Spring 2-9-2012

Groundwater Pollution Risk Assessment under Scenarios of Climate and Land Use Change in the Northern Great Plains

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GROUNDWATER POLLUTION RISK ASSESSMENT UNDER SCENARIOS OF
CLIMATE AND LAND USE CHANGE IN THE NORTHERN GREAT PLAINS

by

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A DISSERTATION

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Doctor of Philosophy

Major: Natural Resource Sciences

Under the Supervision of Professors James W. Merchant and Xun-Hong Chen

Lincoln, Nebraska

February, 2012

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University of Nebraska, 2012

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Modeling groundwater vulnerability to pollution is critical for implementing programs to protect groundwater quality. Traditionally, groundwater vulnerability was modeled based on current hydrogeology and land use conditions. However, groundwater vulnerability is strongly dependent on factors such as depth-to-water, recharge and land use conditions that may change in response to future changes in climate and/or socio-economic conditions. For example, global warming may lead to northward shifts in cropping patterns and changes in crop mixes (and use of farm chemicals). Meanwhile, growing demands for biofuels are resulting in expanding corn acreage, and may lead to pressures to remove land from the Conservation Reserve Program (CRP) or otherwise open lands that are currently not cropped to cultivation. Such changes may have significant implications for groundwater quality. In this research, a modeling framework, which employs four sub-models linked within a GIS environment, was presented to evaluate the groundwater pollution risks under future climate and land use changes in North Dakota. The major sub-models include a groundwater vulnerability model and a biofuels-related land use change model, which were illustrated in two separate studies. The results showed that areas with high vulnerability will expand northward and/or northwestward in Eastern North Dakota under different scenarios. GIS-based models that account for future

changes in climate and land use can help decision-makers identify potential future threats

to groundwater quality and take early steps to protect this critical resource.

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Chapter I

Introduction

1 Background

Groundwater is the principal source of drinking water for nearly 2 billion people, including about 50% of the U.S. population. Nationwide, approximately 40% of the public water supply, serving over 74 million people, is withdrawn from groundwater. Approximately 97% of those persons residing in rural areas of the U.S. use groundwater for drinking (National Research Council, 2000; Sampat, 2000). Dependence upon groundwater is especially great in areas such as Northern China, Eastern Europe, Northern India and the U.S. Great Plains. In many such regions, it is likely that population growth and global warming will, in the near future, lead to greater dependence on groundwater for public water supply (Hall et al., 2008).

As aquifer recharge rates are typically exceedingly slow, groundwater is considered a finite resource in most locations. Increasing evidence of groundwater contamination in recent years, coupled with concerns about human health and ecological effects of contaminants such as nitrates and pesticides, has heightened pressure on public agencies to better manage groundwater (National Research Council, 2000; Sampat, 2000). The application of fertilizer and pesticides on croplands, for example, has often been shown to result in deterioration of the quality of drinking water. Nitrate contamination of groundwater has been associated with fatal blue baby syndrome, increasing incidence of gastric cancer and elevated non-Hodgkin's lymphoma (Karkouti et al., 2005; Knobeloch

et al., 2000; Cantor, 1997). Apart from human health, changes in groundwater quality can also have negative impacts on groundwater-dependent species such as sightless and non-pigmented crawfish and cavefish (Butscher and Huggenberger, 2009). In some cases, research has demonstrated that pollutants such as nitrates initially leaching to groundwater can lead to pollution of surface water, such as streams, ponds, and lakes, if there are significant hydraulic connections between aquifers and water bodies.

Management of groundwater quality, however, presents particularly difficult problems. Detection of contamination and monitoring of water quality are usually difficult and costly. Clean-up of contamination, if possible at all, is often technically complex, extraordinarily expensive and only partially effective. Because restoration of groundwater quality is such a formidable and cost-prohibitive task, great emphasis is placed upon protection of the resource (i.e., prevention of contamination). Of course, groundwater contamination varies spatially; i.e., not all places are equally affected or equally vulnerable. Protection strategies, therefore, need to be targeted so that limited staff, funds and technology can be focused upon those areas most threatened in order to provide the greatest benefit for a given investment. Targeting must be based upon reliable forecasts of the risk of groundwater pollution under a variety of possible future climate/socio-economic/land use scenarios (Twarakavi and Kaluarachchi, 2006). In most instances, modeling and mapping of groundwater vulnerability to pollution is considered a critical first-step in implementing groundwater management programs (National Research Council, 1993).

During the past 35 years, a variety of methods for modeling and mapping groundwater vulnerability have been developed (see, for example, Focazio et al., 2005; Gogu and

Dassargues, 2000; National Research Council, 1993). These models typically involve the analysis of the inter-relationships between key hydrogeologic characteristics (e.g., depth-to-water, soils, aquifer hydrogeology, and groundwater recharge) and, sometimes, land use and land cover (LULC). Land uses that involve application of farm chemicals have shown to have especially important influences on groundwater quality (Scanlon et al., 2007; Eckhardt and Stackelberg, 1999). Although groundwater vulnerability models generally consider similar factors, the models employ different approaches for data integration and analysis. These can be grouped into three categories: index methods (Aller et al., 1985), statistical procedures (Nolan et al., 2002) and process-based methods (Focazio et al., 2005). A review of these models will be provided in Chapter 2.

Groundwater pollution vulnerability models are usually implemented in a "static" mode, i.e., the models assess vulnerability for a single point in time based on current hydrogeologic and LULC conditions (Butscher and Huggenberger, 2009). However, groundwater vulnerability is strongly dependent on factors such as depth-to-water table, recharge and LULC conditions, all of which are influenced by climate conditions and human activities. Climate change can potentially alter the vulnerability of shallow aquifers by affecting depth-to-water table and recharge (Toews and Allen, 2009; Scibek and Allen, 2006; Pointer, 2005; Ducci, 2005). And, human activities such as changes in LULC can also affect groundwater vulnerability. It has been forecast that agricultural land use, and associated application of farm chemicals, may change quite significantly as a result of global warming and/or changing socio-economic circumstances such as increasing demands for biofuels (National Research Council, 2008; Foley et al., 2004; Ojima et al., 1999). For example, elevated grain-based bioethanol demands may lead to

expansion of corn production and increased use of nitrogen-based fertilizers (Simpson et al., 2008). Such changes could significantly impact groundwater vulnerability.

2 Problem Statements

Groundwater quality management and protection measures must be targeted on the most vulnerable areas, but these areas may shift over time in response to global warming and/or land use change. Observed and predicted alterations of climate such as earlier onset of spring, longer growing seasons, spatial and temporal changes in precipitation patterns, and higher mean soil temperatures may lead to northward shifts in cropping patterns, changes in crop mixes (and use of farm chemicals), and/or increased (or decreased) use of irrigation (Ojima et al., 1999; U.S. EPA, 1998). Meanwhile, growing demands for biofuels are resulting in expanding corn acreage, and may lead to pressures to remove land from the Conservation Reserve Program (CRP) or otherwise open lands that are currently not cropped to cultivation (National Research Council, 2008). As a result, in some locations there could be concomitant, though currently unknown, changes in risks of groundwater pollution (Dams et al., 2007; Graham, 2007).

This dissertation seeks to develop a better understanding of relationships between climate change, future LULC change and groundwater pollution risks. The research focuses on the northern Great Plains of the U.S., one of the most important agricultural regions in the nation, but also a region expected to be impacted strongly by climate change and future demands for biofuels. Studies by the National Assessment Synthesis Team (2000) showed that temperatures in the region have risen more than 2 ºF (1 ºC) in the 20th century, with increases up to 5.5ºF (3ºC) in parts of North Dakota and South Dakota (Figure 1.1). This warming trend is expected to continue throughout the region in the 21st

century. The Team also predicted that precipitation will generally increase across this region, potentially enhancing leaching of agricultural chemicals to aquifers. Changing climate may also affect agricultural practices and land use in this region.
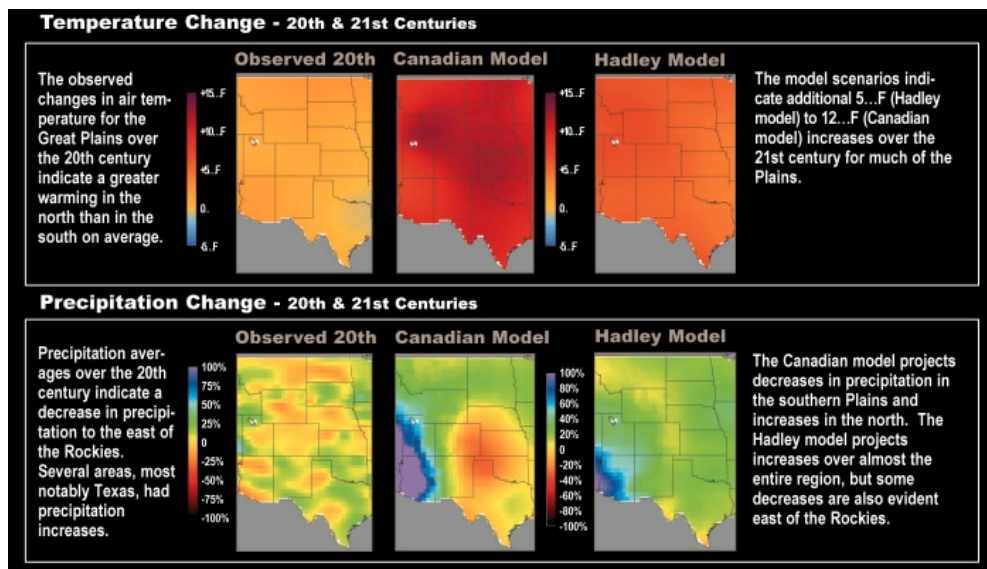
Figure 1.1 Observed and predicted temperature and precipitation changes in the Great Plains (National Assessment Synthesis Team, 2000)

3 Objectives

The overarching goal of this research is to develop and evaluate a regional pollution risk assessment procedure that will provide natural resource managers with information required to protect potentially-threatened groundwater resources. The principal objective is to determine if, how and where groundwater quality in the northern Great Plains may be impacted by projected future climate change and projected land use change driven by increasing demands for biofuels. The principal hypothesis of this research is that global warming and accelerating demands for biofuels will influence land managers to plant more area to large grains (e.g., corn), and such changes in land use will increase risks of groundwater pollution. In this study, groundwater pollution risk will be assessed based on

the potential of nitrate pollution, because nitrate is the most widespread groundwater pollutant in croplands of the Great Plains.

A secondary objective of the research is to develop a modeling framework that employs four sub-models linked within a GIS environment (Figure 1.2) and evaluate its effectiveness. The modeling procedure will be used to forecast conditions for two future time periods (2020 and 2050) under three scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES): a lower greenhouse gas (GHG) emission scenario (B1), a median emission scenario (A1B), and a higher emission scenario (A2).
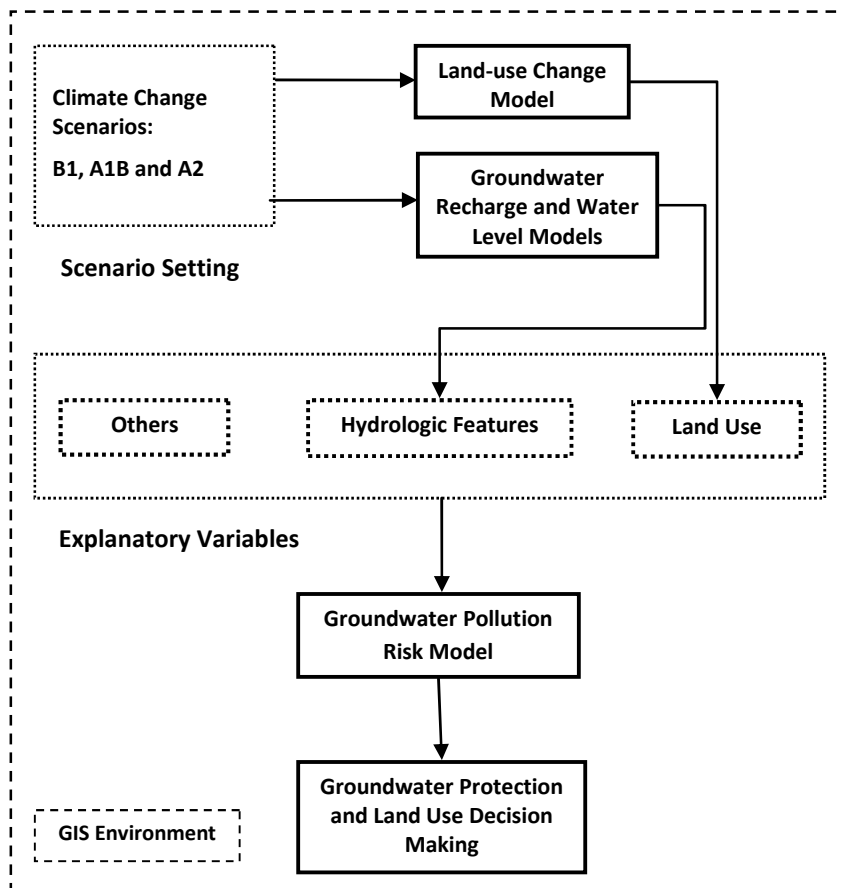
Figure 1.2 Conceptual illustrations of model linkages

4 Dissertation Structure

This dissertation is organized into five chapters:

- Chapter 1 presents the general background, research questions, objectives, dissertation structure and significance of the research. This chapter introduces the core hypothesis that patterns of groundwater pollution risk in the Northern Great Plains will change in response to future climate change and land use alterations, specifically that pollution risk will increase as biofuel crops are planted over larger areas. This chapter also provides readers a general overview of the modeling framework and the importance of this research in groundwater quality management.

- Chapter 2 focuses on development of the basic methodology for modeling groundwater vulnerability, using the Elkhorn River basin in Nebraska as the study area. A comprehensive literature review of groundwater vulnerability modeling techniques is provided. Subsequently, methods for modeling and mapping groundwater vulnerability using readily-available national or state-level geospatial datasets are assessed.

- Chapter 3 addresses future scenarios of climate and biofuels-related land use change in North Dakota, an area of the northern Great Plains where both climate alterations and biofuel cropland expansion are expected to be most dramatic. A land use change model adapted from the Land Transformation Model (LTM) (Pijanowski et al., 2002) is used to provide future land use scenarios required for modeling groundwater pollution vulnerability.

- Chapter 4 integrates the models illustrated in Chapters 2 and 3 with models of groundwater recharge and groundwater level driven by climate change. Future

groundwater recharge is estimated using a percolation index method. Changes in future groundwater level were modeled using a water-table fluctuation (WTF) model. Future land use scenarios developed in Chapter 3 are fed into the groundwater vulnerability model exhibited in Chapter 2. Finally, groundwater vulnerability patterns under future scenarios of climate change and biofuel-crop land use change are mapped, and areas needing additional groundwater monitoring and protection are projected based on the modeling results.

▪ Chapter 5 provides a summary of research methods, an evaluation of study results and presents recommendations for future studies.

Note that Chapters 2, 3 and 4, though they address related topics, are written to stand alone. That is, each chapter is written in a manner similar to a journal article. As a result, readers of this dissertation will find some ideas repeated in these independent chapters.

5 Research Significance

It is expected that this study of groundwater pollution risk in the context of future climate and LULC changes will (1) lead to improved modeling of groundwater pollution risk under possible future scenarios, (2) aid in selecting and prioritizing sites for future groundwater monitoring and groundwater protection, (3) identify strategies to improve the design and targeting of land/water management and incentive policies, and (4) suggest ways that agricultural policies/practices may be employed to limit negative impacts on groundwater. The project will focus upon development and evaluation of regional risk assessment procedures that can provide natural resource managers in the northern Great Plains with information required to support decisions designed to protect

threatened groundwater resources. However, the study results will be applicable to many other regions of the world where groundwater quality is in jeopardy.

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Chapter II

Assessing Groundwater Vulnerability to Nitrate

Contamination in

the Elkhorn River Basin, Nebraska

1 Introduction

Groundwater is a major source of drinking water for about 50% of the U.S. population. Approximately 97% of those persons residing in agricultural areas of the U.S. use groundwater for drinking (National Research Council, 2000; Sampat, 2000). Protection of groundwater quality is an important public-health concern in areas where use of fertilizers and other farm chemicals in cultivation of crops may lead to pollution of aquifers from which drinking water is drawn. Nitrates are a particular concern because they have been associated with fatal blue baby syndrome, increasing incidence of gastric cancer and elevated non-Hodgkin's lymphoma (Karkouti et al., 2005; Knobeloch et al., 2000; Cantor, 1997).

Management of groundwater quality is difficult. Remediation of contamination, if possible at all, is often technically complex, extraordinarily expensive and only partially effective. Because restoration of groundwater quality is such a formidable and cost-prohibitive task, great emphasis is placed upon protection of the resource (i.e., prevention of contamination). Of course, groundwater contamination varies spatially; i.e., not all places are equally affected or equally vulnerable. Protection strategies, therefore, need to be targeted so that limited staff, funds and technology can be focused upon those areas

most threatened to provide the greatest benefit for a given investment (Ceplecha et al., 2004).

In most instances, modeling and mapping of aquifer vulnerability to pollution is considered a critical first-step in implementing groundwater management programs (National Research Council, 1993). During the past 35 years, a variety of methods for modeling groundwater vulnerability have been developed (Focazio et al., 2005; Gogu and Dassargues, 2000; National Research Council, 1993). These models, often implemented in geographic information systems (GIS), typically involve analysis of the inter-relationships between key hydrogeologic characteristics (e.g., depth-to-water, soils, and recharge) and, sometimes, land use and land cover (LULC). The hydrogeologic factors largely govern important groundwater contamination processes such as water infiltration and leaching, biological degradation in the soil, and pollutant dispersion and dilution in the vadose zone. Land use and land cover are especially important for assessing groundwater pollution risk in agricultural areas where application of farm chemicals can influence groundwater quality (Scanlon et al., 2007; Eckhardt and Stackelberg, 1995). Geographic information systems (GIS) are, today, widely used in environmental modeling (Steyaert and Goodchild, 1994). A common difficulty for GIS-based groundwater vulnerability modeling is unavailability of quality geospatial data for key hydrogeologic parameters. Firstly, many of such parameters, such as vadose zone, are only available or partially available as paper maps or literal descriptions in historical hydrogeologic reports. Converting the information to GIS compatible formats may introduce significant uncertainties to the modeling. Secondly, a parameter layer for a specific region (especially large regions) may originate from different sources which vary

in scales and accuracies. Thirdly, in many cases the data sources may be outdated or cannot correspond with our study periods. For example, a groundwater level map compiled in the 1980s may not be relevant to groundwater vulnerability assessment for current periods. Many groundwater vulnerability studies tend to focus on the modeling approach itself while overlooking the reliability of the input hydrogeologic parameters. Hence, an approach based on data extracted from widely-acceptable national and state geospatial datasets is significant to improve the modeling of groundwater vulnerability.

