were significant were the same in both models, with the exception that area of soybeans became insignificant when analyzing the previous year's data.

The higher correlation with previous year's crops suggests that there may be a time lag between a particular land use and the consequential impact on surface water nitrate levels. This seems reasonable, as water migrates at different rates through the basin depending on factors such as land cover and soil properties. However, given the much stronger correlation of nitrates with runoff (0.3015) compared to baseflow (0.0482) it would seem that time lag would not be a significant consideration. If nitrates are primarily arriving at the streams via runoff, they have very little residence time within the basin.

It is difficult to conclude that the better fit with the previous year's relative crop areas is attributable to time lag, because the improvement with this model is so slight and because the two datasets (previous and current years' relative crop areas) are so highly correlated (Figure 31). For example, the correlation coefficient of areas of wheat grown in the current year and previous year was 0.99. When looking at Figure 23, it can be seen that the total area of wheat changed quite a lot over the entire study period, but only slightly from one year to the next. Specified models with previous year's and current year's crop data are very comparable, hence using either previous year's or current year's crop would produce similar nitrate concentration predictions.

Use of Relative Crop Areas

In development of the best fit-model land use-water quality model, best results were obtained when relative area of crops were used as an independent variable, rather than actual areas. Relative areas were much more closely correlated to nitrate concentrations than actual areas (Figure 32). To illustrate, the correlation coefficient of area of previous year's corn and nitrates was 0.031, compared to the coefficient of 0.241 when correlating previous year's relative area of corn and nitrates. Other studies have elected to use the percent area of crops rather than actual area (Broussard and Turner, 2009; Schilling and Libra, 2000).

It is reasonable that the relative area of crops produces a higher adjusted coefficient of determination than absolute area of crops. This indicates that the density of crops grown in an area is significant. It is known that factors other than crops can influence the amount of nitrate loss to surface waters. In basins with a lower relative area of crops, the basin has a higher relative area of other land uses such as forests, grasslands and wetlands. It has been shown that these types of land use can decrease the amount of nitrate loss. In fact, land managers are encouraged to utilize grass buffers along waterways to intercept nitrates and other potential contaminants. The presence of greater relative areas of these other land uses would be expected to result in less nitrate loss.

It can be seen from the correlation plots (Figure 35) that the area of crops is strongly positively related to the area of basin (r=0.8801). Likewise, discharge is moderately positively correlated with basin area (r=0.5467). The strength of the discharge and basin area correlation would likely be much greater if the discharge variable were adjusted for seasonality, which can produce great variance in discharge (Figure 16).

It was found that models developed using the relative total area of all the major crops were very comparable to the models developed using the relative area of individual crop types. When using the previous year's relative crop area, the best-fit model using the individual crop areas had $R^2 = 0.265$, while the best-fit model with relative area of total crops had $R^2 = 0.263$. When using the current year's crop data, the model using total crop data actually had a higher adjusted coefficient of determination, 0.263 compared to 0.262. This is likely because the coefficients of all the individual crop variables were positive. If individual crop variables had produced a mixture of positive and negative variables, the total crop area data would have produced a poorer fit.

Other studies have compared nitrates to both total relative area of crops and relative area of row crops. Broussard and Turner (2009) obtained coefficients of determination as high as 0.61 when regressing percent area in cropland with nitrate concentrations in various watersheds. Schilling and Libra (2000) obtained a coefficient of determination of 0.94 when regressing percent area in row crops with nitrate concentrations in Iowa watersheds. Both studies appear to have used very small sample sizes.

The Influence of Individual Crop Types

The coefficients of the significant crop variables in the best fit land use – water quality model are shown in Table 29. As an example, the contribution to nitrate concentrations from each crop, based on the average relative area of that crop in the study area gauge drainage basin, is shown in the table. These figures are not representative of any particular basin, but are shown for illustrative purposes. For example, to calculate the effect of corn the following formula would be used:

*log10 (nitrate concentration + 1) = 0.992 * log10 (relative area of corn + 1)*

Table 29. Sample nitrate projections due to relative crop areas.

Crop	Coefficient	Average Area (ha)	Average Relative Area	Projected Nitrate Contribution (mg/L)
Corn	0.992	59,669	0.076	0.075
Sugar Beets	2.975	6,539	0.008	0.025
Sunflowers	1.109	16,026	0.020	0.023
Canola	0.874	15,408	0.020	0.017
Wheat	0.887	112,606	0.143	0.126

A hectare of sugar beets have considerably more influence on nitrates than other crops. However, this crop also occupies the smallest area of all the significant major crops. Compared to sugar beets, corn, sunflowers, canola and wheat have coefficients of similar magnitude. The influence of wheat is greatest (0.126 mg/L) because of its greater area and the influence of canola is least (0.017 mg/L) because it has the lowest coefficient and occupies a relatively small area.

Corn

The specified land use-water quality model indicates that increased cultivation of corn results in increased nitrate concentrations in surface waters. However, the weight of the influence of corn in the specified model (Table 29), with a coefficient of 0.992, was not as great as that of beets nor sunflowers (coefficients of 2.975 and 1.109, respectively). It is surprising that the influence of sunflowers is greater, given their lower nitrogen recommendations, 50-150 pounds per acres, compared to corn, 96-240 pounds per acre (Table 3). As a matter of pure speculation, it may be that sunflowers intercept less direct precipitation than corn, resulting in more nitrate loss via runoff. An example of how the relative area of corn influences nitrates is shown in Table 29.

Sugar Beets

Surprisingly, it was found that the relative area of sugar beets had a substantially larger influence than corn on nitrate concentrations, with a coefficient of 2.975 compared to 0.992. One possible explanation for this is over-fertilization by beet farmers. Although beet nitrogen recommendations are lower than those for corn (Table 3), beet growers frequently exceed those recommendations, sometimes applying up to 180 pounds per acre (Sims, 2014).

In attempting to explain the high coefficient of beets, it is helpful to assess the location of beet cultivation. Figure 46 shows the location of all beet cultivation from 2006-2014. Beets are grown in very limited area, close to the main channel of the Red River and distant from headwater areas. It is important to explore how this positioning of beets within the study area may cause the model to associate beet cultivation with higher nitrate concentrations.

It has been observed in some studies that net nitrate concentrations increase as waters move downstream, particularly during periods of high runoff (Bolstad and Swank, 1997). The location of the beet plantings would cause them to only be associated with the large, higher-order basins, and disassociated with smaller headwater basins. Although larger basins, and their correspondingly longer stream networks, are associated with lower nitrate concentrations in the model (see their negative coefficients in Table 23), average nitrates increase moving down the main channel of the Red River.

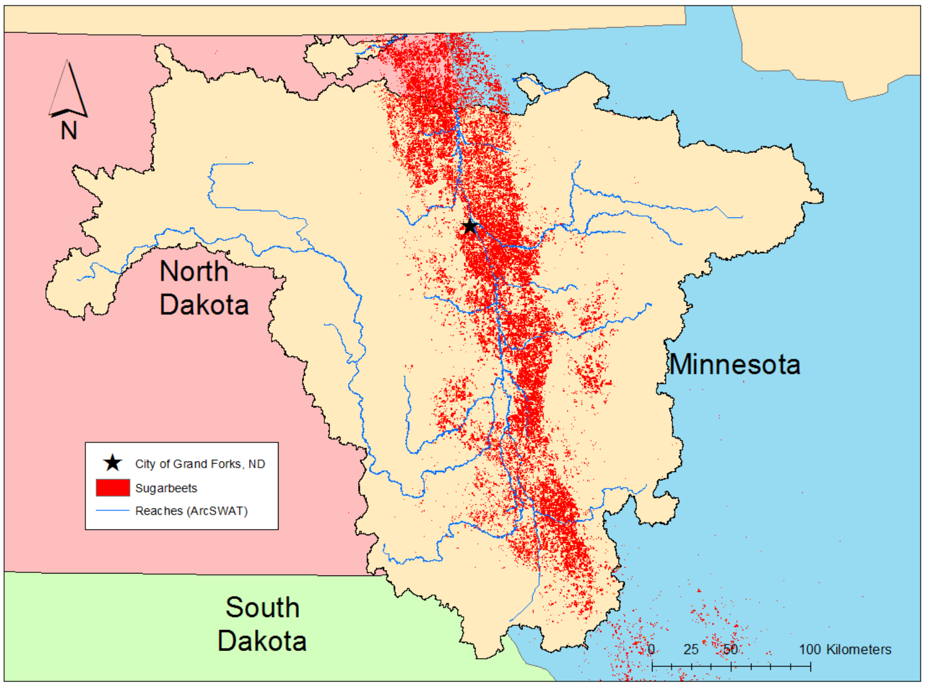


Figure 46. Location of sugar beet plantings from 2006-2014. Data source: USDA, 2015a.

To illustrate this increasing nitrate load in downstream areas, a few points within the study area were chosen and their average nitrate concentrations compared. USGS gauges 05064500, 05082500 and 05092000 are located directly in the Red River with 05064500 being furthest upstream and 05092000 furthest downstream (see Figure 15). Their average respective nitrate concentrations from 2006-2014, calculated from available nitrate observations, were .227 mg/L, .228 mg/L and 0.302 mg/L. It appears that, at least within the main reach of the river, nitrates increase moving downstream. These values can then be compared with those observed at USGS 05080000, 0.006 mg/L. This gauge is located in the Red Lake River tributary of the

Red River, slightly removed from the main channel. Nitrates there are dramatically lower than those within the Red River.

Larger rivers are not as effective at removing nitrates as smaller headwater streams (Alexander and Smith, 2000). This can be partly attributed to a lower ratio of surface and substrate areas to total volume in the larger rivers. Many of the processes that remove nitrates, such as denitrification and uptake by flora, occur at the surface or substrate. Additionally, the photic zone of larger rivers may be smaller, as a percentage of total volume, allowing for less biological processes which would utilize the nitrates.

The location of the beets directly along the Red River and only within basins gauged directly in the river would cause the regression to identify small areas of beets as being correlated with high concentrations of nitrates and assign the beet variable a large coefficient. If this is the case, an omitted variable bias could exist, meaning some of the nitrates attributed to beets by this model could be either attributable to other independent variables or variables not included in this analysis.

Soybeans

This analysis was not able to statistically identify the impact of soybean crops on nitrate loss. Despite the fact that soybeans are the most widely produced crop in the study area (Figure 23), the relative area of soybeans variable was insignificant in the final land use – water quality model. The coefficient estimate of soybean has been inconsistent through different specifications with opposite signs and indefinite statistical significances. Whenever significant, the coefficient was relatively small. When the current year's relative crop area was regressed, the soybean variable tended to be significant and have a positive coefficient.

From the results produced here, it could be concluded that soybeans have little or no effect on nitrate loss. This might be expected considering that the South Dakota Fertilizer Recommendations Guide states that soybeans require no nitrogen content in their soils (Gerwing and Gelderman, 2005). Soybeans are legumes, and legumes participate in symbiotic relationships with bacteria which are capable of fixing nitrogen, reducing the need for nitrogen fertilizer input (Van Kessel and Hartly, 2000). The variability in the significance of the soybean variable and the magnitude and direction of the soybean coefficient could also be influenced by the corn and soybean rotation, which has been common in the study area (Napier and Tucker, 1999).