The principal objective of this study was to develop and evaluate a basic methodology of modeling groundwater pollution risk that can be implemented over large regions in the Northern Great Plains using national or state-wide datasets (e.g. USGS National Elevation Dataset, USGS Active Groundwater Level Network, and the well log databases*). The research focused on assessment of groundwater pollution risk at the water table (the ground is fully saturated below the water table) in agricultural areas, with an emphasis on nitrate contamination. The model was used to develop a groundwater vulnerability map for the Elkhorn River Basin, which was validated using observed nitrate pollution data.

2 Background

Groundwater vulnerability models generally fall into one of three categories (Focazio et al., 2005): index models (Aller, et al., 1985), statistical models (Nolan et al., 2002) and process-based models (Tiktak, et al., 2006). Index models are usually formulated as equations using a weighted linear combination of factors to compute a pollution potential index. The DRASTIC model has been used with exceptional frequency (Lynch et al.,

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* e.g. well log databases are available in most Northern Great Plain states, including Nebraska Test Hole Database, South Dakota Lithologic Log Database, and North Dakota Groundwater Data Portal. For details see Discussion.

DRASTIC, is derived from the seven variables used in the model: **D**epth-to-water table; **R**echarge (net); **A**quifer media; **S**oil media (texture); **T**opography (slope); **I**mpact of the vadose zone; and, **C**onductivity (hydraulic) of the aquifer (Eq. 2.1). Ratings and weightings are commonly based on expert knowledge (Merchant, 1994) or actual pollutant concentration (Panagopoulos et al., 2006; Rupert, 1999).

The DRASTIC model has been widely used in research and has often been modified. For example, Guo et al. (2007) developed DRARCH, a variation on the classic DRASTIC model in which contaminant absorption characteristics of the vadose zone were added as a new factor, and the soil and topography factors were dropped. Rupert (1999) modeled groundwater vulnerability using three of the seven DRASTIC factors – depth-to-water, net recharge, and soil media – factors that were found to be statistically correlated with observed groundwater quality data. And, a number of studies have demonstrated that the DRASTIC model can be enhanced by incorporating information on land use, land cover and land management (Dappen and Merchant, 2004; Gogu and Dassargues, 2000; Rupert, 1999).

DRASTIC Index

$$D_R D_w + R_R R_w + A_R A_w + S_R S_w + T_R T_w + I_R I_w + C_R C_w = \text{Pollution Potential}$$

Where:
  R: Rating
  W: Weight

D	Depth to Water
R	(Net) Recharge
A	Aquifer Media
S	Soil Media
T	Topography (Slope)
I	Impact of the Vadose Zone
C	Conductivity of the Aquifer

Eq. 2.1

Since the development of the DRASTIC model, many other index models have been developed. These include the Protective cover and Infiltration conditions (PI) model (Goldscheider, 2005), the Groundwater occurrence, Overlaying lithology and Depth to water (GOD) model (Foster, 1987), the Aquifer Vulnerability Index (AVI) model (Van Stempvoort and Evert, 1993) and SINTACS (the acronym SINTACS comes from the Italian names of the factors that are used, including Soggicenza (depth to groundwater), Infiltrazione (effective infiltration), Non saturo (unsaturated zone attenuation capacity), Tipologia della copertura (soil/overburden attenuation capacity), Acquifero (saturated zone characteristics), Conducibilita (hydraulic conductivity), and Superficie topografica (topographic surface slope) (Civita, 1993). Index methods are often attractive because they are conceptually simple, usually require few datasets, and are easily implemented in GIS. Their performance, however, is often reported as mixed (Neukum et al., 2008; Tesoriero and Voss, 1997). Major drawbacks of index methods include (1) the subjectivity inherent in determination of the rating scales and weighting coefficients and (2) the interpretation of the results which are expressed as dimensionless pollution potential index values (Antonakos and Lambrakis, 2007; Merchant, 1994). Nevertheless, such methods, if used judiciously, can provide quick and reasonable estimates of regional pollution risks (Zektser, et al., 2004).

Statistical models evaluate groundwater vulnerability based on statistical relationships between observed groundwater contamination and related predictor variables. Statistical models generate coefficients that best fit observed water quality data, and thus reduce the subjectivity involved in assigning factor ratings and weights needed by index models (Focazio et al., 2005). Such models may employ geostatistical delineation of

contaminated areas (Almasri and Kaluarachchi, 2004), logistic regression analysis of relationships between predictor variables and observed contamination occurrence (Gurdak and Qi, 2006; Nolan et al., 2002), and Weights of Evidence (WofE) modeling, a Bayesian-probabilistic approach (Masetti et al., 2007; Arthur et al., 2007; Raines et al., 2000). Logistic regression has been used with especially great frequency (Helsel and Hirsch, 1992). Tesoriero and Voss (1997) applied logistic regression to estimate the probability of nitrate concentrations greater than 3 mg/L in the Puget Sound Basin. Gudak and Qi (2006) modeled the risk of nitrate contamination in the High Plain Aquifer. Nolan et al. (2002) used logistic regression to predict the probability of nitrate contamination of recently recharged groundwater in the conterminous United States. These studies generally show good correlation between groundwater vulnerability (probability of contamination) and observed contamination; however, it is important to note that all were carried out in areas that had extensive datasets for groundwater quality as well as hydrogeologic factors required to generate robust statistical relationships for modeling. When required data are not available at sufficient spatial, temporal and/or categorical resolution, the resulting statistical relationships between predictor variables and groundwater contamination may be unreliable. Thus, statistical models are best suited for use in regions where there are dense networks of observation wells that can provide groundwater quality data.

Process-based modeling methods attempt to simulate physical processes of groundwater hydrogeology and associated pollutant fate, transport and dispersion. Such models use established understandings of important physical, chemical, geological and biological processes, which are described by deterministic equations. For example, Tiktak et al.

(2006) used EuroPEARL, a one-dimensional, mechanistic pesticide leaching model, in a GIS to map pesticide leaching in Europe. Sinkevich et al. (2005) implemented the Generalized Preferential Flow Transport Model (GPFM) in a GIS to locate areas with high risk of contamination by agrochemicals. Such models account for the physical processes of water movement and the associated fate and transport of contaminants, and hence can produce accurate estimates of contaminant concentration. However, compared with index and statistical models, process-based models are inherently difficult to implement and are often cost-prohibitive because they typically require a large amount of input variables to the model and computationally intensive algorithms. Although simplifying assumptions (such as steady-state or one-dimensional flow conditions) are often used to reduce mathematical complexity in these models, such assumptions may introduce uncertainties in modeling results.

Index models, statistical models and process-based models each have merits and drawbacks. Trade-offs must be considered among the costs of implementation, scientific defensibility, and the level of uncertainty required to meet the objectives of decision makers (Focazio et al., 2005). In this research, a new modified DRASTIC index model is used to provide an inexpensive, fast and robust assessment of groundwater pollution risk in regions where extensive groundwater monitoring data may not be available.

3 Methods

3.1 Study Area

This research was conducted in the Elkhorn River Basin of northeast Nebraska (Figure 2.1). The Elkhorn River Basin is representative of much of the northern Great Plains

region where the proportion of land devoted to agriculture is among the highest in the nation. Extensive use of farm chemicals in the region has often been shown to be associated with groundwater pollution. In Nebraska, for example, the nitrate concentration in 33.4% of groundwater samples collected from 1974-2008 exceeded 10 mg/L, the federal drinking water safety standard for nitrate (Nebraska Department of Environmental Quality, 2009). Based on a preliminary analysis of the groundwater quality data in the Elkhorn River Basin (University of Nebraska-Lincoln, 2000), the mean nitrate concentration in more than 40% of around 500 sampled wells in the last decade was found to exceed 10 mg/L, indicating a potential threat to the health of local residents.

The terrain of the basin generally descends toward the east with elevations ranging from about 800 to 300 meters above mean sea level. Mean temperatures are between 21-24°C in July and August, about -7 °C in January, and between -4 and -1 °C in December and February (Huntzinger and Ellis, 1993). Mean annual precipitation varies from around 56 centimeters in the western part of the study area to about 76 centimeters in the eastern part, and the precipitation reaches its peak in May and June (Huntzinger and Ellis, 1993). The dominant land uses are cropland and pasture/rangeland (Frenzel et al., 1998). The western third of the basin lies in the Nebraska Sand Hills region, where widespread rangelands and sandy infertile soils dominate. The central part of the basin is a region of Loess Hills where land use is a mixture of rangeland and cropland. The eastern basin, a glaciated region, is predominantly used as cropland (Frenzel et al., 1998).
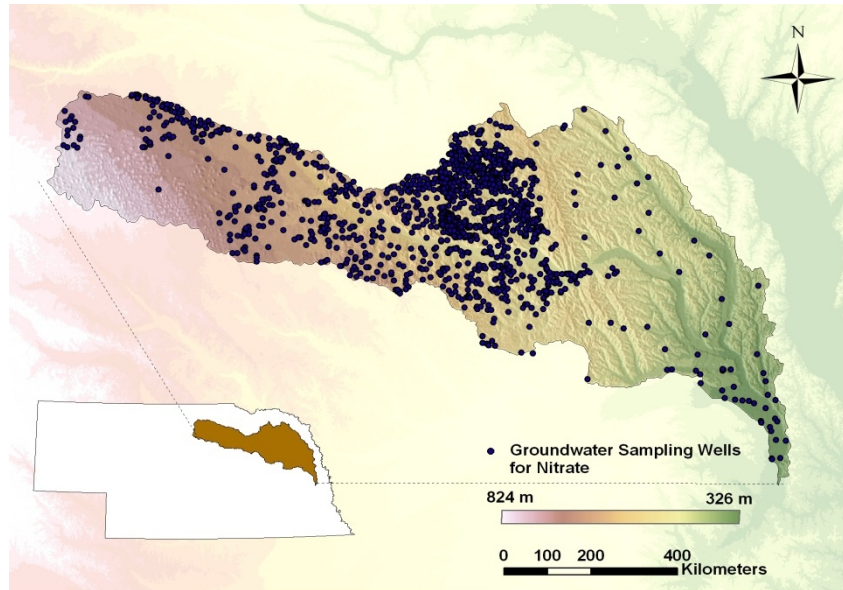
Figure 2.1 Terrain of the Elkhorn River Basin

The hydrogeology of the basin varies from the Sand Hills to the eastern glaciated area in the Lower Elkhorn River Basin (Nebraska Department of Natural Resources (NDNR), 2009). In the Upper Elkhorn, alluvial sand and gravel deposits of Quaternary age are widespread, and most precipitation infiltrates into the sandy soil with little runoff (Frenzel et al., 1998). Low-permeability glacial-till deposits occur in the Lower Elkhorn (Huntzinger and Ellis, 1993). The principal aquifers in the Elkhorn River Basin vary in saturated thickness from 0 to approximately 244 meters, and the depth-to-water table ranges from 0 to more than 61 meters (NDNR, 2009).

The Elkhorn River Basin is similar to many Great Plains' watersheds in that the extent and quality of available geospatial data, as noted in Section 3.3 below, varies. However, the basin also has an extensive groundwater quality monitoring network of over 700 wells. Though unevenly distributed (Figure 2.1), these wells provide data on nitrates that is important for validation of the model proposed in this research. For both these reasons, the Elkhorn River Basin was selected as the focus for this study.

3.2 Model Design and Implementation

A revised DRASTIC model, DRSTIL (Eq. 2.2), was developed to model groundwater vulnerability. The DRSTIL model varies from DRASTIC in two significant ways. First, aquifer characteristics and conductivity were dropped because this research focuses on groundwater vulnerability at the water table (below which the ground is fully saturated) and these factors are largely related to the transport, diffusion and degradation of contaminants below the water table. Second, adapting work by Dappen and Merchant (2004), a land use factor was added to reflect the impacts of agricultural practices (such as fertilizer application) on groundwater quality.

$$\begin{aligned} &\textbf{Groundwater Vulnerability Score} = \\ &\mathbf{D_R D_w + R_R R_w + S_R S_w + T_R T_w + I_R I_w + L_R L_w} \end{aligned}$$

D	Depth to Water
R	(Net) Recharge
S	Soil Media
T	Topography (Slope)
I	Impact of the Vadose Zone
L	Land Use

Where
  R: Rating
  W: Weight

Eq. 2.2

As in DRASTIC, each of the DRSTIL factors (**D**epth-to-water table; **R**echarge (net); **S**oil media; **T**opography; **I**mpact of the vadose zone; **L**and use) was assigned ratings and a numerical weighting to reflect its relative importance in estimating groundwater pollution potentials. Ratings are intended to reflect the relative significance of data values (mapped "classes") within each factor (Merchant, 1994). For example, locations where the water table is deep below the surface are assumed to be less vulnerable to pollution than locations where the water table is shallow because, all other things being equal, the greater depth-to-water should indicate lower likelihood of contaminants reaching an aquifer. Therefore, areas having greater depth-to-water are assigned a lower numerical

rating than locations with a shallower water table. All factors were assigned ratings on this basis (see Aller et al., 1985).

A departure from the standard approach to assignment of ratings was adopted for this research. The ratings for each factor layer (in the ESRI Grid format) were assigned by normalizing the grid values of the layer to a 0-1 scale. For factors with larger values indicating higher pollution potentials (e.g. recharge and land use), the ratings were calculated using the following approach: $(V - min\ V)/(max\ V - min\ V)$, where V, min V and max V represent the values, maximum value and minimum value of the factor in the original dataset. For factors with smaller values corresponding to higher pollution potentials (e.g. DTW, soil, topography and impact-of-vadose-zone), the ratings were normalized as: $(max\ V - V)/(max\ V - min\ V)$. This approach allows variables to have different means and standard deviations but equal ranges.

Weights were assigned to each factor following guidelines given in the DRASTIC documentation (Aller et al., 1985). Aller et al. (1985) proposed two approaches for weighting the factors in DRASTIC: a pesticide and a general version. Pesticide weights were designed to reflect the processes that most affect pesticide transport into the subsurface with particular focus on soil (Frederick, 1991; Aller et al., 1985). General DRASTIC weights were recommended for use in studying other potential pollutants such as application of fertilizers (Frederick, 1991). Since the focus of this research is on the vulnerability of groundwater to pollution from nitrates, the weightings for each factor were derived from those developed for the general DRASTIC (Table 2.1). Although land use was not included in the original DRASTIC model, it was assigned the weight of 5 due to its direct relationship with nitrate pollutant loadings.

3.3 Development of the Factor Layers

Six map layers were developed in ArcGIS (Table 2.1). All layers were developed in raster mode at a resolution of 300 meters. It should be noted that there is a trade-off between the accuracies of different data sources in the selection of the resolution. In Table 2.1, NED data feature the highest resolution at 30 meters, while PRISM data have a resolution of around 4 kilometers. All the map layers were re-projected to a North American Datum (NAD) 1983 State Plane Coordinate System, and resampled to 300-meter grids.

Table 2.1 Factors used in the DRSTIL method, and corresponding data sources and weights

Map Layer	Primary Data Sources	Assigned Weights
Depth-to-Water	USGS Active Groundwater Level Network	5
Recharge	Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group (http://www.prism.oregonstate.edu/)	4
Soil Media	USDA Soil Survey Geographic Data (SSURGO)	2
Topography	USGS National Elevation Dataset (NED)	1
Impact of the Vadose Zone	Nebraska Test Hole Database (well log datasets)	5
Land Use	2005 USDA Cropland Data Layer (CDL)	5

Most of the datasets required for modeling can obtained or derived in the national geospatial database such as USDA SSURGO and USGS NED. State-wide datasets such as well-log datasets, although varying in their sources for different states, are available in most Northern Great Plains states. For example, the well log datasets are available in the Nebraska Test Hole Database (http://snr.unl.edu/data/geographyis/NebraskaTestHole/

NebraskaTestHoleIntro.asp), South Dakota Lithologic Log Database (http://www.sdgs. usd.edu/other/db.html), and North Dakota Groundwater Data Portal (http://www.swc. state.nd.us/4dlink2/4dcgi/wellsearchform/Map%20and%20Data%20Resources).

3.3.1 Depth-to-Water (DTW)

Depth-to-water (DTW), defined as the distance from the ground surface to the groundwater table, impacts the time required for contaminants to reach the water table. As DTW increases, the probability of groundwater pollution by nitrates generally decreases. The procedure (Figure 2.2) performed to develop the DTW surface was based on an integration of interpolated water table depth and water table elevation, a method proposed by Snyder (2008). Snyder (2008) held that estimation of the water table can be
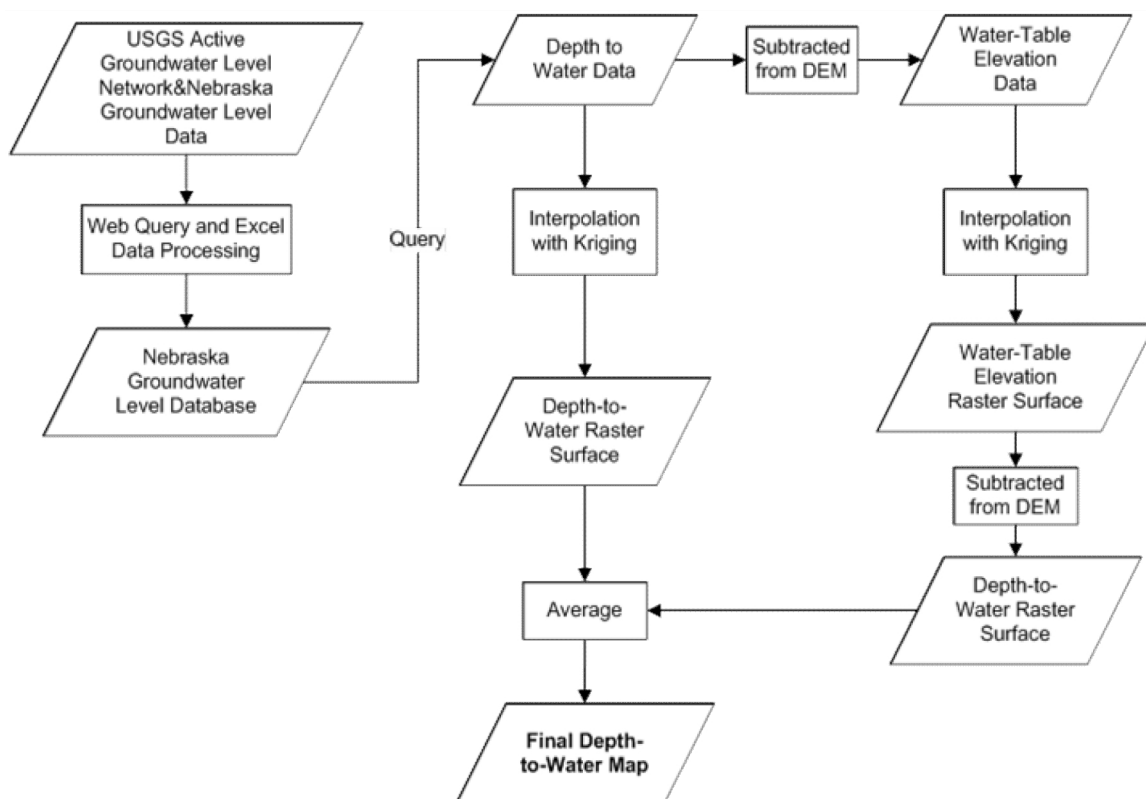
Figure 2.2 Flowchart for mapping the depth-to-water (DTW)

improved by integrating the interpolated water table with water table elevation. The water table interpolated from DTW data tends to be shallower under hills and deeper under valleys than the real water table. By contrast, the water table interpolated from the water table elevation data tends to be deeper under hills but shallower under valleys. Therefore, it was hypothesized that averaging results from the two interpolation estimates would improve representation of the actual water table.

Data for 732 observation wells were extracted from the USGS Active Groundwater Level Network and wells monitored by the Nebraska Department of Natural Resources. Only wells having nitrate concentration records for years between 2000 and 2008, and a well depth of at least 48.8 meters (160 feet) (the average well depth for the Elkhorn River Basin) were selected (Figure 2.3). Locations of surface water features, such as major streams, lakes, wetlands, and springs were obtained from the USGS National Hydrography Dataset (NHD) and used to indicate where the DTW approximates 0 (Snyder, 2008). ArcGIS was used to randomly plot 1,000 points (where the DTWs are 0) on these surface water features. Subsequently, those points and the points of observation wells were merged, and two new attributes, DEM elevation and water table elevation were added. DEM elevation for those points was extracted from the National Elevation Dataset (NED) using Hawth's Tool, an add-on created for ArcGIS that provides a set of spatial analysis tools not included in the ArcGIS software (http://www.spatialecology.com/htools/). And the water table was calculated by subtracting water depth from the DEM elevation. Using kriging, a water-depth surface and a surface of groundwater-table elevation were derived respectively. The final DTW map was produced by averaging those two surfaces (Figure 2.4).
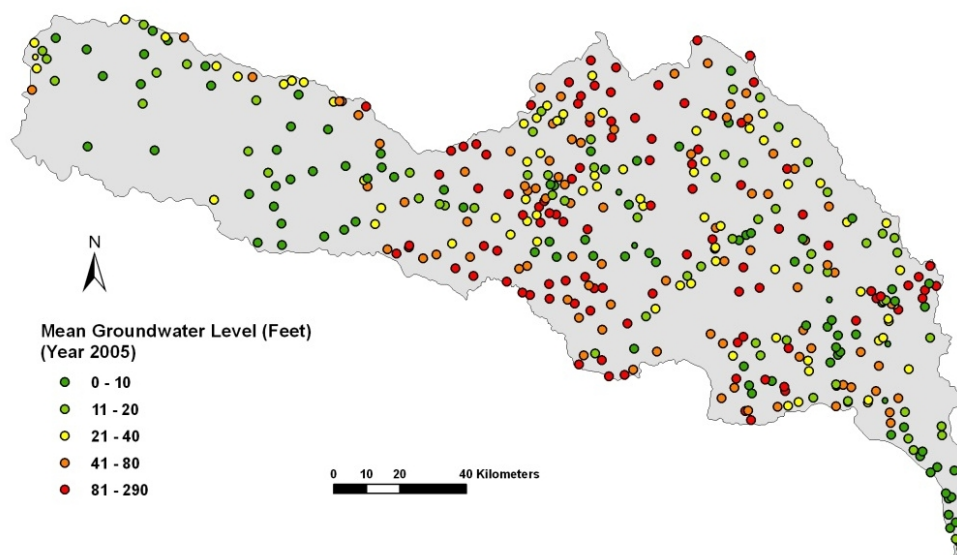
Figure 2.3 Groundwater level monitoring wells in the study area
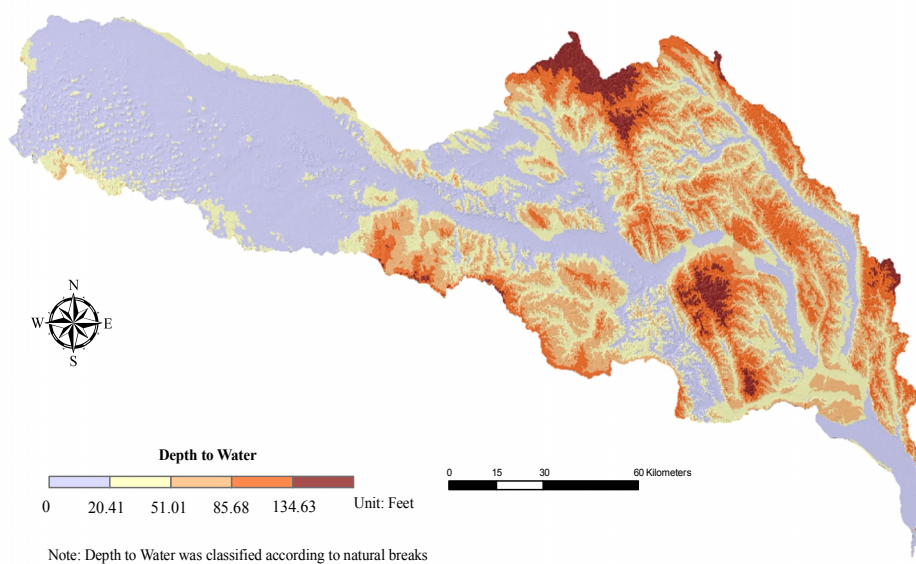
Figure 2.4 DTW map for the study area

In general, the configuration of the water table in unconfined aquifers is known to approximate the configuration of the land surface (Desbarats et al., 2002). The interpolated DTW map for the Elkhorn River Basin was, on this basis, judged to be a reasonable representation of the real groundwater table.

3.3.2 Recharge

Aquifers are recharged by precipitation, snow melt, and surface runoff. A recharge factor is important because water that migrates from the surface to the water table often transports contaminants (Aller et al., 1985). If one considers dilution to be a constant, in general greater recharge corresponds with greater pollution potential.

There have been many methods developed for mapping groundwater recharge (Scanlon et al., 2002). These include soil-water balance models (Toews and Allen, 2009; Scibek and Allen, 2006, 2005; Arnell, 1998), empirical models (Chen et al., 2002), and distributed models (Croley and Luukkonen, 2003; Eckhardt and Ulbrich, 2003). However, these methods are generally technically complex and unsuitable for large regional analyses since the data on key physical parameters are usually not available for large regions. In this research, a simplified approach based on precipitation, irrigation amounts and recharge-to-rainfall ratios were used. The estimated recharge was computed using the formula in Eq. 2.3.

$$R = r \times (P + I) \qquad \text{Eq. 2.3}$$

where R denotes recharge, r is recharge-to-rainfall ratio, and P and I stand for, respectively, precipitation and irrigation.

Data layer on mean annual mean for the period 2000-2008 were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group (http://www.prism.oregonstate.edu/). For irrigated lands, the amount of irrigation water typically applied was estimated based on the crop irrigation requirement (NDNR, 2009). Data layer on Recharge-to-rainfall ratios were developed based on published

Topographic Regions Map of Nebraska (Conservation and Survey Division (CSD), 1973)

and corresponding recharge rates (Table 2.2). To facilitate the calculation of recharge, we

assumed the same recharge ratios for precipitation and irrigation.

Table 2.2 Recharge ratios corresponding to topographic regions in Nebraska (Nebraska Natural Resources Commission, 1986)

Topographic Region	Natural Recharge Ratio (%)
Valleys	20-30
Plains	3-5
Dissected Plains	10-15
Sand Hills	25-30
Rolling Hills	1-5
Bluffs and Escarpments	1-2

The calculated recharge is shown in Figure 2.5. Higher recharge in the western Elkhorn

River Basin and in river valleys is associated with areas having sandy soils or

unconsolidated and highly permeable materials, while lower recharge occurs in areas

with thick low-permeable glacial deposits.
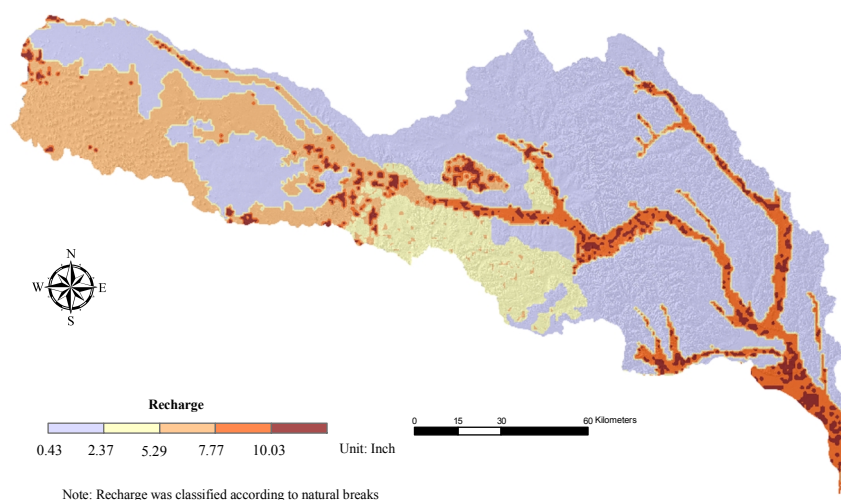
Figure 2.5 Estimated recharge for the study area

3.3.3 Soil

Processes of biodegradation, sorption and volatilization can all be affected by soils characteristics (Aller et al., 1985). Soils serve as the dominant sink for retention of nitrate (Barrett and Burke, 2002), and impact the leaching of nitrate to deeper horizons. In this research, soils in the Elkhorn River Basin were characterized according to their nitrate attenuation capacity. Attenuation was estimated by considering permeability, water holding capacity, and biotic/abiotic degradation (Figure 2.6). Permeability and water holding capacity affect the amount of water passing through the soil profile (Canter, 1996), while microbial and abiotic mechanisms can stabilize and assimilate nitrate in the soil.
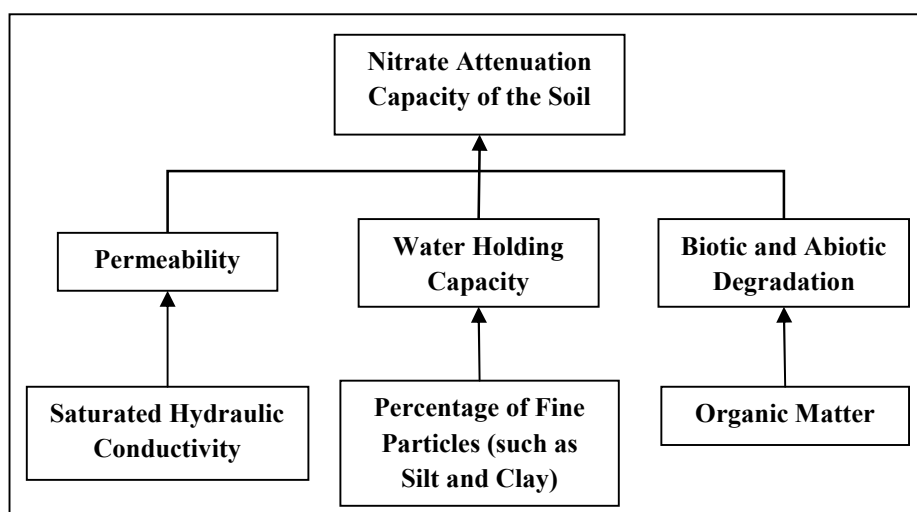
Figure 2.6 Characterization of nitrate attenuation capacity

Soils characteristics were extracted from the USDA Soil Survey Geographic (SSURGO) database. Saturated hydraulic conductivity, silt and clay percentage and organic matter, were used to quantify permeability, water holding capacity, and biotic/abiotic degradation, respectively. In general, soils that are comprised of a large percentage of fine particles (i.e. silt and clay) have higher water holding capacity (Canter, 1996).

Carbon in the organic matter of the soil may act as an important substrate for microbial and abiotic mechanisms that stabilize nitrates (Barrett and Burke, 2002)

Soil characteristics often exhibit collinearity (Ige et al., 2007). Therefore, factor analysis was used to generate an index based on saturated hydraulic conductivity, silt percentage, clay percentage, and organic matter. The analysis was implemented in SPSS software, and the results are shown in Table 2.3 and Table 2.4. The first component was observed to account for most of the total variance (81.74%), and thereby this component was used to represent the composite soil characteristics in subsequent research. The component score coefficient matrix (Table 2.4) was employed to generate a soil index (Eq. 2.4), with Organic, Clay, Silt and Ksat respectively referring to percentage of silt, percentage of clay, organic matter and saturated conductivity. The index is positively correlated with organic matter, silt and clay, and negatively correlated with the saturated hydraulic conductivity. Finally, based on Eq. 2.4, a map layer of the soil index was developed (Figure 2.7).

$$Soil\_Index = 0.224 Organic + 0.297 Clay + 0.290 Silt - 0.289 Ksat \qquad \textbf{Eq. 2.4}$$

Table 2.3 Eigenvalues of the factor analysis*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.269	81.737	81.737	3.269	81.737	81.737
2	0.573	14.326	96.064			
3	0.084	2.104	98.167			
4	0.073	1.833	100.00			

*Extraction Method: Principle Component Analysis

Table 2.4 Component score coefficient matrix

**Component Score
Coefficient Matrix**

	Component
	1
Ksat	-.289
Organic	.224
Clay	.297
Silt	.290

Generally, the Lower Elkhorn River Basin, a region covered by glacial deposits, is associated with higher nitrate attenuation potentials, while the Upper Elkhorn River Basin, covered with sandy soils, is associated with lower attenuation potentials.

Soil Index for Nitrate Attenuation Capacity

| -2.57 | -0.91 | -0.17 | 0.45 | 0.9 |

0   15   30   60 Kilometers

Note: The soil index was classified according to natural breaks. The smaller index indicates lower nitrate attenuation capacity, and vice versa.
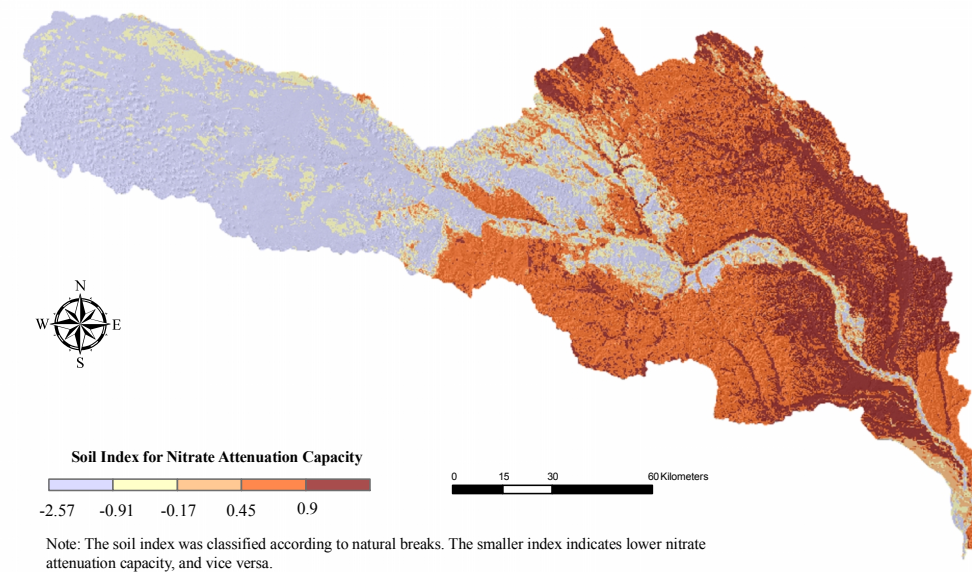
Figure 2.7 Soil index map for the study area

3.3.4 Topography

Slope affects the likelihood that a contaminant deposited on the land surface will infiltrate the soil. As slopes become increasingly steep, pollutants are more likely to runoff than to seep into the subsurface (Aller et al., 1985). The topography factor was derived from the NED by using the slope program in ArcGIS (Figure 2.8).
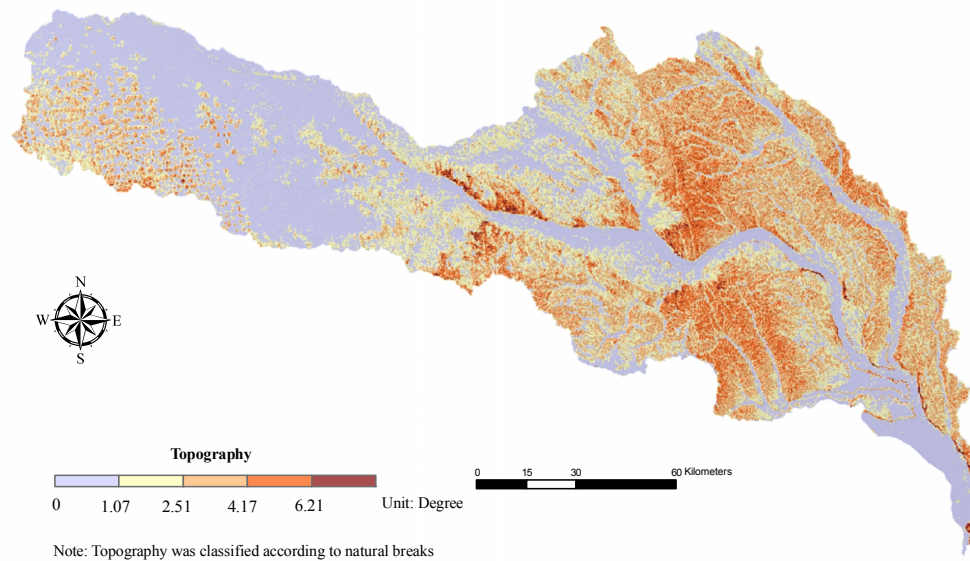
Figure 2.8 Slope map for the study area