Wheat

The coefficients of the relative area of wheat variable, 0.887, was slightly smaller than that of corn, 0.992 (Table 23). This is not surprising. Although the recommended nitrogen content for wheat is about the same as that of corn; corn is a row crop while wheat is a dispersal crop. Row crops do little to impede runoff and leave much of the ground exposed, allowing additional erosion and weathering of the soils (Turner and Rabalais, 2003). Given the large roll runoff plays on nitrate loss in this study area, row crops such as corn should be associated with greater nitrate export than dispersal crops such as wheat.

Canola and Sunflowers

Both canola and sunflower variables were very erratic; becoming significant with the addition of some variables, losing significance with the addition of other variables. The direction of the coefficients oscillated between negative and positive. To illustrate, the sunflower coefficient changed from -1.477 to 1.109 with the addition of the stream length, basin area and wetland area variables, while the fit of the model only improved from 0.225 to 0.265 (Table 23).

The unpredictability of the canola and sunflower variables is likely due to their small sizes relative to the other crops. In Table 12 it is shown that alfalfa, canola, dry beans and sunflowers have the smallest areas of the eight crops assessed. As the relative area of a crop within a basin diminishes, its impact also becomes diminished as it is drowned out by other variables, such as the influence of more prevalent or more significant land uses, physical properties of the basin, natural processes and other variables (Schilling and Libra, 2000).

Compounding the dampening effect of its small size is the small expected contribution of canola and sunflowers to the surface water nitrate concentration, given that both have fertilizer recommendations lower than that of corn (Table 3). Additionally, canola is a dispersal crop and would be expected to contribute less nitrates.

Alfalfa and Dry Beans

Two of the crops considered in this analysis were neither significant nor included in the final model, alfalfa and dry beans. Based on the results of this study, it does not appear that these two crop types significantly contribute to nitrate concentrations in the surface waters. As mentioned above, this is likely due, in part, to the small areas planted in these crops.

It would not be expected that alfalfa would result in greater nitrate concentrations. Like soybeans, alfalfa is a legume. It has the lowest fertilizer application recommendations of all crops (Table 3). Additionally, alfalfa is a dispersal crop which could be expected to intercept precipitation resulting in less soil erosion and runoff. Also, being a perennial plant, there would be less disturbance in areas grown in alfalfa, leading to less exposure of soil nitrogen to air and precipitation which would result in its oxidation and export. It might have been expected that the alfalfa variable would have generated a negative coefficient, since its presence in a basin would likely be associated with lower than average nitrates in the waters of that basin.

Dry beans were never significant in any of the regressions. This is not unexpected, given that, of all the crops, relative area of beans produced the weakest coefficient when correlated with nitrates (Figure 32). The absolute area of beans produced a much stronger correlation coefficient (-0.1586 compared to -0.0189). Like alfalfa and soybeans, dry beans are legumes and do not require as much nitrogen input as most crops. However, the fertilizer recommendations for dry beans are higher than alfalfa and soybeans (Table 3), and dry beans are row crops. For these reasons they might have been expected to contribute some nitrate to the streams.

Non-Crop Variables

Non-crop variables, such as discharge and stream length, were included in the analysis to improve the fit of the model. The inclusion of non-crop variables, particularly runoff, had a profound effect on the quality of the model. A summary of the coefficients of the significant non-crop variables in the best fit land use – water quality model are shown in Table 30, along with the average value for each variable. Included in the table is the predicted contribution to the nitrate concentration, as calculated from the average variable value and the coefficient. It should be remembered that the average values of the non-crop variables shown are averages of all basins for dates on which there were nitrate observations available and are not representative of the conditions in any particular basin at any particular time.

Table 30. Sample nitrate projections due to non-crop variables.

Variable	Coefficient	Average Value	Nitrate Concentration (mg/L)
Runoff (m^3/day)	0.152	1,282,834	8.50
Baseflow (m^3/day)	-0.045	994,701	-1.86
Stream Length (km)	-0.094	2,982	-2.12
Basin Area (ha)	-0.116	785,574	-4.83
Wetland Area (ha)	0.091	122,489	2.90

Runoff and Baseflow

The constituent parts of discharge, baseflow and runoff, had been calculated using EcoHydRology package for R (Fuka et al., 2014). It was found that better results were obtained when the individual components of discharge, baseflow and runoff, were applied to the model rather than a total discharge variable. The inclusion of both the baseflow and runoff variables increased the adjusted coefficient of determination from 0.039 to 0.225.

The coefficient of runoff was found to be positive and the coefficient of baseflow was found to be negative. The significance, magnitude and direction of the runoff variable is a bit surprising, in consideration of the results of most other studies which identify baseflow to be the primary flux of nitrates (Schilling and Libra, 2003; Jordan et al., 1997). A few papers can be found which observe higher nitrates in runoff, such as Booth and Campbell (2007), which used a combined factor of runoff and fertilizer quantity. The results of this study indicate that, during periods of greater runoff, such as after rain events, the concentration of nitrates can be expected to be higher. During periods of little to no runoff, when all stream flow is derived from baseflow, nitrate concentrations would be expected to be lower than average.

Figure 19 shows runoff at the Pembina, ND USGS gauge, which receives discharge from 98% of the delineated study area. It can be seen that runoff is highest in April. Although precipitation tends to be higher in the late spring and early summer months (MNDNR, 2016), it is reasonable that runoff would be highest in April, with snowmelt and spring rains contributing to saturated soil conditions. In Table 10 it is shown that mean nitrate concentrations at USGS 05051300 are highest in June, 1.89 mg/L, followed closely by April with 1.71 mg/L. April has the highest maximum observation, 10.30 mg/L. These nitrate concentrations and runoff data are in agreement with the findings of this study, that months with high runoff tend to have high nitrate concentrations.

It should be considered that the timing of high runoff correlates with other activities in the basin which may influence nitrate concentrations. Spring planting, with the associated disturbance due to tillage, exposes nitrogen species within the soil to precipitation, which would be expected to result in nitrate runoff. The timing of this planting will vary depending on the crop type and weather, but will generally occur in April or May (Table 13). These are months of high runoff, accounting for over 50% of the annual runoff (Table 8). The high coefficient attributed to runoff may be more indicative of the activities occurring in those months than the influence of the actual runoff process.

An additional consideration which may contribute to the elevated nitrate levels with increased runoff is the application of fertilizer. Bierman et al. (2012) found that 89.2% of corn farmers in the region applied their primary fertilizer application in the spring, although it has been difficult to identify specific date ranges. With saturated soils and spring rain, much of this fertilizer might be expected to runoff directly to streams, rather than percolating into the soil.

The baseflow variable, with a negative coefficient, contributes less nitrate to surface waters than runoff. This can be interpreted to show that, during times of zero runoff, the mean nitrate concentrations are lower than average. Many studies have found baseflow to be the more significant flux of nitrates. It would seem surprising that those studies were able to distinguish a clear signal of land use influence on baseflow nitrates, given the extremely slow movement of groundwater (Van der Kamp and Hayashi, 1998). These findings would be even more surprising in a study area like the Red River Basin where the conductivity of the soils is very low due to high content of clay and silt. It is precisely this low conductivity which has led to the extensive installation of drainage (Rahman et al., 2014). In consideration of this, it doesn't seem unusual that the influence of land use is more easily detected in runoff.

The results of this study, in finding that runoff contributes a much greater amount of nitrate to the streams, are not in agreement with most other studies. The methods used in identifying baseflow and runoff should be considered. This study used the EcoHydRology package for R to identify the baseflow and runoff components of total discharge. This program utilizes the Lyne and Hollick filter, which uses a statistical approach which does not consider the physical characteristics of the study area (Ladson et al., 2013). Although the physical properties of a watershed undoubtedly influence the relative amounts of baseflow and runoff, this statistical method of segregating the two fluxes has been found to be sufficient in many studies (Arnold et al., 2000).

Finally, it should be considered that the discharge variables represent fluxes of nitrate through the basin, but do not explain the origin of the nitrate. This study found that during times of high runoff, a greater concentration of nitrates were observed in the streams and those nitrates were likely arriving at the streams in the runoff. It is reasonable to assume that the origin of the nitrates was from fertilizer applications. Future studies should attempt to integrate the discharge and land use variables into one factor, as done in the study by Booth and Campbell (2007).

Stream Length and Basin Area

Basins with longer stream networks and larger basins produce lower nitrate concentrations. The processes by which streams are able to transform nitrate include denitrification and uptake by aquatic organisms (Peterson et al., 2001). One study found that smaller headwater streams can transform more than 50% of their inorganic nitrogen input (Peterson et al., 2001). At higher nitrate levels the in-stream transformation processes can reach their capacity, suggesting that stream length and nitrate transformation may not be truly linear (Peterson et al., 2001). Overall, the obverse relationship between nitrates and stream length identified is supported by the findings of other studies (O' Brien et al., 2007).

It is also interesting that stream length is only significant in June, when viewing the temporal subset regression results in Table 26. It has been suggested that the length of the stream may play a role in removing nitrates due to denitrifying processes that occur along the substrate of the stream and at the stream surface (Galloway et al., 2003). The lack of significance of the stream length variable in May supports this, since discharge is highest in May. A greater discharge will result in a smaller surface to discharge ratio or substrate to discharge ratio, reducing the role of those denitrifying processes. Additionally, the lack of a significant stream length variable in October may be due to a lower rate of biological production in the stream during the late summer and early autumn months, resulting in less biological uptake of nitrogen species.

It was also found that basins with larger areas were associated with lower nitrates. This relationship might be attributed to processes similar to those that are related to stream length. Larger basins provide larger areas for processes such as denitrification and uptake to reduce the concentrations of nitrates. Additionally, larger basins would be expected to have longer stream networks; the two variables produce a correlation coefficient of 0.9252 (Figure 35). With this in mind, there may be some concerns about including both the stream length and basin area variables in the same regression. However, stream length and basin area are fundamentally different variables and inclusion of both variables did not radically change the results.

Wetlands

The relationship of wetlands to nitrate concentration identified by the analysis was surprising. Most surprising was the positive influence of the wetland coefficient. Generally, wetlands are perceived to enhance water quality (Detenbeck et al., 1993; Gillis, 1990; Verhoeven et al., 2006). Basically, a wetland can provide storage for surface water, allowing for processes to transform nitrates into organic or atmospheric species (Mitsch et al., 2005). It was also found that the area of wetlands, rather than the relative area of wetlands, was the more useful variable. This was in contrast to other land uses, which provided a better fit with relative area data.

This study found that higher concentrations of nitrates are observed in basins with greater areas of wetlands. One condition which could diminish the ability to remediate nitrate contamination is their location within the basin. It has been found that, the farther a wetland is located from a stream, the less ability it has to reduce nitrate concentrations (Detenbeck et al., 1993; Gillis, 1990). It is shown in Figure 25, which shows the locations and area of all study area wetlands from the National Wetland Inventory, that many of the wetlands are in headwater areas, removed from the main channels of the Red River and its tributaries. These remote wetlands may be useful in remediating waters within headwater basins, but have little effect in areas closer to the Red River where wetlands are sparse.