3.3.5 Impact of the Vadose Zone Media (VZM)

Characteristics of the vadose zone media, the unsaturated area below the soil profile and above the unconfined water table, are important for assessing nitrate attenuation processes such as biodegradation, chemical reaction, volatilization, and dispersion. The VZM influences the routing and rate of movement of water and, thus, the time for attenuation processes to occur (Aller et al., 1985). Silt and clay in the VZM can increase the time and opportunities for attenuation. Therefore, the thickness of silt and clay in the VZM was used as an indicator of nitrate attenuation. The VZM index was derived from lithology records in the Nebraska Test Hole Database. Lithologic descriptions for each record were reclassified into one of seven groups: soil, silt/clay, sand/gravel, sand/silt/clay, sandstone/limestone, bedrock and other hard materials (such as shale and lignite). The percentage of silt/clay was computed by dividing the accumulated thickness of silt/clay above the water table by the DTW in each test hole. The DTW in each test-hole location was queried from the DTW map layer as shown in Figure 2.4. The

percentages of silt/clay in test holes were interpolated using Kriging to a surface for the Elkhorn River Basin. Finally, the thickness of silt/clay in VZM was generated by multiplying the layers of silt/clay percentage in the VZM and DTW using the ArcGIS Raster Calculator (Figure 2.9). The final VZM map layer is shown in Figure 2.10.
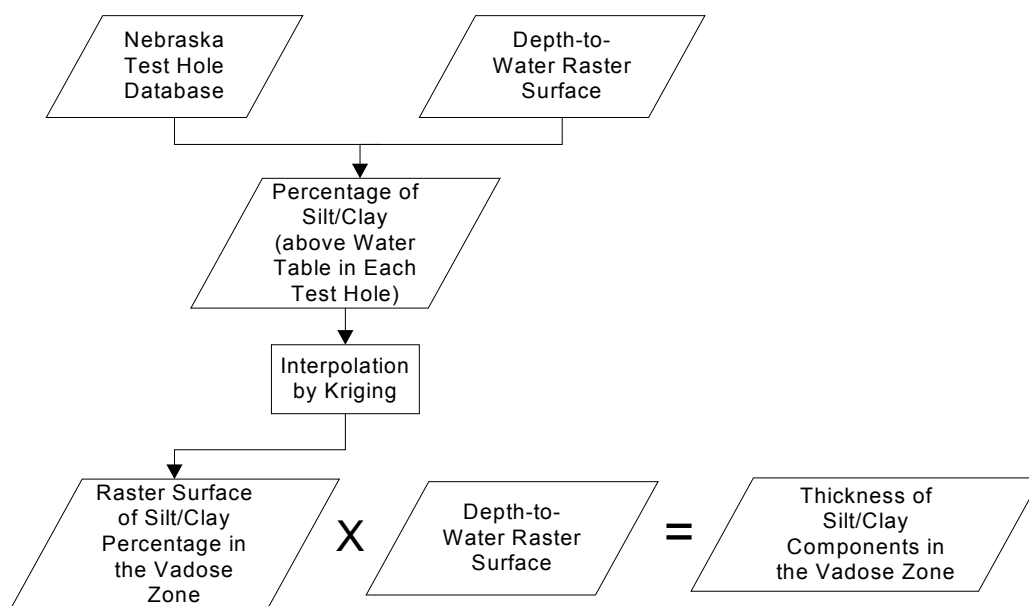
Figure 2.9 Flowchart for mapping the VZM factor
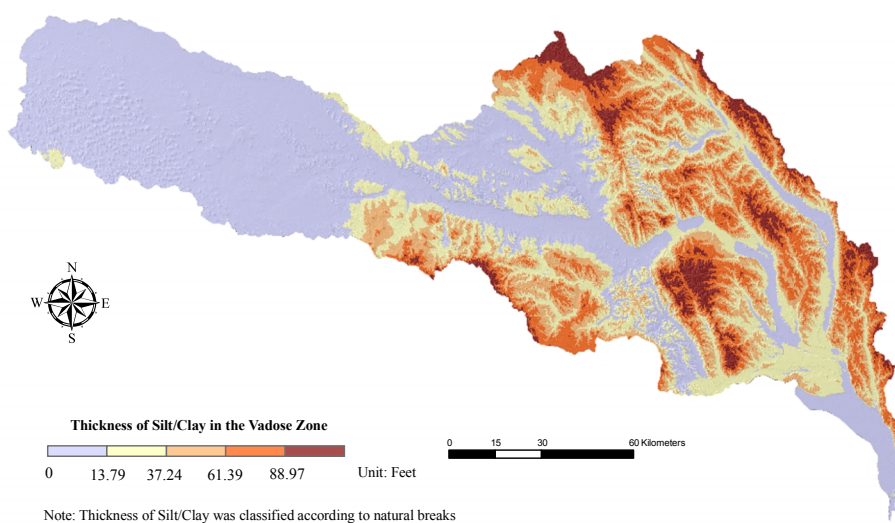
Figure 2.10 The impact-of-the-vadose-zone map for the study area

3.3.6 Land Use

Land use has frequently been found to be related to nitrate loadings in groundwater (Panagopoulos *et al.*, 2006; Dappen and Merchant, 2004; Rupert, 1999). In agricultural regions such as the Elkhorn River Basin, nitrate contamination in groundwater is quite likely associated with nitrogen (N) fertilizer applications (and sometimes manure) on croplands. In this study, N fertilizer application rates were used to assign land use ratings (Table 2.5). Land use and land cover were derived from the 2005 Cropland Data Layer (CDL) (Figure 2.11), developed by National Agricultural Statistics and Service (NASS). Estimated fertilizer application rates for different land use and land cover types were derived from the *Nutrient Management Guide for Major Agronomic Crops in Nebraska* (Ferguson, 2006). It is noteworthy that both soybeans and corn were assigned the same rating (Table 2.5). Corn and soybeans are often grown in rotation to control pests and conserve soil fertility. Although soybeans can fix atmospheric N and require little N fertilizer input, many studies have found that nitrate leaching from soybeans in a corn-soybean rotation is similar to, or even greater than that from corn (Zhu and Fox, 2003; Klocke et al., 1999; Katupitiya et al., 1997; Randall et al., 1997). Other land use types, such as urban, water, wetlands and forests, were assigned a rating of 0 because they are impervious surfaces or are unlikely to be affected by farm chemicals.

3.4. Computing the DRSTIL Index

The final DRSTIL-based groundwater vulnerability map for the Elkhorn River Basin was developed using a linear equation (see Eq. 2.2). All factor maps were resampled to 30m resolution, co-registered and analyzed in concert as outlined in Section 3.2.

Table 2.5 Fertilizer application rates and corresponding rating scores for different crops

Crop Type	Soil N Plus Fertilizer N Required (lbs/acre)	Ratings
Alfalfa	0	0
Barley	160	0.68
Canola	150	0.64
Corn	235	1
Dry Edible Beans	80	0.34
Pasture/Range	50	0.21
Potato	200	0.85
Safflower	100	0.43
Sorghum	132	0.56
Soybean	0	1
Sugar beet	130	0.55
Sunflower	125	0.53
Spring and Drum Wheat	50	0.21
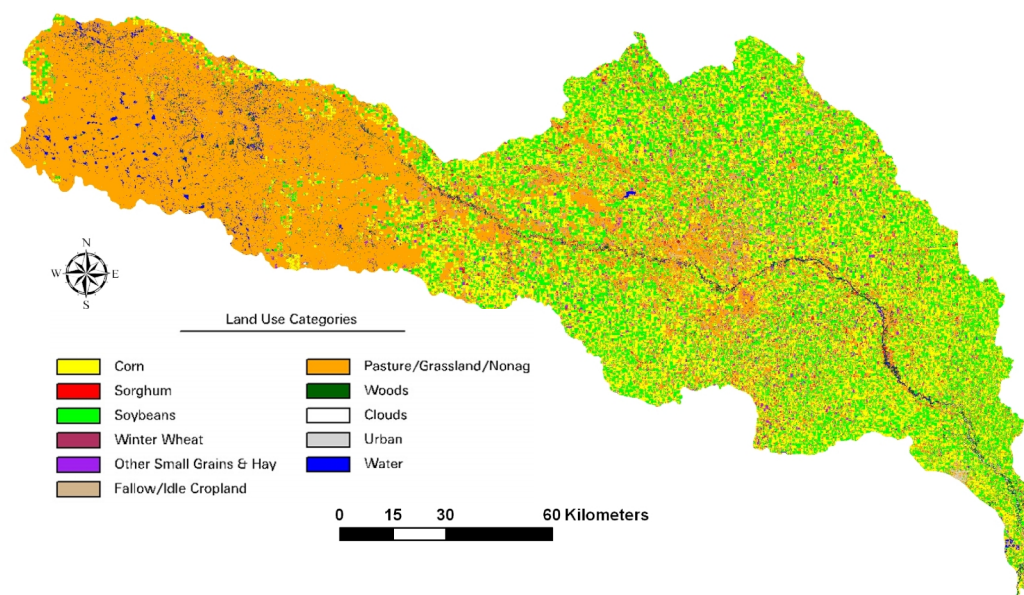
Figure 2.6 Land use and land cover for the study area

4 Results

4.1 Modeled Groundwater Vulnerability

The developed groundwater vulnerability map was shown in Figure 2.12. Approximately, 0.4% of the Upper Elkhorn River Basin was classified as having very low pollution risk, 3.6% having low pollution risk, 46.9% having moderate pollution risk, 45.8% having high pollution risk, and 3.3% is classified having very high risk. In the Lower Elkhorn River Basin, 1% of the area is classified as having very low pollution risk, 27.6% having low pollution risk, 41.6% having moderate pollution risk, 17.5% having high pollution risk, and 3.4% having very high risk. Generally, areas of higher vulnerability coincide with parts of the Upper Elkhorn River Basin where alluvial sand and gravel deposits of Quaternary age dominate. Areas of low vulnerability occur in the Lower Elkhorn River Basin where low-permeability glacial-till deposits prevail.

Groundwater Vulnerability

Very Low   Low   Moderate   High   Very High

Notes: Groundwater vulnerability score was classified and interpreted based on the following rule: less than 12 (very Low); 12 ~ 15 (low); 15 ~ 18 (moderate); 18 ~ 21 (high); above 21 (very high)
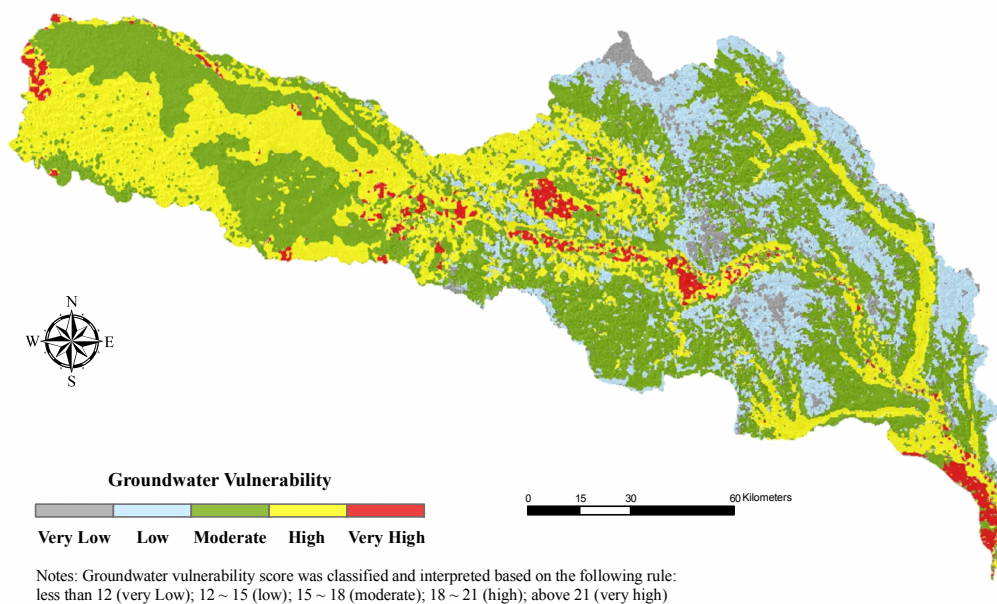
Figure 2.7 Estimated groundwater vulnerability for nitrate in the Elkhorn River Basin

4.2 Validation

The map of estimated groundwater vulnerability to nitrate was assessed by comparing the predicted groundwater vulnerability with observed nitrate concentration. Nitrate concentrations were extracted from 503 wells in the Quality-assessed Agrichemical Contaminant Database for Nebraska Ground Water (University of Nebraska-Lincoln, 2000).Wells without screen information or with a screen depth greater than 160 feet (approximately the depth of the groundwater table) were discarded, because our objective was to study the conditions of groundwater vulnerability near the water table (at the top of unconfined aquifers). Water quality assessed for samples collected from very deep wells is unlikely to reflect conditions at the water table. The nitrate values for wells sampled multiple times during the period 2000-2008 were averaged for each well. Only wells that had nitrate concentrations at or exceeding 10 mg/L, the EPA National Primary Drinking Water standard, were used (http://water.epa.gov/drink/contaminants/index.cfm) to assess the groundwater vulnerability map. The median nitrate concentration of wells falling into each vulnerability category was correlated with the vulnerability. There was a significant positive relationship between median nitrate concentration and the groundwater vulnerability levels (Coefficient of determination (R^2) = 0.87) (Figure 2.13). Therefore, the groundwater vulnerability map was observed to be generally consistent with observed nitrate contamination.
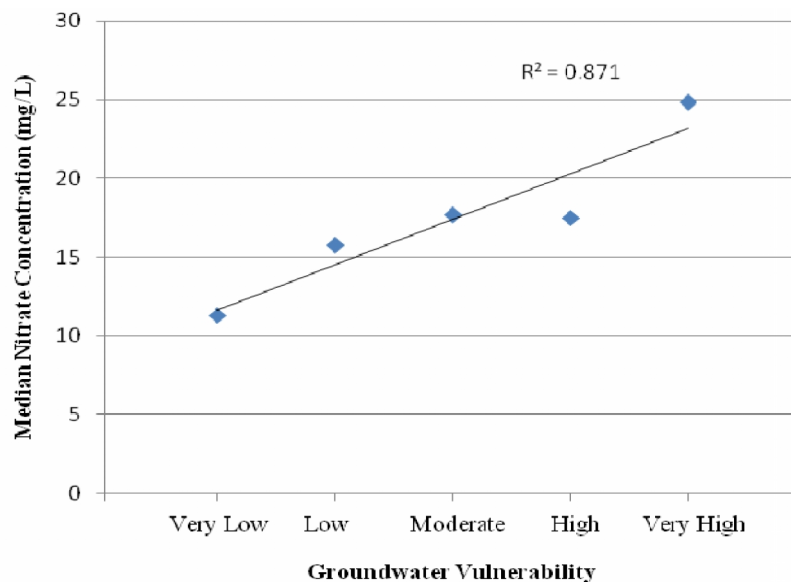
Figure 2.8 Correlation between median nitrate concentration and groundwater vulnerability

It should be noted that in this study the EPA Drinking Water standard was selected as the critical threshold to indicate those wells with high nitrate concentration and public health concerns. However, in future research other thresholds such as the background concentration of nitrate may be considered. Background concentration is defined as the minimum concentration indicative of any contamination caused by anthropogenic sources (Panno et al., 2006).

5 Discussion

As noted above, there is a general consistency between the groundwater vulnerability map and observed nitrate contamination in the Elkhorn River Basin, but inconsistencies also occur in some areas. For example, many wells having low nitrate concentration were observed to be located in the valley bottom where groundwater vulnerability was modeled as high or very high. This probably reflects an underlying weakness in comparing groundwater pollution potential to observed pollution. High pollution risk does not necessarily equate with actual contamination, or vice versa. In the Elkhorn River

watershed, the river valley is generally a discharge area for the basin. Reduced nitrate concentration in the valley bottom likely results from a progressive mixing between newly recharged high-nitrate groundwater and slowly circulating and denitrified discharged groundwater from upland areas (Figure 2.14).
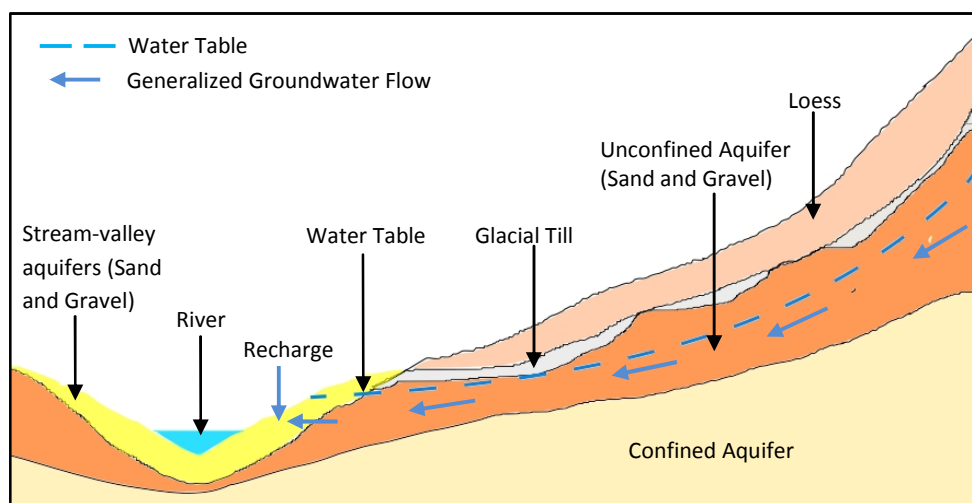
Figure 2.9 Groundwater flow in a river valley

It is also noteworthy that groundwater vulnerability modeling inherently involves spatial and categorical generalization of hydrogeology and other factors, and the relationships between factors, may affect groundwater quality. The accuracy of factor layers is always subject to uncertainties due to data availability and quality, geostatistical interpolation, and temporal fluctuation. Subjectivity in assignment of ratings and weights can also bring uncertainties to the modeling result. Some factors, which may be critical to nitrate attenuation processes (such as subsurface redox conditions and root zone depth), were not incorporated in the model because these data were not available. And, nitrate data used to assess the modeled vulnerability map are usually a mixture of groundwater from different well-screen depths in the aquifers. Thus, it is important that results of groundwater vulnerability modeling be used with great care in groundwater management.