Furthermore, it might be considered that, in headwater basins with a high density of wetlands, the wetlands may provide a more rapid flux of nitrate to streams under some circumstances. Considering the importance that of runoff identified in this model, with runoff contributing the great majority of nitrates, it could be considered that periods of high runoff may result in wetland flooding and overspill. Nitrates that had been stored within the wetland systems are then driven into stream networks, contributing to elevations in nitrate concentrations.

This phenomenon, in which wetlands reach such critical loads of nutrients that they become sources rather than sinks, has been observed (Verhoeven et al., 2006). Some prairie potholes are prone to intermittent spillage, in which they contribute dissolved or suspended material to down-grade surface waters (Leibowitz and Vining, 2003). If this is the process by which wetlands are contributing nitrates to the streams, it supports the findings in Table 26, which indicate that, of the months individually assessed, wetlands were only significant in June, the rainiest month. These findings provide some possible explanations for the positive influence of wetlands on nitrate concentrations.

The greater significance of the absolute area of wetlands variable indicates that wetlands' contributions to nitrate concentration are directly related to the area of the wetlands. Although it seems reasonable to consider that the amount of nitrate contributed would be directly related to absolute area, the consequent concentration is also influenced by the total discharge, which is related to basin size. For this reason, it is difficult to explain why the relative area variable does not provide superior results. However, this insignificance of relative areas of wetland on water chemistry had been observed in another Minnesota study (Gillis, 1990).

Contributing to the complexity of interpreting the significance of wetlands in this study is the awareness of the crudeness or the methods by which the wetland areas were identified. The process of simply deleting areas of wetland which were now identified as cropland may not have produced reliable results. Also, this process can only assess changes to wetlands that existed during the time of the National Wetland Inventory and cannot identify new wetland within the study area, such as constructed wetlands or wetlands which have emerged due to changes in hydrology.

Doubts about the usefulness of the wetland data are supported when viewing Figure 26, where it can be seen that the area of wetlands increases in some years, such as 2009. This is an interesting observation, since cultivation of a wetland would likely require some type of drainage. Once a land manager had invested in drainage it seems unlikely that they would then retire the land from crop production. Also, having been cultivated at one time, the area may no longer be a fully functional wetland, due to changes in topography, soil or vegetation. Regardless, total wetland area within the Red River Basin identified by the methods in this study only changes by about 2%, which would not be expected to have a large influence on the hydrology. Changes within individual basins could be more extensive than the Red River Basin average.

Updates to the National Wetland Inventory within the study area are in progress (MNDNR, 2015), which will provide more accurate data for additional analysis. However, in addition to the extent and location of wetlands, it would be helpful to obtain more specific variables and factors describing the character of individual wetlands. For example, recharge and discharge wetlands may have different impacts on nitrate as will ephemeral and perennial wetlands (Euliss et al., 2014). Improved wetland data from the National Wetland Inventory update will be a valuable tool in future water quality studies within the area of interest.

Point Source Discharge

Point source and tiling data were problematic, and this may be reflected in the lack of significance of these variables. The point source data seemed inconsistent and it is suspected that the data were incomplete. For example, within the four years that the Crookston WWTP is listed in the database, there are no discharges reported (there are annotations that the plant is out of compliance). Other WWTPs went many months without discharge, then reported very high discharges for several consecutive months.

The fact that point source data are reported monthly also made them difficult to work with. Since the discharges could have occurred at any point in the month, it is difficult to determine to which nitrate observations they should be compared. For this analysis, the monthly point source mass was compared to any nitrate values observed in that month. If the discharge had occurred at the end of the month, the regression would have attempted to define relationships between surface water nitrates and nitrates from point source discharges which had not yet occurred.

Tiling

As mentioned earlier, subsurface drainage data were difficult to obtain. There is little doubt that tiling alters the hydrology of a landscape, and many studies have investigated its effect. However, without adequate spatial data the relationship of drainage to nitrate losses cannot be assessed.

The use of the North Dakota subsurface drainage dataset did not produce significant results. There were several caveats to its use. The dataset obtained was a list of permit applications. It is not know when or if these projects were completed. All projects were assumed to have been completed and dates of completion were estimated.

In North Dakota, drainage projects exceeding 80 acres are required to be permitted, a requirement that has been in effect since 1957 (Sando, 2015). However, the permit database only contained information for three permit applications prior to 2003, indicating that many projects are omitted from the database. Furthermore, there is no compelling reason to believe that the North Dakota rules regulating drainage are being enforced.

It seems likely that the aggregated effect of smaller drainage projects and unpermitted larger projects could substantially influence the transport of nitrate in the study area. This effect could wash out the signal of the drainage projects for which there are data available. A lack of quality data regarding the location, extent and timing of drainage projects precludes productive analysis of this variable.

Dummy Variable

A basin dummy variable was included in a regression with other independent variables. This was accomplished by including a categorical variable which identified to which basin each observation belonged. The inclusion of the dummy variable resulted in the largest adjusted coefficient of determination, 0.315, but all other variables except baseflow and runoff became insignificant. The significance of the dummy variable was not unexpected. This indicated that there are variations within the basins which significantly affect the nitrate concentrations within the basin.

Given the size of the AOI, it would be expected that the hydrological characteristics of the basins, such as slope and soil permeability, vary considerably. These variables can influence the rate of nitrogen loss. There may be significant land use factors which vary from basin to basin and are not addressed in this model, such as population densities, unidentified point or nonpoint nitrogen discharges or non-crop land cover such as grassland, shrubland and forest. These can all contribute to the unaccounted for variance in the model.

Spatial Subsets

It was decided to also create spatial subsets of data for further analysis. As mentioned previously, the Devils Lake Basin occupies about 11% of the Red River Basin, but its surface waters seldom intermingle with those of the Red River. For this reason, it is reasonable to suspect that the land use within the Devils Lake Basin would not as significantly impact the nitrate concentrations in other basins. A subset of data was prepared which included all delineated basins within the Red River Basin which did not lie within Devils Lake Basin (Figure 36). This subset had a sample size of 2331.

The specified model derived with the dataset which excluded the Devils Lake Basin is shown in Table 25. This model was prepared using the previous year's relative crop areas. The adjusted coefficient of determination, 0.296, was an improvement over the coefficient obtained when the entire dataset was analyzed, 0.265. This indicates that the nitrate concentrations within the Red River are not as greatly influenced by land use within the Devils Lake Basin as in other parts of the study area.

There are notable differences between the model obtained when excluding Devils Lake Basin and that obtained when considering the entire study area. When omitting the Devils Lake areas, the soybean variable becomes significant and the resulting coefficient is greater than that of corn. A simple explanation for this may be that soybeans are less widely produced in the Devils Lake Basin than in the overall study area. In 2014, 18% of Devils Lake Basin was soybeans and 26% of the Red River Basin (including Devils Lake Basin) were soybeans.

Basin area became insignificant when excluding the Devils Lake area, while the influence of stream length became greater. These two variables would be expected to be very closely related. They are strongly correlated (r=0.9252, Figure 35), likely because larger basins would be expected to have greater total lengths of streams. With this in mind, it can be understood why, as the influence of basin area decreases, the influence of stream length increases. However, less easily understood is why the exclusion of the Devils Lake area rendered basin area insignificant, although it can be observed that the stream network in the Devils Lake Basin are relatively shorter than those in the overall study area.

An additional spatial subset of data was prepared which included only non-overlapping basins, as shown in Figure 38. This was done to address concerns that areas that were included in more than one basin were being oversampled and were being given disproportionate weight in the analysis. Furthermore, when reviewing the scientific literature, studies employing methods similar to this study always used independent basins when developing datasets (Schilling and Libra, 2000). This spatial subset had a sample size of 2007.

The largest independent basins were identified and a subset of data relevant to those basins was created. A slightly smaller basin was substituted for a larger basin if it provided a substantially larger dataset. Analysis of this dataset was performed and the specified model can be seen in Table 25. To a small degree, this dataset provided a better fit when compared to the results using the entire study region, producing an adjusted coefficient of determination of 0.282 compared to 0.265. Given the small difference between the two coefficients, it does not appear that there should be any concerns about the use of overlapping basins.

Monthly Subsets

In consideration of the variability of nitrate concentrations, discharge and land use throughout the year, it was decide, in the manner of Schilling and Lutz (2004), to temporally subset the data by month and more closely assess the relationships between independent variables and nitrate during specific periods. This analysis was intended to capture the influence of specific temporal events, such as tilling and fertilizer application, which would be expected to result in different relationships between land use and nitrates at different points in the year. Additionally, this analysis could provide a better understanding of the influence of the discharge variables, which play a significant role in nitrate concentrations (Table 30) and display a great amount of variability throughout the year (Figure 17).

The data were divided into monthly subsets and the months of May, June and October were selected for closer scrutiny. When subsetting data by month, many of the physical variables, such as wetland area, stream length and basin size, remain unchanged. Essentially, only the effect of the influence of the discharge variables and the temporal variation in nitrates will be captured within the subsets.

The results of the analyses with monthly subsets can be seen in Table 26. These subsets had reduced sample sizes, as noted in the table. In all cases, regressions with these subsets accounted for more of the nitrate variability than regressions with the entire dataset. This is reasonable, since the subsets eliminate some of the temporal variations of discharge, agricultural activities and other variables not considered here. October produced the highest R^2, 0.430, when analyzing the previous year's crop data and 0.353 with the current year's. Schilling and Lutz (2004) found that, in an Iowa watershed, August and October provided the strongest relationships between runoff and nitrates in surface water. Given the apparent importance of runoff in this study area, this would be supportive of the high adjusted coefficient of determination observed in the October subset.

The June subset adjusted coefficient of determination was higher than that of May, 0.350 compared to 0.287, when assessing previous year's crops. June also tended to produce more significant crop variables. This may be related to the higher average monthly precipitation in June, 9.4 cm compared to May's 6.4 cm (MNDNR, 2016). The results of analyses of the temporal subsets indicated that seasonal variation is an important consideration in land use –

water quality studies. Comments related to the temporal effects on specific variables are included in those variables' respective sections of this discussion.

Economic – Land Use Model and Economic Scenarios

The economic – land use model developed in this study was able to predict the land use within the AOI when provided with economic data within the range of historical values. This provided a baseline set of economic and land use conditions within the basin. The baseline conditions (Table 27) represent the output of the economic – land use model when crop prices are at their baseline 2006-2014 value (Table 21). Realistic economical scenarios were then developed from historical data. These scenarios included implementation of a crop subsidy program, a land conservation program and a fertilizer tax and increases in crop prices. The scenarios were then provided as inputs to the economic – land use model to identify projected land use.

Economic Scenarios

The increased price of major crops and the crop subsidy scenarios were both expected to result in increased cultivation of the major crops. They both incentivize crop production, though one does so by increasing revenue per unit of production (price increase) and the other does so by increasing revenue per area of production (subsidy). The subsidy amounts stated in the economic scenarios are derived from actual historic data, albeit crudely, due to the elusiveness of detailed subsidy data. An attempt was made to identify years where individual crop prices were comparable to the baseline crop prices and per-hectare subsidy payments for those years were calculated. In consideration of this methodology, the payments proposed within the subsidy scenario should be reasonable.