The groundwater vulnerability model, DRSTIL, was adapted based on the traditional DRASTIC model. Based on a comparison of modeled groundwater vulnerability and observed nitrate contamination in the study area, this modeling approach can work reasonably. Compared with the DRASTIC model (Aller et al., 1985), DRSTIL drops aquifer and hydraulic conductivity factors from the DRASTIC model, and adds a new land use factor. Aquifer characteristics and conductivity were dropped because this research focuses on groundwater vulnerability at the water table. A land use factor was added to reflect the contaminant loadings associated with land use. The techniques for developing factor layers were designed using national or statewide datasets to make sure the techniques transferable to other places in the Northern Great Plains. For example, a statewide well log database, i.e. Nebraska Test Hole Database (http://snr.unl.edu/data/geographygis/NebraskaTestHole/NebraskaTestHoleIntro.asp), were used to develop the VZM layer. Similar well log databases, such as South Dakota Lithologic Log Database (http://www.sdgs.usd.edu/other/db.html), and North Dakota Groundwater Data Portal (http://www.swc.state.nd.us/4dlink2/4dcgi/wellsearchform/Map%20and%20Data%20Resources), were available in other Northern Great Plains states, and can be used to develop the VZM layers.

6 Summary and Conclusions

A modified DRASTIC model, DRSTIL, was used to evaluate the vulnerability of aquifers to nitrate contamination in the Elkhorn River Basin, Nebraska. The DRSTIL method provides a fast means for estimating groundwater vulnerability using six factors that can be mapped based on commonly available databases. This study demonstrates that this modeling approach can effectively model groundwater pollution risk over large regions

in the Northern Great Plains using national or state-wide datasets. The methodology is suitable for use over large areas, but is not intended to be employed for making local-level decisions.

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Chapter III

A Geospatial Modeling Framework for Assessing Biofuels-related Land Use Change

1 Introduction

1.1 Biofuels-driven cropland expansion

In the last decade, the land devoted to growing corn and soybeans in the northern Great Plains states (including Iowa, Nebraska, Minnesota, South Dakota, and North Dakota) has expanded significantly (Table 3.1). An important driver of this expansion is the increasing demand for biofuels (Carriquiry, 2007; Secchi and Babcock, 2007). Demands for corn, used to produce bioethanol, and soybeans, used to produce biodiesel, are expected to be strong in the foreseeable future (Woodard, 2007). The expansion of corn and soybean production is very likely result in a spectrum of potential negative environmental and ecological consequences (Kennedy, 2007; de Oliveira et al., 2005). For example, increases in land devoted to corn and soybeans may lead to pressures to remove land from the Conservation Reserve Program (CRP), drain wetlands, and open lands that are currently not cropped to cultivation, and concomitant loss of critical wildlife habitat (Brook et al., 2009).

Table 3.1 Expansion of corn and soybeans land between 1988 and 2008 in five states (data retrieved from http://www.nass.usda.gov/Data_and_Statistics/) (unit: thousand hectares)

Crop/Year State	Corn/1988	Corn/2008	Soybean/1998	Soybean/2008
Iowa	4573.1	5382.5	3298.3	3945.8
Minnesota	2306.8	3116.2	1983	2853.1
Nebraska	2792.4	3561.4	971.3	1983
North Dakota	323.8	1032	303.5	1537.9
South Dakota	1274.8	1922.3	712.3	1659.3

In addition, the expansion of corn and soybeans can affect the quality of both surface and ground water because cultivation generally requires significant inputs of fertilizer and other farm chemicals that can be flushed into water bodies or leach into groundwater (Thomas et al., 2009). The deterioration of water quality accompanying land use conversion is a major threat to both human health and ecosystems.

Better understanding of the relationships between land use and land cover change (LULCC), its drivers and consequences is critical to the development of effective environmental management strategies. An important component of such work is to develop viable models to project biofuels-related LULCC.

1.2 Geospatial models for forecasting cropland changes

A number of geospatial models have been developed to forecast patterns and processes of LULCC (Pontius et al., 2008). Models such as SLEUTH (Clarke et al., 1997), the Land Transformation Model (LTM) (Pijanowski et al., 2005, 2002), and CLUE/CLUE-S (Verburg et al., 2002, 1999) have been widely applied to project loss of agricultural land (Fan et al., 2007) and urban sprawl (Pijanowski et al., 2002; Clarke et al., 1997), but have rarely been used for forecasting areal change in specific cultivated crops.

When efforts have been made to model changes in specific crops, they have almost always been founded on data compiled for highly aggregated spatial units such as counties, statistical districts or countries. For example, de la Torre Ugarte and Ray (2000) used the Policy Analysis System (POLYSYS), a complex economic demand-supply model, to estimate the national distribution of U.S. bioenergy crops at the Agricultural Statistics District (ASD) level. Smeets et al. (2006) used the Quickscan model to forecast bioenergy crop production in 2050 at the global scale. Modeling based on such coarse, aggregated units often masks local changes and has low utility for managing consequences of LULCC (Verburg et al., 1999). A modeling approach that is location-specific is needed. Such an approach must be able to operate at multiple spatial and temporal scales in order to distinguish long-term, regional trends from short-term, local fluctuations in land cover arising from management practices such as, for example, crop rotation.

1.3 Research objective

The principal objective of this research was to develop a grid-based spatially-explicit modeling framework that is capable of both dealing with frequent short-term changes in cropping practices and capturing long-term trends in LULCC. The model was evaluated by employing it to simulate the recent history of corn and soybeans expansion, and to generate future scenarios of cropland change, for the state of North Dakota.

1.4 Background

In recent years, a few attempts have been made to model biofuels-related cropland change using grid-based approaches. Tuck et al. (2006) mapped the potential distribution

of bioenergy crops in Europe based on a set of simple rules defining suitable climate conditions and elevation. Their modeling approach, however, lacked calibration and validation needed to evaluate the modeling accuracy. Hellmann and Verburg (2011) used a spatially-explicit model to forecast changes in biofuel crops in Europe. The area of biofuel crops was initially determined at the national level by an integrated assessment model, GTAP-IMAGE, and the arable land was allocated based on a spatially-explicit model Dyna-CLUE. Then, the future locations of biofuel crops within the arable lands were determined based on a suitability-based multi-criteria evaluation. However, the modeling results were only partially validated using aggregated statistical data rather than actual land use maps of the study region. Evans et al. (2010) assessed landscape suitability for growing biofuel feedstocks based on two species distribution models: suitability maximum entropy (Maxent) and support vector machines (SVM). Although the methodology used a spatially-explicit procedure, their data aggregation and modeling results were nevertheless based on spatially broad units (i.e., at the county level). Moreover, their modeling approach was validated using corn production data for only two consecutive years (2006 and 2007), a short period that can hardly be used to determine the capacity for this approach to forecast long-term trends.

1.5 Spatial and Temporal Scale

Scale is an inherent attribute of geographic phenomena (Verburg et al., 1999; Cao and Lam, 1997). In studies of LULCC, both spatial and temporal scale must be considered; moreover, one must account for both extent (i.e., the entire study area or the modeling time period) and resolution (i.e., the smallest mapping unit or time period represented in the dataset). Figure 3.1 illustrates a study area having different spatial resolutions and

extents. As the spatial resolution increases (from 4×4 to 1×1), one can portray features with greater detail; as the spatial extent increase (from 4 to 36), the study area become larger. In LULCC studies, spatial extent and resolution are often related. For example, at smaller spatial extents it is common to encode data at finer spatial resolution so that details can be discerned. At larger extents, spatial resolution may be coarsened to reveal more general LULCC patterns. Similarly, the extent and resolution of temporal scale are also important in the analysis of change. From a temporal perspective, extent is the length of the time period analyzed, while resolution is expressed as the smallest time interval utilized in analysis (e.g., day, month, season, or year). In general, LULUC research observations made over short time intervals (fine resolution) are required for intra-annual modeling, while data having coarser temporal resolution (e.g., annual or longer) are often acceptable for long-term (e.g., inter-annual and decadal) modeling.
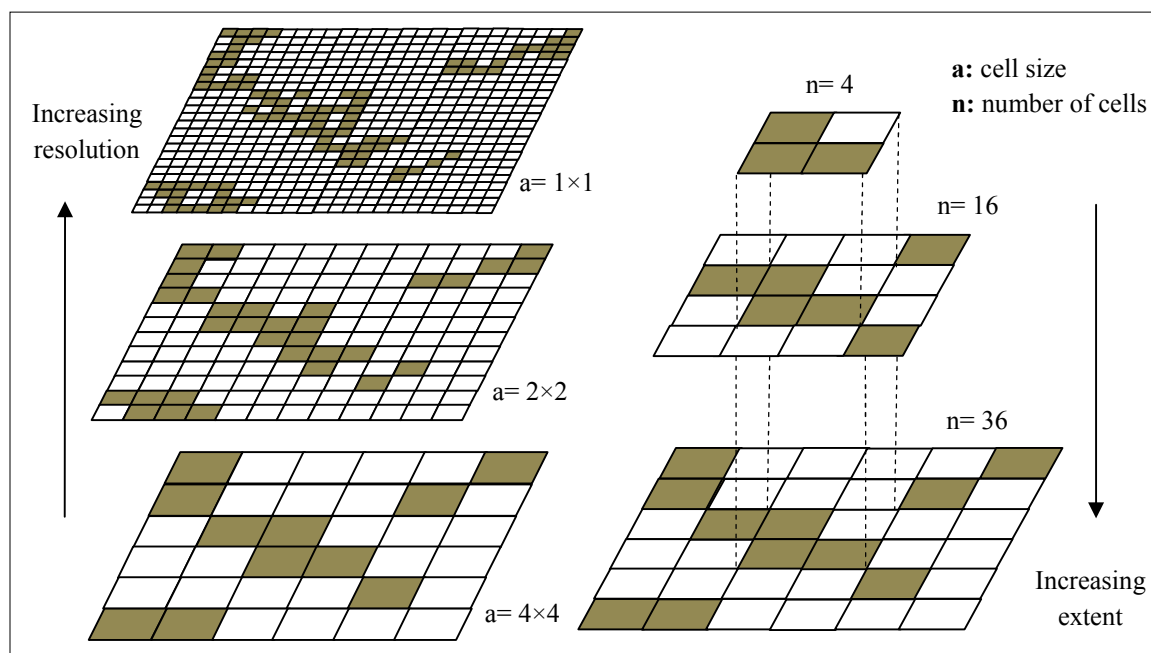
Figure 3.1 Changes in two components of spatial scale: resolution (left) and extent (right)

Croplands are complex and dynamic systems which can be represented at different spatial and temporal scales. Changes in scale can affect the observation of LULCC and related spatial patterns (Goodchild and Quattrochi, 1997; Turner, 1990), and hence the modeling of biofuels-related LULCC. Figure 3.2 shows how observations of cropland vary as spatial and temporal extents change. For example, studies of crop physiological changes usually are conducted with data having limited geographic and temporal extents (e.g., several square meters and over one or two seasons) and fine resolution (e.g., individual crop and daily observations). Moderate spatial and temporal scales are better suited to studies of planting rotational patterns. Coarse resolution is often best for research focused on long-term agricultural LULCC, and crop rotations will often be masked at these scales.
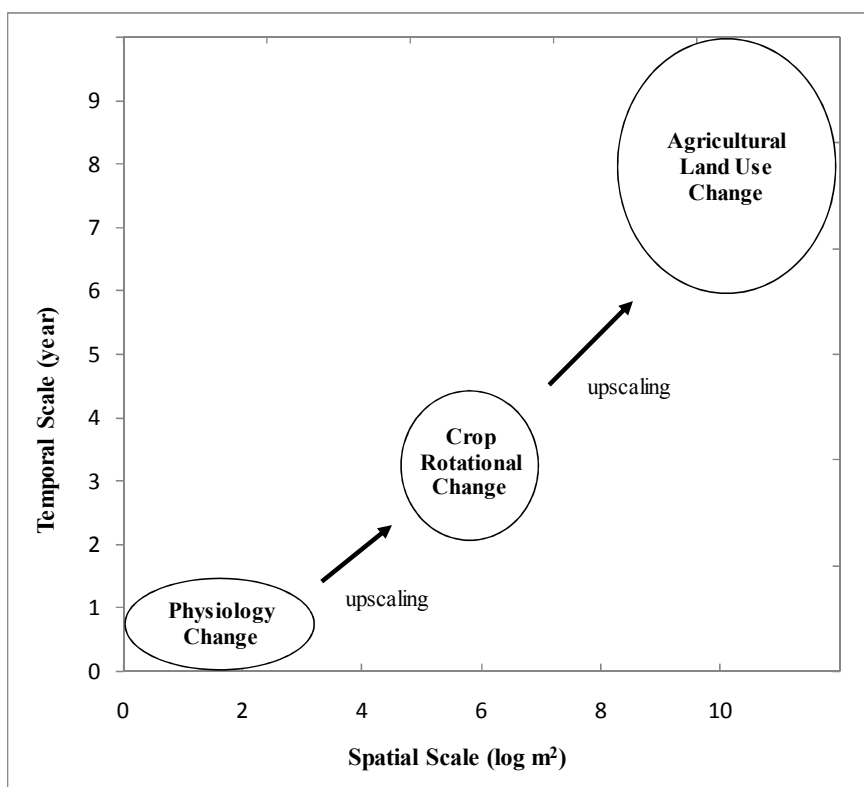
Figure 3.2 Agricultural land use change processes affected by spatial and temporal scales

LULCC models are inherently scale-dependent (Bian, 1997). To model regional agricultural LULCC, it is usually necessary to spatially aggregate data in order to minimize effects of crop rotation and other short-term land cover changes driven by fluctuating crop markets and agricultural policies (e.g., change from wheat to corn, from fallow to crop, or from rangeland to soybeans). Such short-term changes can introduce significant year-to-year "noise", making it difficult to model long-term LULCC. To reveal the general LULCC patterns at a regional level, this noise can be largely removed by spatial and temporal aggregation of the LULC data.

2 Methodology

In this research, a grid-based geospatial modeling approach was developed to forecast changes in two important biofuels crops: corn and soybeans. In the northern Great Plains, corn and soybeans are commonly grown in rotation. Since the pattern of corn-soybean rotation for a specific location is difficult to predict, the model treats the two crops as a single class of land cover, i.e., "biofuels crop". This approach was designed to capture general patterns/trends and generate location specific results, while reducing the effects of short-term, local fluctuations (e.g., crop rotations) associated with croplands. The model was evaluated by employing it to simulate the recent history of corn and soybean expansion in North Dakota.

The modeling framework includes two major modules: the quantity module and the spatial allocation module (Figure 3.3). The quantity module was used to determine/forecast the total amount of change in corn/soybeans cropland (i.e., the number of cells of other land use types to be transformed into corn/soybeans) during a particular time period. The spatial allocation module was then used to spatially distribute these

changes (i.e., to determine which specific cells in the grid to transform). This approach was based on a common assumption in LULCC modeling - that spatially-explicit geographic processes can be constrained by less spatially-precise economic or policy making processes (Lambin et al., 2000; Verburg et al., 1999).
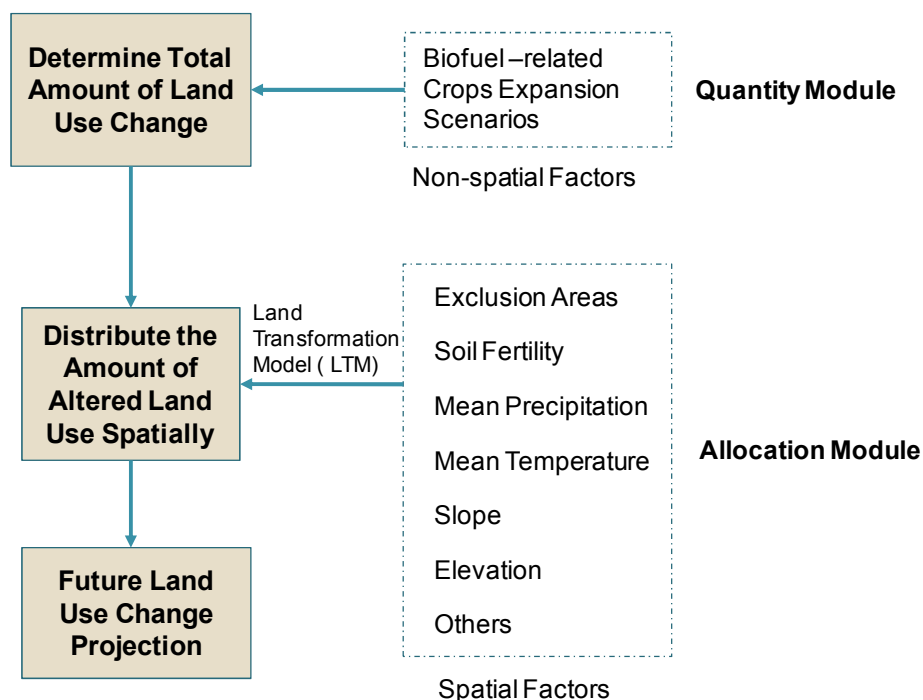
Figure 3.3 Framework for modeling cropland change

Forecasting future change in cropland area is complicated by several issues: (1) corn and soybeans serve multiple functions (e.g., as biofuels, food, and other commodities) and compete with other crops; (2) biofuel demands can be affected by factors both inside and outside the region; and (3) crop yields will vary in response to both marketing conditions and weather/ climate events. The quantity module, as implemented in this study, projects future corn/soybean distribution using statistical extrapolation of historical trends in crop area. This approach, while simple, is computationally straightforward and is believed to

capture important components of the factors outlined above without the need to independently model each.