The price increase scenario would be expected to provide greater incentive to those farmers with more productive soils, while the subsidy scenario would incentivize farmers regardless of the productivity of their land. In viewing the baseline economic ranges in Table 21, it can be seen that, from 2006-2014, a period of great crop price variability, the difference between the baseline and maximum crop prices is an increase of 54%. So, a 100% price increase scenario may not be a realistic, but a 50% increase is. The percent increase in price was applied uniformly to all major crops because, as seen in Figure 3, the prices of major crops tend to move together. As the increased price of one crop leads to increased production, other crops fall out of production, decreasing supply, leading to shortages and price increases, stimulating production.

The conservation program and fertilizer tax scenarios are designed to create less favorable conditions for crop cultivation. A conservation program creates an alternative revenue source for farmers which might be competitive with crop revenue in less fertile areas. The conservation program payment proposed in the scenario is based on actual Conservation Reserve Program payments in the study area, so should be relevant.

A fertilizer tax results in a per-hectare increase in costs. The range of fertilizer tax percentages (5-20%) were initially arbitrarily selected. Subsequent review of the literature found one study which suggested a 100% fertilizer tax (O' Shea and Wade, 2009). In light of this, the range of tax rates selected for this study does not appear to be unreasonable.

The tax would be expected to have an obverse effect of that of subsidies. Both the increase in direct costs due to the tax and the alternative revenue source provided by the conservation program vary by crop, since the subsidies target specific crops and the tax is a function of the historic fertilizer cost by crop type. Also, the direct costs affected by the tax and the conservation program payment are both allocated per-hectare.

All the scenarios are simplistic. For example, the crop price scenario ignores macroeconomic feedbacks, such as increases in the prices of canola and sunflower due to declining production as more cropland is planted in major crops, so called “indirect land use change”. The fertilizer tax scenario disregards the farmer’s option to apply less fertilizer and accept the consequent decreases in yield and revenue. The conservation scenario does not consider some of the requirements, and their costs, that have been included in typical conservation programs.

Impact of Economic Scenarios on Land Use

The scenarios were applied to the economic – land use model to evaluate how changing economic conditions influence land use in the study area. This resulted in projected changes to the baseline land use conditions. Figure 39 depicts the predicted changes at USGS gauge 05092000, which drains 98% of the study area, as can be seen in Figure 15. The economic – land use model responded as expected to changing economic conditions. Price increases lead to increased production of all the major crops, mostly at the expense of grassland. The price increases influenced corn to the greatest extent, the area of which increased from 11% under baseline to 23% when crop prices increased 50%. This is sensible, because the price scenario drives profitability as a function of per-area yield, which is highest in corn (Table 18). Obviously, the 100% price increase resulted in an even greater relative area of corn cultivation, 28%, but that scenario was regarded as unlikely.

The conservation scenario had the expected effect of decreasing areas of the major crops and increasing grassland, with the larger incentive payment generating more profound results. Since the conservation payments are allocated per hectare, it represents an opportunity cost of agricultural production; it is an alternative land use which provides an alternative source of income. To evaluate how the conservation program affects land use, the program payment ("opportunity cost") can be added to the direct costs of the other land uses, which are the production of the various crop types. To justify production of crops, the revenue from that crop would then need to be greater than the direct costs of those crops plus the program payment that would have been received if the land had instead been enlisted in the conservation program.

The conservation scenario results in an identical opportunity cost increase for all crops. Under the conservation scenario, the areas of soybeans decreased the most, 23% at baseline to 19%. Soybeans have the lowest yield coefficient (Table 18), so an increase in costs (including opportunity costs) results in a loss of profitability (profitability = yield * price) over a greater range of prices.

Fertilizer taxes result in decreases in cultivation of crops which receive the most fertilizer inputs, most notably corn and wheat. These results are similar to those observed in a study by O' Shea and Wade (2009), in which a modeled 100% fertilizer tax resulted in a modeled 28-35% reduction in agricultural land use and a 15% reduction in nitrogen application to remaining agricultural land. The effect of the fertilizer tax on profitability of each crop is a function of that crop's historical fertilizer expense. The increase in tax did very little to increase grassland, since most of the crop area lost by corn and wheat was gained by soybeans. Corn has the highest fertilizer expense ($281.56/hectare, Table 21), followed by wheat ($175.24/hectare), then soybeans ($33.17/hectare). With the additional tax on fertilizer, these large differences in fertilizer expense caused areas which had been more profitable when planted in corn and wheat to become more profitable in lower cost soybeans.

It can be seen that the influence of the subsidy scenarios on land use was as expected, with each the area of the subsidized crop increasing. The changes were not large, as the amount of the subsidies were fairly modest. Overall, price increase scenarios generate the largest change in land use. However, there are many other scenarios that could be evaluated. Alternative price increases, fertilizer tax rates, conservation payments and subsidy payments would generate different land use changes.

Impact of Economic Scenarios on Water Quality

Since it can be seen in Figure 39 that different economic scenarios result in different relative areas of land use, it can be expected that the outputs of these scenarios, when provided as inputs to the land use – water quality model, will produce different projected nitrate concentrations. Having identified projected land use in each gauge drainage basin under each economic scenario, those land uses were presented to the land use – water quality model to predict their influence on nitrate concentrations.

Table 28 shows the projected change in nitrate concentration from baseline for each of the basins under each of the economic scenarios. In viewing the average change in each basin, it can be seen that the price increase scenario results in the most extreme increase in nitrates, 46% due to the 50% price increase scenario and 67% due to the 100% price increase scenario. The uniform increase of price of all major crops affects the area planted in those crops disproportionately. Crop price increases result in much larger increases in areas of corn than other crops. With the highest nitrate coefficient of the three major crops, this increase in corn results in a large increase in nitrate export.