The spatial allocation module is based on an existing LULCC model, the Land Transformation Model (LTM). The LTM is a grid-based spatially-explicit, well-tested and freely-available model that integrates environmental and socio-economic drivers with historic land use datasets to simulate LULCC (Pijanowski et al., 2002). The core of the LTM is an Artificial Neural Network (ANN), which uses a machine learning approach for modeling complex land use change. The ANN consists of an input layer comprised of a set of nodes that represent driving factors, an output layer consisting of only one node that represents the suitability for a certain land use type (e.g., urban land in an urban growth study, or cropland in this study), and one or more hidden layers in between (Figure 3.4). The nodes within adjacent layers are connected through Active Transfer Functions (ATFs). For more information about ANN, see Haupt et al. (2009).
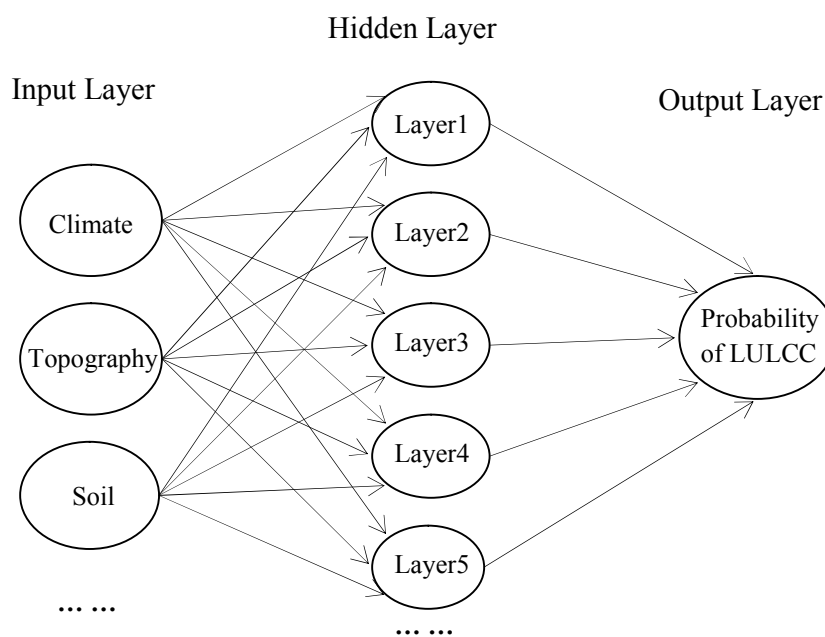
Figure 3.4 A simple 3-layer artificial neural network

Most previous applications of the LTM have focused on simulating urban growth (Pijanowski et al., 2005; Tang et al., 2005; Pijanowski et al., 2002), but the flexibility of the ANN embedded in the LTM allows for the simulation of other types of LULCC. Theoretically, any factor can be used as an input to an ANN, and the output can be any variable that is of interest in a study. The selection of input factors and output variable(s) largely depends on the purpose of the simulation. Moreover, an ANN is capable of handling complex non-linear relationships between factors, and of acquiring knowledge from incomplete, redundant, and noisy datasets without predefined rules, both of which are characteristics common in models of LULCC (Gosav and Praisler, 2008; Kajita et al., 2005; Mas et al., 2004; Pijanowski et al., 2002; Hilbert and Ostendorf, 2001).

Through a learning/calibration process using historical datasets, the LTM ANN adjusts the weights of ATFs to establish functional relationships between the driving factors and land use conversions. In other words, the ANN "learns" by acquiring knowledge based on the past history of land use change. Once trained, the ANN can be used to simulate land use change either retroactively, by attempting to replicate past observed changes, or to forecast future changes.

In this research, the LTM is employed to model corn/soybeans cropland changes. The probability of transforming a cell from other land use types to corn/soybeans cropland is set to be the output of the ANN, and a flexible set of factors (e.g., slope and soil organic matter) that may affect cropland expansion are selected as the inputs. The model essentially generates a suitability map for croplands, and then selects the cells exhibiting the highest suitability to convert. Pijanowski et al. (2002) identified six steps in the

implementation of the LTM: (1) mapping historic cropland; (2) identifying driving factors; (3) preprocessing the raster layers for both land use and driving factors; (4) testing the model with all inputs; (5) calibrating and validating the model; and (6) identifying transitional cells to create possible scenarios of future land use. The model performance is typically evaluated by examining the agreement between observed (or historical) LULCC and simulated cropland changes quantified using the Percent Correct Metric (PCM) and Kappa statistic (for details of PCM and Kappa, see Sousa et al. 2002; and Pijanowski et al. 2005).

The following procedure was employed to prepare data for the LTM (Figure 3.5).

(1) Reclassify the original fine-resolution (30 m × 30 m) land use data into a binary representation, i.e., target croplands (e.g., corn and soybeans) as value 1, and other land use types as value 0.

(2) Aggregate the binary data to 1500 m ×1500 m cells and assign each cell an attribute value representing the areal percentage of the target cropland.

(3) Average the cell attribute values (i.e. target cropland areal percentages) from multiple land use data that represent consecutive time periods, to generate a new land use data with a multi-year temporal resolution (Figure 3.5 shows two-year temporal averaging).

(4) Finally, reclassify the averaged data into a binary representation, i.e., an averaged percentage greater than or equal to a pre-set threshold reclassified to value 1, otherwise 0.
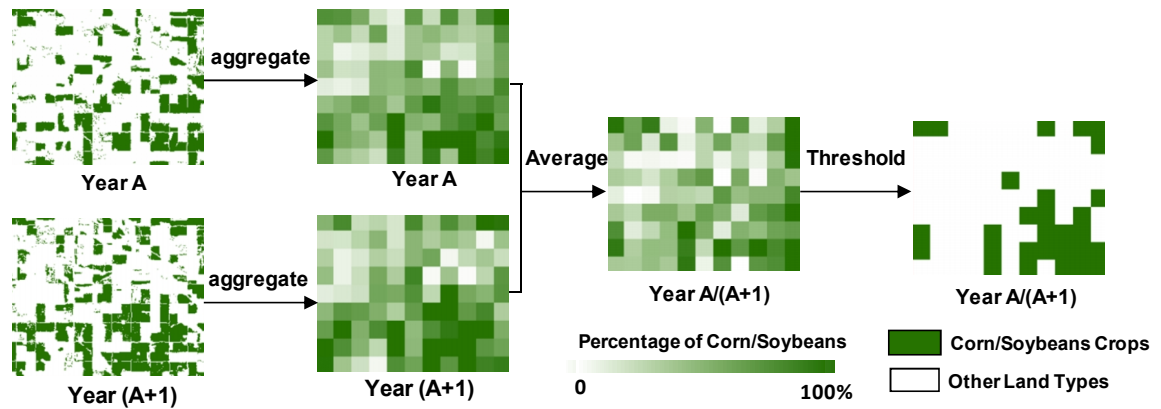
Figure 3.5 Spatio-temporal scale averaging

The selection of spatial and temporal resolution is critically important as the ideal resolutions will vary according to the application (e.g., target cropland, data availability, and spatio-temporal ranges of crop rotation and market fluctuations). In the case study of corn and soybean croplands in North Dakota, the spatial resolution was set to approximate the size of a crop section (1500 m × 1500 m) which minimized LULCC variability while maintaining a credible level of spatial explicitness. The temporal resolution was set to two years in order to reduce the impacts of short-term (i.e., inter-annual) fluctuations in LULCC stemming from annual crop rotation as well as climatic anomalies and volatile crop market conditions.

3 Application of the Model in North Dakota

3.1 Study Area

North Dakota was selected as the study area because it is representative of the northern Great Plains states, a region that has been experiencing significant changes in land use thought to be driven in part by increasing demand for biofuels (Table 3.1). A state-level analysis was chosen because it was a scale useful for both federal and state policymakers.

North Dakota has a continental climate typified by cold winters and hot summers; however, during the past century average temperatures in North Dakota have increased up to 3 °C (U.S. Global Change Research Program, 2000), among the highest in the Northern Great Plains. The state is the leading producer of wheat, barley, sunflowers and dry edible beans in the U.S. However, since the late 1990s, cropland change in North Dakota has been characterized by rapid expansion of corn and soybeans (Schnitkey, 2010). Corn and soybeans have generally either displaced other crops (such as wheat and sunflowers) or been planted on lands formerly in the Conservation Reserve Program (CRP). In 1997, the top three agricultural commodities were wheat, cattle and sunflower, accounting for 39.3%, 12% and 8.3% of the state total farm receipts respectively. By 2008, however, the three most important farm commodities changed to wheat, soybeans and corn at 33%, 14.4% and 14.3% respectively (Economic Research Service, 1998).

3.2 Data Preprocessing

A time series (1997-2008) of land use data for North Dakota were obtained from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Cropland Data Layers (CDLs) (www.nass.usda.gov/research/Cropland/SARS1a.htm). The 1997-2005 CDLs are available at 30 m resolution, and 2006-2008 CDLs are available at 56 m resolution. As noted above, corn and soybeans were combined into a single land use type in this study. Following the procedure shown in Figure 3.5, the CDLs for the years 1999, 2000, 2004, 2005, 2007 and 2008 were first reclassified into binary data (corn/soybeans as 1, and others as 0); then the binary data (at 30m spatial resolution) were aggregated in ArcGIS to generate 1500m-resolution grids of corn/soybean areal percentages (Figure 3.6). The percentages were then averaged between 1999 and 2000,

2004 and 2005, 2007 and 2008 to produce three maps for 1999/2000, 2004/2005 and 2007/2008. Cells in each two-year map were subsequently reclassified using the following rules: all cells that contained at least 40% corn and/or soybeans were reclassified to corn/soybeans cells (value = 1), while other cells were given the value zero. This procedure resulted in three maps for 1999/2000, 2004/2005 and 2007/2008 (Figure 3.7).
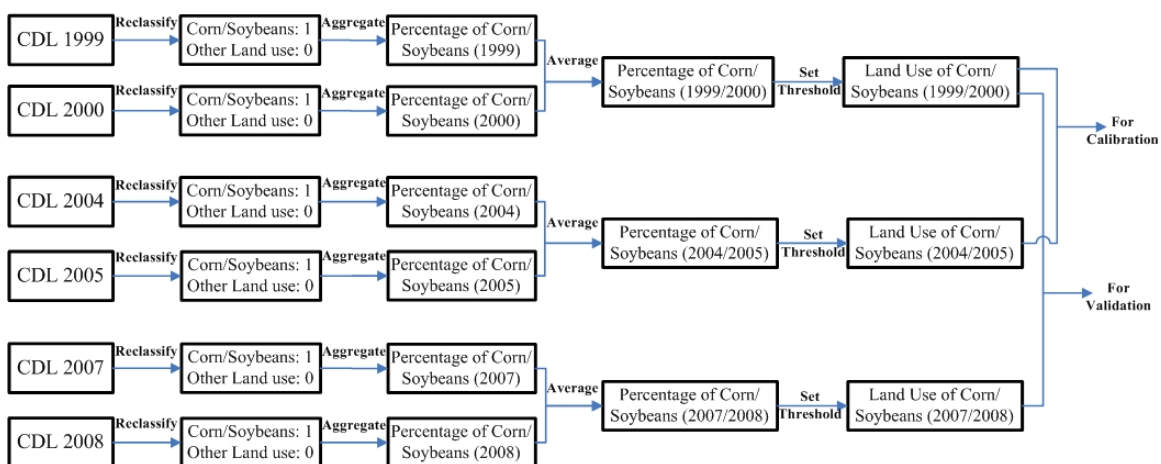
Figure 3.6 Procedure to prepare the land use maps for modeling

(a)

Distribution of Corn/soybeans Cropland in North Dakota (Year 2004/2005)

(b)

Distribution of Corn/soybeans Cropland in North Dakota (Year 2007/2008)
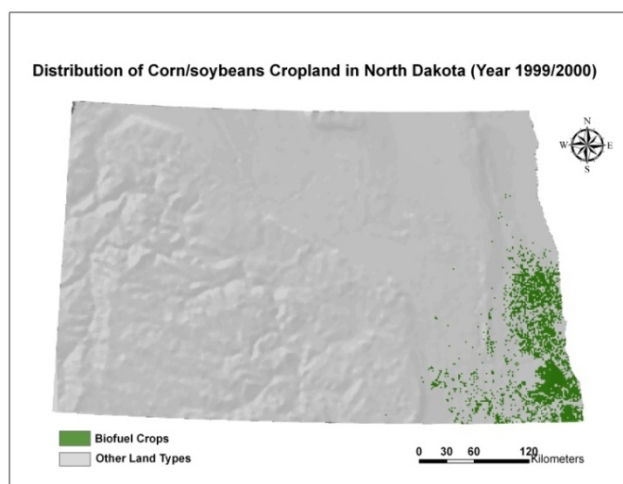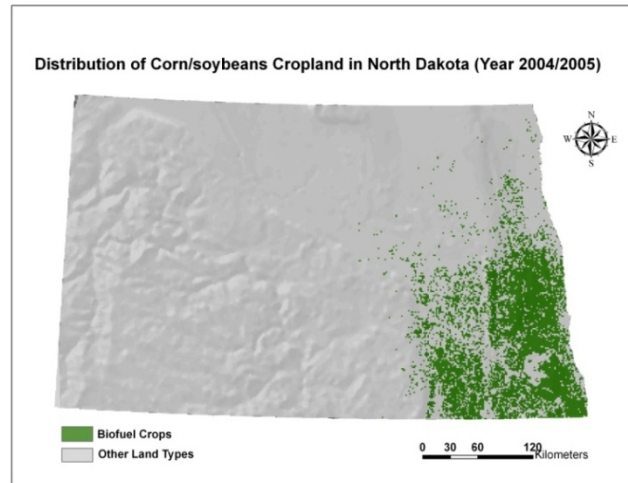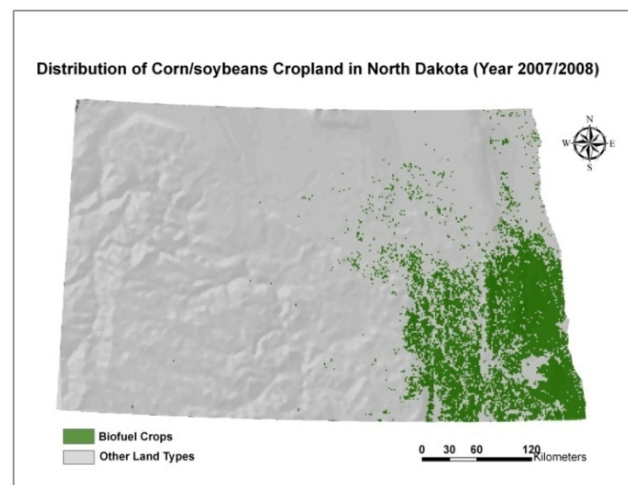
(c)

Figure 3.7 Corn/soybeans cropland maps for 1999/2000 (a), 2004/2005 (b) and 2007/2008 (c) (data were derived based on CDLs for North Dakota)

Six environmental variables were chosen as the driving factors for modeling biofuel cropland in North Dakota (Table 3.2): terrain elevation, terrain slope, soil organic matter, cation exchange capacity (CEC) of the soil, the 30-year mean precipitation (1971-2000), and the 30-year mean temperature (1971-2000). All are important to establishing the suitability of land for growing crops (Bowen and Hollinger, 2002; Kravchenko and Bullock, 2000). Elevation and slope data were derived from the USGS National Elevation Dataset, and resampled into 1500m-resolution grids. Soil organic matter and CEC were

extracted from the USDA STATSGO database using the Soil Data Viewer (http://soils.usda.gov/sdv/). The shapefiles of soil organic matter and CEC were then converted into 1500 m-resolution grids. The mean precipitation and mean temperature were extracted from Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system (http://www.prism.oregonstate.edu/) and converted into 1500 m-resolution grids. Exclusionary zones (including public lands, wetlands, urban areas and water bodies) were extracted from the Land Ownership for the Western United States (http://sagemap.wr.usgs.gov/) and 2000 CDL.

Table 3.2 Factors used to predict cropland change

Factor	Relationship to Cropland Change	Data Source
Elevation and Slope	Topography influences water availability, and physical and chemical properties of soil (Kravchenko and Bullock, 2000) which can affect crop yields.	USGS National Elevation Dataset
Soil organic matter and CEC	Organic matter can release plant nutrients, including nitrogen and phosphorus as it is broken down in the soil. CEC can affect the soil's capacity to hold nutrients releasable for plant growth (Griffin, 2004).	USDA NRCS STATSGO Database
Mean Precipitation and Mean Temperature	Precipitation is generally related to the spatial distribution of soil moisture, which is important for agricultural cultivation. Annual mean temperature can affect crops' temperature requirements for growth.	PRISM Climate Group (http://www.prism.oregonstate.edu)

The area of corn and soybeans cultivation in North Dakota was modeled for a 21-year period (1999-2020). It was assumed that corn/soybeans could compete with other types of land use at any location except in "exclusionary zones". An exclusionary zone is an area which is not likely to change to agricultural use (e.g. urban lands, wildlife protection

areas, and water bodies). We assumed, too, that the urban area in North Dakota stayed static during the modeled time period since the urban area in North Dakota has not expanded significantly during the past few decades (based on population data from U.S. Census Bureau).

3.3 Model Calibration and Validation

The LTM was calibrated by training the ANNs using the averaged biofuel cropland maps of 1999/2000 and 2004/2005 (Figure 3.7 (a) and (b)). The calibration generated multiple candidate ANNs with different ATF weights, as wells as a set of simulated biofuel cropland change (during 1999/2000–2004/2005) maps created using these ANNs. Selection of an ANN for use in this research was guided by PCM and Kappa statistics that were used to compute the agreement between observed change and simulated change. The criteria for evaluating the model are shown in Table 3.3. The ANN with the largest PCM and Kappa values was then selected as the calibrated model.

Table 3.3 Criteria for assessing model performance for Kappa and PCM (adapted from Pijanowski et al., 2005)

	Kappa	**PCM**
<0.2	Poor	Very Poor
0.2-0.4	Poor	Poor
0.4-0.6	Acceptable	Good
0.6-0.8	Good	Very Good
>0.8	Excellent	Excellent

The observed change in cropland and the simulated change generated by the calibrated model are shown in Figure 3.8. The PCM and Kappa statistics were 64.39% and 0.61 respectively. According to Table 3.3, the model performance was rated as good. This result indicates that most of the observed cropland change during the 1999/2000-2004/2005 period can be successfully simulated by the model.
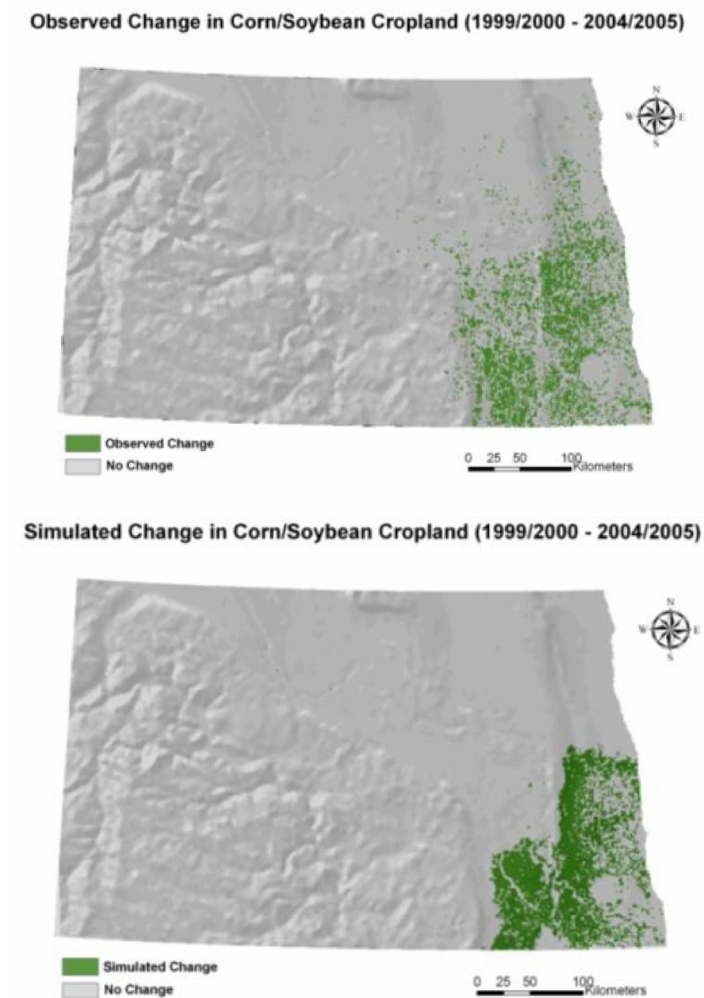
Figure 3.8 Comparison of observed and simulated change in cropland (1999/2000-2004/2005)

In order to validate the performance of the calibrated model, the model was rerun using the same factors to generate a biofuel cropland change map between 1999/2000 and 2007/2008 (Figure 3.9). This map was compared with the observed change map for the

same periods. The PCM and Kappa statistics were 68.63% and 0.65 respectively, indicating good performance of the model for replicating the observed historical cropland change.

Observed Change in Corn/Soybean Cropland (1999/2000 - 2007/2008)

Simulated Change in Corn/Soybean Cropland (1999/2000 - 2007/2008)
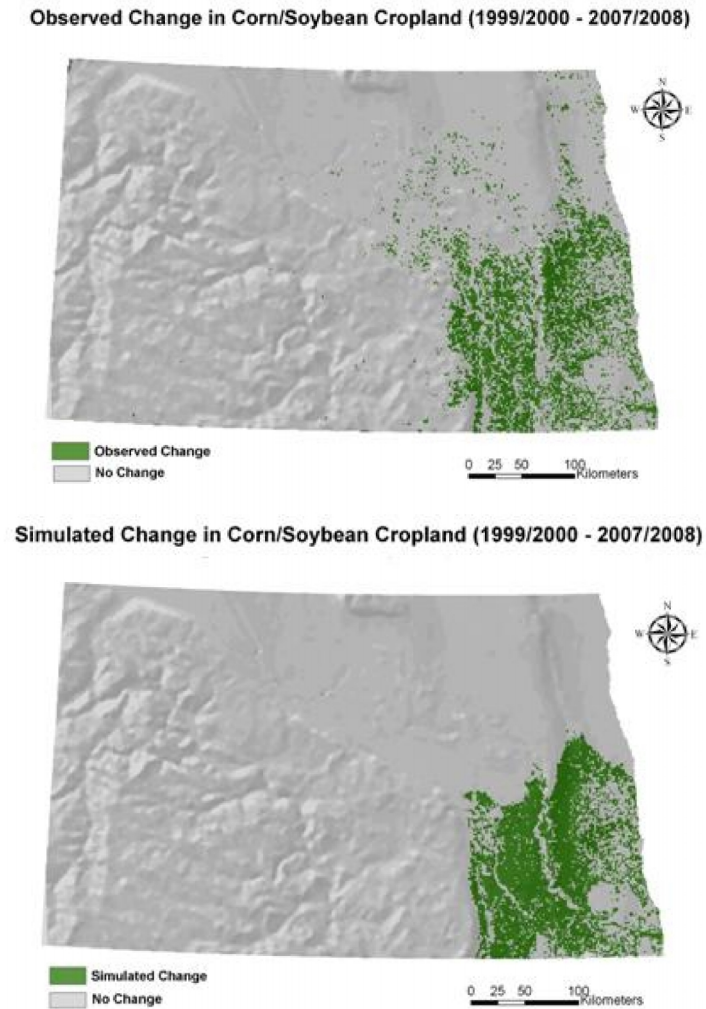
Figure 3.9 Comparison of observed and simulated changes in corn/soybeans cropland (1999/2000-2007/2008)

3.4. Future Scenario Projection

The calibrated model was then used to forecast the future corn/soybeans cropland for the year 2020. First, three scenarios of possible increases in corn/soybeans area that could result from demands for biofuels were generated using simple extrapolation based on

historical agricultural statistics (National Agricultural Statistics Service, 2010). Linear, third-ordered polynomial and Weibull equation formulas were used to fit the historical corn/soybeans acreage respectively. These three formulas were assumed to project potential increases of corn and soybeans acreage in 2020 for fast, medium, and slow expansion scenarios respectively (Figure 3.10). The fast scenario indicates that corn/soybeans will continue to increase rapidly due to high biofuel demands in the near future. The medium and slow scenarios indicate the current high rate of increase in corn/soybeans acreage will gradually decrease. This may reflect the growing competition between biofuels and food industries for corn and soybeans (Horelik, 2008). The results of fast, medium and slow projections were used to calculate the number of cells to be converted to corn/soybeans cropland during the period between 1999/2000 and 2020 under each of the three scenarios. The LTM was then activated to spatially distribute the cells using the 1999/2000 cropland map as an initialization map and assuming that the cells with higher conversion probabilities will convert first.
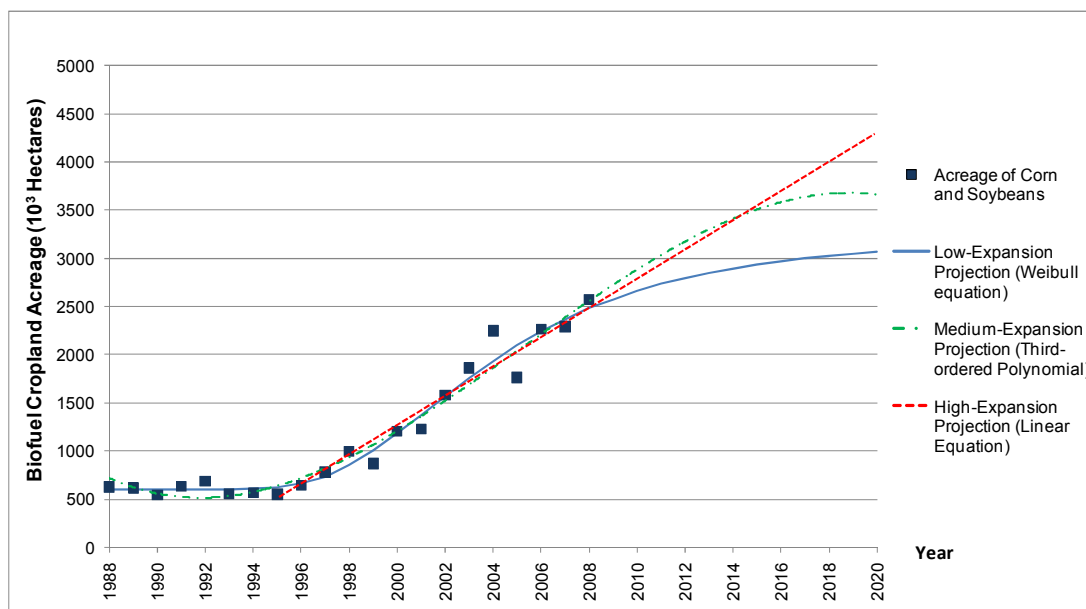
Figure 3.10 Three scenarios of cropland change

The projections of future corn/soybeans changes are shown in Figure 3.11. As expected, under all three scenarios (low, medium and high expansion) most change in corn/soybeans cropland was projected to occur in eastern North Dakota, the Lake Agassiz Plain and the Northern Glaciated Plains, where the soil is generally fertile, the topography is relatively flat, and the climate is warmer and wetter than in the western parts of the state.

4 Discussion

4.1 Understanding the modeling results

Two major phenomena can be identified in the modeling results: (1) biofuel crops were more concentrated in Southeastern North Dakota in the simulation map than in the observation map; and (2) biofuel crops are expanding northwestward from Southeastern North Dakota. Based on the driving factors used in this model, southeastern North Dakota is the most suitable area for agricultural cultivation because of its fertile soils, low and flat topography, and warm and wet climate. As the demand for biofuel crops keeps increasing, biofuel croplands expand from highly suitable areas (i.e., southeastern North Dakota) to moderately suitable areas (i.e., central North Dakota). The expansion of biofuel croplands follows the gradient of suitability for biofuel crop cultivation.

4.2 Evaluation of the Modeling Approach

The modeling approach employed in this study of North Dakota produced an acceptable simulation of historical cropland expansion, and yielded reasonable projection scenarios. The LTM was used in this study because it has been shown to be capable of dealing with complex relationships and noisy datasets. The LTM was implemented using procedures

Corn/Soybean Cropland Distribution in 2020 (Low Expansion Scenario)

Simulated Change
No Change

0 25 50   100
Kilometers
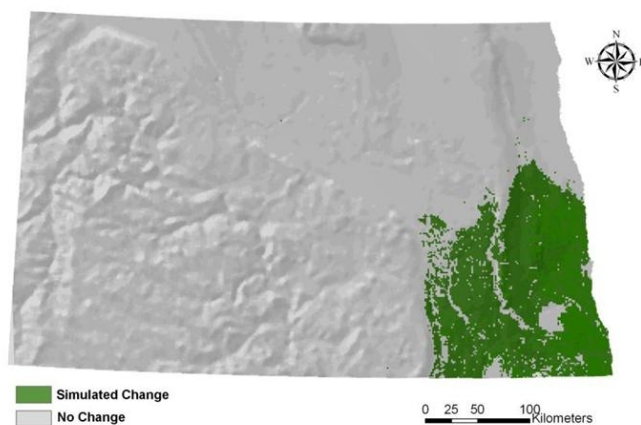
Corn/Soybean Cropland Distribution in 2020 (Median Expansion Scenario)

Simulated Change
No Change

0 25 50   100 Kilometers
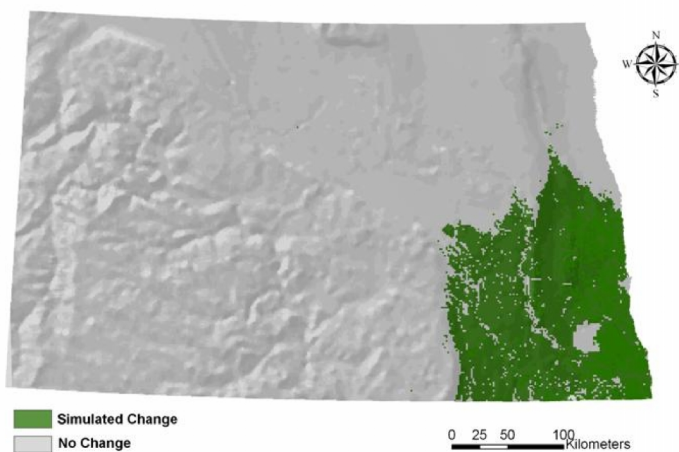
Corn/Soybean Cropland Distribution in 2020 (High Expansion Scenario)

Simulated Change
No Change

0 25 50   100 Kilometers
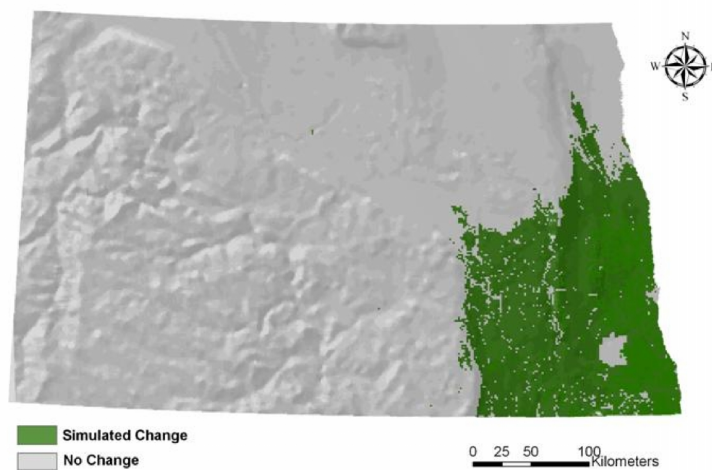
Figure 3.11 Modeled change in corn/soybeans cropland in 2020 under scenarios of low, medium and high expansion

similar to those that have been used in urban land change modeling (Pijanowski et al., 2005; Tang et al., 2005; Pijanowski et al., 2002), the major difference being in the data preprocessing which was used to mask the spatial and temporal variations caused by crop rotations and other short-term, local fluctuations, such as farmers' planting decisions.

It should also be noted that the modeling approach is more spatially explicit than methods commonly use in modeling crops used for biofuels. Many such methods employ broad units such as countries and statistics district (Smeets et al., 2006; de la Torre Ugarte and Ray; 2000). This model is also capable of distinguishing long-term regional trends in LULCC from frequent short-term changes (e.g., crop rotations) in cropping practices. The short-term changes such as crop rotations were generally overlooked in most existing studies, probably because they used either spatially broad units or very large grids size. Hellmann and Verburg (2002) noticed the phenomena of crop rotation but failed to analyze the short-term changes in their spatial patterns.

However, the LTM was observed to have a number of limitations. For example, the ANN embedded in the LTM is essentially a "black-box" and, therefore, it is difficult to identify and quantify causal relationships between driving factors and LULCC. In addition, the LTM, used in a static or semi-dynamic mode, does not account for LULCC dynamics that may occur during the simulation period. For example, the spatial distribution of land in a specific year may affect the land use in the following year, and driving factors may change as well.

Several assumptions were made to simplify the modeling process. First, biofuel crops were assumed to expand from areas with high agricultural suitability to ones with lower

suitability. As mentioned earlier, the model essentially generates a suitability map for croplands, and then selects the cells exhibiting the highest suitability to convert. Thus, non-biofuel crops in areas of high suitability may be among first to be replaced by biofuel crops. The model goodness-of-fit indicates this assumption is valid. Second, the climatic factors used in the model were long-term (1970-2000) mean values. Climate change may affect the patterns of biofuel crops and other land uses. Changes in temperature and precipitation in the future may make some areas more or less suitable for cultivating biofuel crops, and hence affect the projection of future biofuel crops. Finally, the relationships between the driving factors and land use change were assumed to be static over time. Once the ANN is trained using historical data (i.e., 1999/2000 – 2004/2005), the weights of ATFs between nodes do not change during the simulation (i.e., 1999/2000 – 2007/2008) and forecasting (i.e., 1999/2000 - 2020) periods, which means the ANN's functional relationships between the input layer and output layer stay static.

Although the model performed acceptably well, it was observed that the current implementation has several limitations:

1. To make the modeling location-specific, a threshold of 40% was used to define crop cells. A similar approach has been adopted for land use representation by the CLUE-S model, resulting in one dominant (>50%) land type occupying pixels of land use map (Verburg et al., 2002). In our study, a threshold of 40%, instead of 50%, was chosen in consideration of the trade-off between the goodness of modeling fit and the representative fraction of biofuel crops within each cell. After the application of the threshold, the preprocessed cropland reference maps contained only two types of cells: corn/soybeans and other land types; thus, the

variation within each class was lost. The selection of the threshold is important to the accuracy of the model. As a test, the model was rerun and recalibrated using different thresholds. It was found that PCM and Kappa statistics of the recalibrated model improved as the threshold decreased (as shown in Figure 3.12). Applying a lower threshold produced more biofuel crop cells and hence provided a larger land change contrast for the model, but exaggerated the observed spatial distribution of corn/soybeans croplands. An optimal threshold should provide a good fit while representing a reasonable fraction of interested land use classes (biofuel crops) within each cell. A threshold of 40% appears to provide a reasonable fit, although additional work is needed to choose the most appropriate threshold.
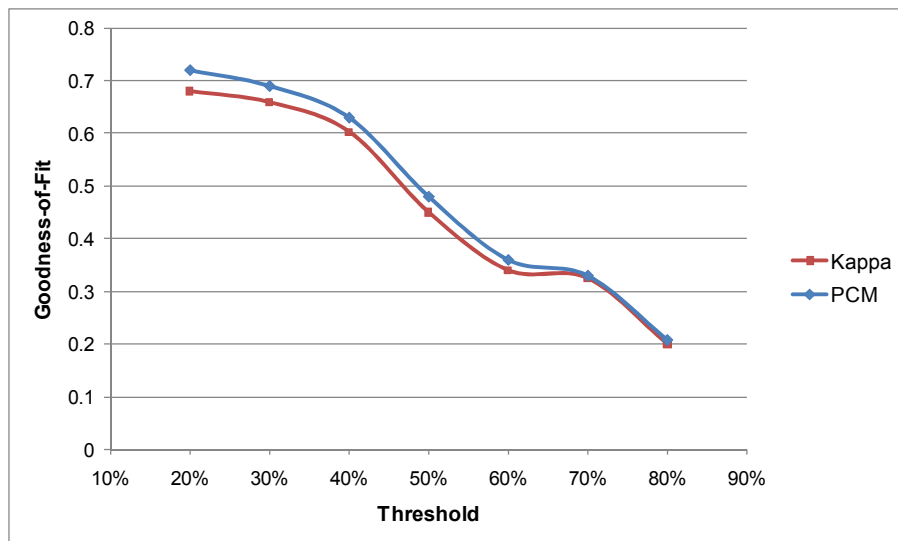
Figure 3.12 Model goodness-of-fit versus thresholds of the model (model goodness-of-fit was indicated by the PCM and Kappa values)

2. The demand for biofuels was not computed using state-of-the-art socio-economic models. As mentioned before, the quantitative module is flexible enough to link to sophisticated external models. Thus, future work should focus on improving such

forecasts by incorporating cost and risk factors to the crop production using aggregated projection models such as IMAGE/GTAP (Hallmann and Verburg, 2008) and POLYSYS (de la Torre Ugarte and Ray, 2000).