The changes in nitrate under the 50% price increase scenario pictured in Figure 41 show that a uniform application of this scenario across the entire study area produces a range of changes in nitrate concentrations. Although most of the AOI experienced modest nitrate concentrations of 0 to 50%, some gauge drainage basins exhibited increase of over 100%.

The corn and wheat subsidy scenarios result in slight increases in nitrates, with the largest increase, surprisingly, due to the wheat subsidy in spite of its lower subsidy ($12.71/hectare compared to $17.57/hectare) and its smaller coefficient in the land use – water quality model (0.887 compared to 0.992). However, the wheat subsidy scenario produced a smaller projected area of soybeans, which do not contribute to nitrate concentrations in the land use – water quality model. This effect of soybeans on nitrates can be seen more clearly when viewing the soybean subsidy scenario, which resulted in an increase in area planted in soybeans, from 23% to 24%, and a decrease in nitrates in every basin.

The conservation program scenario resulted in larger nitrate decreases than the fertilizer taxation scenario. Even under a 20% fertilizer tax scenario, the nitrate decrease was smaller than that of the conservation scenario. However, when considering the merits of these two nitrate reduction strategies, it should be considered that the conservation program payment is an expense to the government, while the fertilizer tax is a source of revenue. Taking this into account, many would find fertilizer taxation a more favorable policy.

These projections vary considerably from basin to basin, due to physical distinctions between the basins. Those with more fertile land will tend to be more favorable to crop production and will have higher nitrates. Those with larger runoff discharges relative to baseflow discharge, stream length, basin size and/or wetland area will be expected to exhibit higher nitrate concentrations, as can be seen when comparing the coefficients of these non-crop variables in Table 30. These variations in nitrates due to physical conditions within the basins can be seen in Figure 40, which shows the nitrate concentrations under baseline conditions. It can be seen that properties within basins that are close together tend to be more similar than properties within basins which are further apart, as areas of high and low nitrate concentrations tend to be somewhat clustered, with lower concentrations in the western part of the study area and higher concentrations in the eastern and southern area.

Efficiencies of Nitrate Mitigation Strategies

It has been shown that the implementation of a conservation program or a fertilizer tax will result in lower nitrates. A comparison of these strategies is shown in Table 31. This table provides a good reference for considering these nitrate mitigation strategies. The conservation program provides about a 32% cheaper reduction strategy than the fertilizer tax. However, the cost of the conservation program is borne entirely by the government, while the tax is paid by the producer. It should be considered that deployment of either of these programs will have longer-term macroeconomic effects, resulting in decreases in crop production, and consequent decreases in supply and increases in price, leading to additional production and increased nitrates.

Table 31. Comparison of nitrate mitigation strategies.

Scenario	Who Pays?	Cost	Nitrate Reduction	Cost Per 1% Reduction
Conservation Program	Government	$ 47,365,492	10%	$ 4,736,549
5% Fertilizer Tax	Producer	$ 29,518,057	4%	$ 7,379,514
10% Fertilizer Tax	Producer	$ 57,585,862	8%	$ 7,198,232
15% Fertilizer Tax	Producer	$ 84,203,416	12%	$ 7,016,951
20% Fertilizer Tax	Producer	$109,310,751	15%	$ 7,287,383

CHAPTER VI

CONCLUSION

This study intended to assess the change in land use in the Red River Basin from 2006 to 2014, evaluate the influence of economic conditions on land use and identify the relationships between land use and nitrate concentrations. It was found that:

- Land use has changed considerably during the study period. Overall, corn area increased greatly, soybean area remained fairly constant and wheat area decreased.
- Economic conditions do influence land use. Uniform increases in the price of major crops result in disproportional increases in areas of corn. Taxes on fertilizers tend to decrease areas of wheat to a greater extent than areas of corn. A conservation program will cause a much steeper decline in soybean areas than areas of other crops.
- Crop type does affect the nitrate concentrations observed in a basin. Corn, canola, sunflowers and wheat had similar contributions to nitrates, while sugar beets had a much greater positive influence on nitrates. Alfalfa, dry beans and soybeans were not found to statistically contribute to nitrates.
- As economic conditions change, so will land use and nitrate concentrations. Conservation programs and fertilizer taxes will both produce decreases in nitrates,

- but conservation programs are the more economically efficient of the two strategies.

This study provides a straightforward statistical approach to assessing land use impacts on water quality without the use of cumbersome water models. It identifies readily available data, within the public domain, which can be used in subsequent economic, land use and water quality analyses as well as identifying open-source tools and techniques, such as the use of the R statistical program and packages, which greatly streamline data acquisition and processing. The approach is fairly straightforward and the statistical analysis is uncomplicated, yet it provides a cursory understanding of the complex processes of hydrological modeling. The project incorporates a larger sample size than many, incorporates relevant variables and produces interesting results, which often conflict with those of similar studies.

This project also provides many opportunities for future work. Foremost, deficiencies in the availability of data were noted. Improved tracking of fertilizer use, tile drainage projects and points source discharge, updates to the wetland inventory, release of spatial conservation program data and an inventory of existing drainage projects are warranted. Higher quality projected yield and non-crop land use data, such as the location and extent of forests and grasslands, would doubtlessly improve results. More sophisticated data analyses, including the explorations of nonlinear relationships, should be employed. Additional physical variables could be introduced in the land use – water quality model, such as slope and soil properties. A more comprehensive economic model, with risk-management and non-economic considerations should be developed. Finally, synthesis of independent variables could improve the land use – water quality, such as producing an interaction term which includes both land use and discharge variables.

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