3. The premise underlying the modeling factor selection in the case study is that topography, soil and climate conditions govern the agricultural suitability for corn/soybeans, and corn/soybeans will most likely expand from areas with higher suitability to those with lower suitability. These factors were selected based on a review of related literature (e.g. Bowen and Hollinger, 2002; Kravchenko and Bullock, 2000). At the scale of a state, these factors were assumed to drive the long-term, regional LULCC patterns for corn/soybeans. However, there could be other potential factors contributing to the observed LULCC. For example, locations of existing biofuel plants are associated with the cost of transporting corn/soybeans from production areas (Hellmann and Verburg, 2011; Scheffran and BenDor, 2009). But the role of biofuel plants in affecting spatial patterns of corn and soybeans is still unclear (e.g. no association was found between ethanol plant location and corn production increase (Voss et al., 2010)).

Perhaps the biggest limitation of the current modeling framework is that it is based on one-way relationships between the driving factors and land use change, and ignores the impacts of land use change on the driving factors, for example, converting various types of lands into uniform biofuel croplands may change the local-scale climate. Lacking of spatio-temporal interactions between the driving factors and LULCC is a common problem in many current LULCC models. Future research should involve development of tools to address such issues.

5 Conclusions

In this research, a grid-based modeling framework for modeling biofuels-related LULCC was developed based on the LTM model. Through spatial and temporal aggregation, averaging, and threshold-based reclassification, this modeling framework seeks to minimize the effects of short-term, local fluctuations and capture long-term, regional trends in biofuels-related LULCC. The combination of a quantitative module and an ANN-based spatial allocation module provides a means to effectively simulate the amount and locations of biofuel cropland changes.

Compared with other biofuel crop models, this model features the following two major advantages: (1) the modeling approach is location specific on a grid basis, enabling the modeling results readily applicable to other environmental models such as a groundwater vulnerability model, and (2) The model is capable of distinguishing long-term trends in LULCC from frequent short-term changes (e.g., crop rotations) in cropping practices.

This model is the first spatially-explicit land use model developed to simulate the distribution of biofuel crops in North Dakota. Compared with traditional models for biofuel crops, this model features the following two major advantages: (1) the modeling approach is location specific on a grid basis, enabling the modeling results readily applicable to other environmental models such as a groundwater vulnerability model, and (2) The model is capable of both dealing with frequent short-term changes (e.g., crop rotations) in cropping practices and capturing long-term trends in LULCC.

The case study presented here demonstrates that the model proposed can reasonably replicate biofuels-related LULCC in North Dakota focusing on changes in corn and

soybeans that may be driven by increasing demands for biofuels. The modeling approach is able to simulate the recent history of corn and soybeans expansion, and generate future scenarios of cropland change to the year 2020. The projections suggest that future biofuels-related LULCC is most likely to occur in Eastern North Dakota. This is consistent with trends observed in recent decades and described in other studies (see, for example, Galle et al. 2009). The modeling framework can be potentially adapted to simulate other types of land use change and could be applied in other agricultural regions which are undergoing LULCC.

Models such as that proposed in this study can provide natural resources decision-makers a means to understand the geographic extent of future cropland change in order to better address accompanying environmental consequences. As demand for biofuels continues to grow, more land is likely to be converted to biofuel crops. This model, if coupled with environmental impact models, could assist decision-makers in formulating land use policies and developing environmental management strategies to address negative impacts of biofuel cropland expansion.

Future research should explore integrating spatio-temporal dynamics into the biofuel crops modeling. The current model assumes a steady-state behavior of the artificial neural network (ANN) where inputs are either static in time or periodically varying. But it does not include explicit topological or spatial structure and temporal properties (Ermentrout, 1998), and thus cannot simulate the land use change progressively in response to changes in factors (e.g. climate variations) during the modeling period. A spatio-temporal dynamic ANN needs to be developed in the future works.

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Chapter IV

Modeling Vulnerability of Groundwater to Pollution under Future Scenarios of Climate Change and Biofuels-related Land Use Change

1 Introduction

Globally, at least two billion people depend upon groundwater as the principal source of their drinking water (National Research Council, 1993; Sampat, 2000). Those living in areas such as Northern China, Eastern Europe, Northern India and the U.S. Great Plains are especially likely to rely on groundwater. Recent forecasts suggest that the combined effects of population growth, global warming and land use change will, in the near future, lead to even greater reliance on groundwater for public water supply (Hall et al., 2008; Rosenzweig et al., 2007).

In most instances, modeling and mapping of aquifer susceptibility to pollution is considered a critical first-step in implementing programs to protect groundwater quality (National Research Council, 1993). Groundwater pollution risk assessment models typically involve geospatial analysis of the inter-relationships between landscape characteristics (e.g., depth-to-water, soils, aquifer hydrogeology, and recharge) and land use. Agricultural land use, involving application of farm chemicals, has been shown to be an especially important factor influencing both observed, actual groundwater quality and predicted pollution risk (Scanlon et al., 2007). Most groundwater pollution risk models assume land use to be static, but clearly this may not be a valid assumption. In

the near future, agricultural land use may change quite significantly as a result of global warming and/or changing economic circumstances such as increasing demand for biofuels (National Research Council, 2008; Foley et al., 2004; Ojima et al., 1999).

In the northern Great Plains, the proportion of land devoted to agricultural land uses is among the highest in the nation. Observed or predicted alterations of climate such as earlier onset of spring, spatial and temporal changes in precipitation patterns, and higher mean soil temperatures may lead to northward shifts in cropping patterns, changes in crop mixes (and use of farm chemicals), and/or increased (or decreased) use of irrigation (Ojima et al., 1999; U.S. Environmental Protection Agency, 1998). At the same time, growing demand for biofuels is resulting in increasing corn acreage, and may lead to pressures to remove land from CRP, drain wetlands, or otherwise open lands that are currently not cropped to cultivation (National Research Council, 2008). As land use changes, in some locations there will be concomitant, though currently unknown, changes in risks of groundwater pollution (Graham, 2007; Dams et al., 2007).

The overarching goal of this research is to determine if, how and where the vulnerability of groundwater to pollution in the northern Great Plains may be impacted by projected land use change driven by both climate change and increasing demands for biofuels. In this study, the focus is on the vulnerability of groundwater to pollution from nitrates, a constituent of chemical fertilizers used widely in the Great Plains and known to have implications for human health (Power and Schepers, 1989).

2 Backgrounds

The northern Great Plains region (Nebraska, South Dakota and North Dakota) is characterized by high natural variability of climate, highly fertile soils and widespread agricultural land use. Major crops grown include corn, soybeans and wheat. During the 20th century, the average temperature of this region rose by more than 1 ºC, with increases up to 3ºC observed in parts of North Dakota and South Dakota (US Global Change Research Program, 2000). Precipitation has also increased over most of the region (US Global Change Research Program, 2000). It is expected that average temperature will continue to rise into the 21st century, and increasing precipitation is also expected to occur in many areas (IPCC, 2007). Models employed by, respectively, the Canadian Climate Centre (CCC) and the UKMO-Hadley Center (HADLEY) indicate increasing minimum and maximum temperatures and precipitation in the northern Great Plains (Figure 4.1a, b, c) (Ojima et al., 2002).

In recent years, there has also been significant land use and land cover change in the region. The U.S. Department of Agriculture (USDA) has documented that, during the period 2002-2007, thousands of acres were converted from wheat to corn in the northern Great Plains (Figure 4.2). Brooke et al. (2009) estimated that from 2007 to 2009 up to 5.5% of lands in the Conservation Reserve Program (CRP) were changed to cropland in some counties of this region, largely driven by high corn prices and demands from the corn ethanol industry (see also National Research Council, 2008).
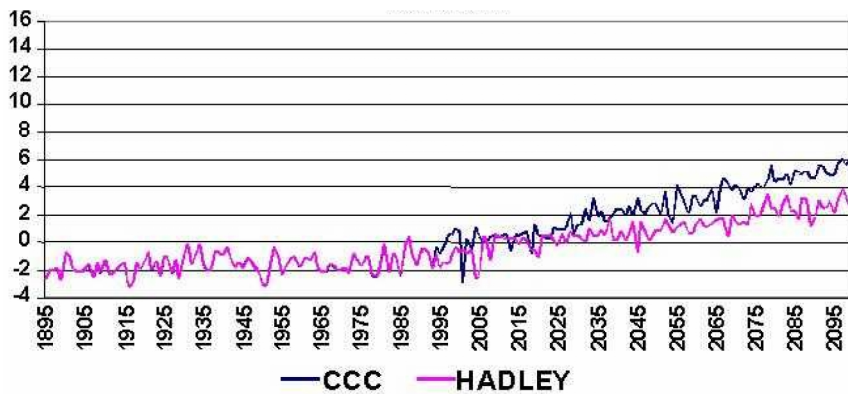
(a) Minimum temperature times series (ºC)
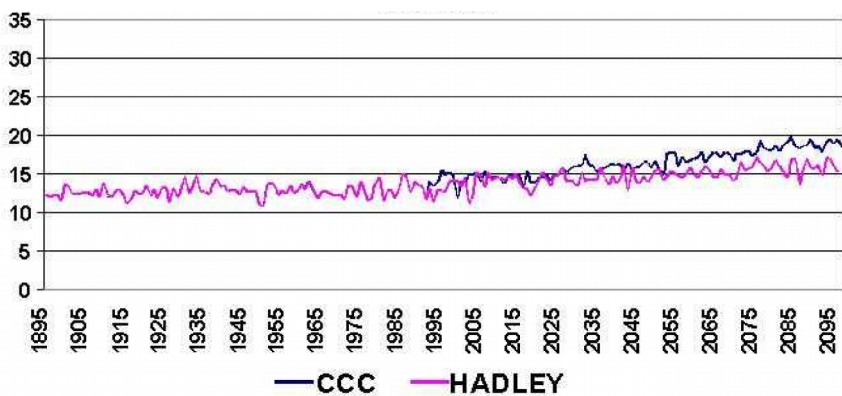
(b) Maximum temperature times series (ºC)
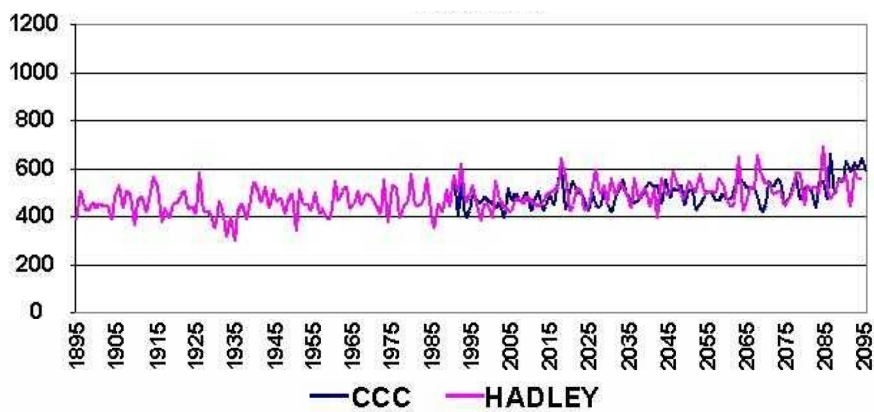
(c) Precipitation times series (mm)

Figure 4.1 Time series of temperature and precipitation in the Northern Great Plains (Ojima et al., 2002)

**Corn Harvested for Grain -
Change in Acreage: 2002 to 2007**

1 Dot = 2,000 Acres Increase
1 Dot = 2,000 Acres Decrease

United States Net Increase
+18,018,019

07-M166
U.S. Department of Agriculture, National Agricultural Statistics Service

**All Wheat Harvested for Grain -
Change in Acreage: 2002 to 2007**

1 Dot = 2,000 Acres Increase
1 Dot = 2,000 Acres Decrease

United States Net Increase
+5,412,993

07-M175
U.S. Department of Agriculture, National Agricultural Statistics Service

Figure 4.2 Changes in acreage for corn and wheat (Source:
http://www.nass.usda.gov/research/2002mapgallery/)

It has been projected that agricultural land use will continue to expand as a result of increasing demands for biofuels and global warming (National Research Council, 2008; Foley et al., 2004; Ojima et al., 1999). Biofuel crops (i.e. corn and soybeans) are expected to dominate the future agricultural landscape of the northern Great Plains as a result of (1) increasing demands for bioethanol stemming from the federal Renewable Fuel Standard (RFS) which requires increasing use of ethanol-blended gasoline (Brooke et al., 2009); and (2) rising average temperatures that will make the region (especially North Dakota) increasingly suitable for biofuel crops that prefer a warmer climate and longer growing season. It has also been noted, however, that shifts in climate and land use patterns may result in a range of potentially negative environmental consequences including elevated groundwater pollution risks (Kennedy, 2007; de Oliveira et al., 2005).

Traditionally, the methodologies used to evaluate groundwater pollution risk have been based on a "static" assumption that groundwater systems do not change significantly over time (Butscher and Huggenberger, 2009). However, groundwater pollution is strongly dependent on factors such as depth-to-water, recharge, and land use and land cover (LULC) conditions, all of which are influenced by climate conditions and land use. A warming climate, for example, could alter the vulnerability of shallow aquifers by affecting depth of the water table and recharge (Toews and Allen, 2009; Scibek and Allen, 2006; Pointer, 2005). Ducci (2005) proposed that patterns of regional groundwater pollution vulnerability will vary between drought, average, and wet periods. Apart from climate change, changes in LULC, and associated application rates of farm chemicals, could also affect groundwater vulnerability. For example, the expansion of corn

production will likely be accompanied by increased use of nitrogen-based fertilizers, a major source of nitrogen leaching into groundwater.

At present, there are significant gaps between studies of groundwater pollution vulnerability modeling, land use change and climate change. Few studies have focused on exploring the impacts of both climate change and land use change on groundwater vulnerability patterns, especially at the regional level. Decision-makers need better methods to identify "hotspots" that will facilitate allocation of resources for groundwater protection. This research presents an approach to modeling that integrates groundwater vulnerability, climate change, and land use change essential for future water quality management in the northern Great Plains region.

3 Study Area

North Dakota was selected as the study area because it is representative of the northern Great Plains states, a region that has been experiencing significant changes in both climate and land use. The state has a continental climate typified by cold winters and hot summers. As noted above, however, during the past century average temperatures in North Dakota have increased up to 3 °C (U.S. Global Change Research Program, 2000), among the highest in the Northern Great Plains.

Apart from climate change, North Dakota is also typical of the U.S.'s zeal for biofuels. Nine state incentive programs and six laws and regulations are in place to govern the biofuels' production, transportation and sale (U.S. Department of Energy, 2011). It has joined with Northern Great Plains states such as South Dakota, Nebraska and Iowa under

the Energy Security and Climate Stewardship Platform (Midwestern Governors Association, 2007) to create regional biofuels corridor program.

North Dakota spans four principal ecoregions (Figure 4.3): the Lake Agassiz plain, the Northern Glaciated Plains, the Northwestern Glaciated Plains, and the Northwestern Great Plains. The Lake Agassiz Plain, situated along the eastern edge of the state, features highly fertile soils and includes the most productive farmlands in the state. The regions west of the Lake Agassiz Plain gradually rise in elevation and have lower soil fertility. North Dakota is the leading producer of wheat, barley, sunflowers and dry edible beans in the U.S. However, since the late 1990s, cropland change in North Dakota has been characterized by rapid expansion of corn and soybeans (Schnitkey, 2010). Corn and soybeans have generally either displaced other crops (such as wheat and sunflowers) or been planted on lands formerly in the Conservation Reserve Program (CRP). In 1997, the
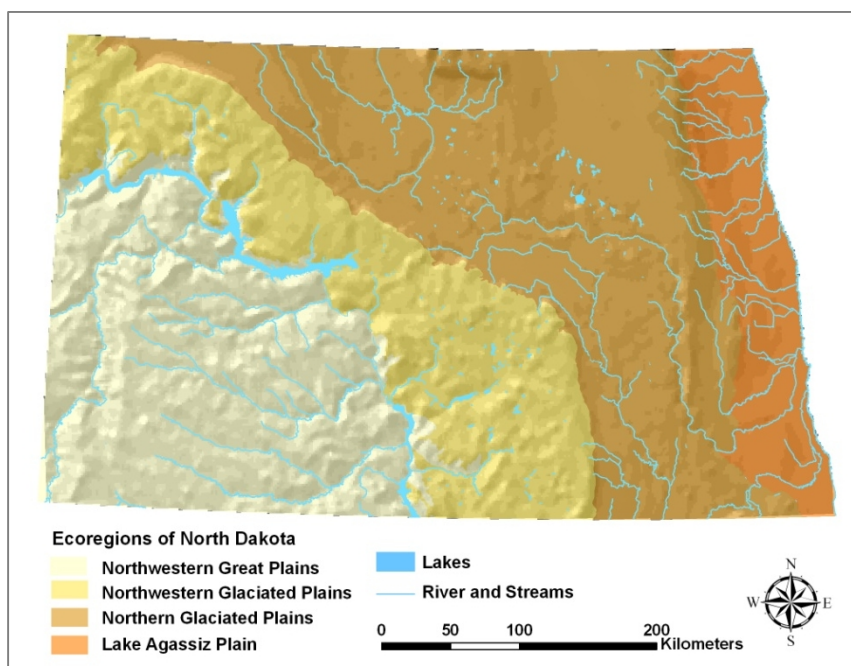
Figure 4.3 Major Ecoregions of North Dakota (The map was generated from U.S. Environmental Protection Agency (EPA) Level III Ecoregions and the U.S. Geological Survey (USGS) National Hydrography Dataset)

top three agricultural commodities were wheat, cattle and sunflower, accounting for 39.3%, 12% and 8.3% of the state total farm receipts respectively. By 2009, however, the three most important farm commodities changed to wheat, soybeans and corn at 29.4%, 16.1% and 12.7% respectively (Economic Research Service, 2010).

4 Methods

4.1 General Modeling Framework

Three sets of models, linked within a GIS environment (Figure 4.4), were used to forecast groundwater pollution vulnerability for two future periods (Years 2020 and 2050) under three scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES). The following subsections (4.2-4.7) summarize the development of: (1) future climate change scenarios, (2) future biofuels-related land use scenarios, (3) future groundwater recharge and groundwater level, and (4) future regional groundwater pollution risk. All geospatial modeling was carried out using ArcGIS software. Geospatial data were converted to raster format at a resolution of 1500 meters, a cell size approximating the size of a crop section in North Dakota and consistent with the largest scale of climate change models.

4.2 Basic Modeling Scenarios

Scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) were used for modeling (Nakicenovic et al., 2000). The SRES scenarios have been widely applied in climate change impact and adaptation studies conducted worldwide (Ruosteenoja et al., 2003). These scenarios, based on four narrative storylines designated as A1, A2, B1 and B2, describe possible
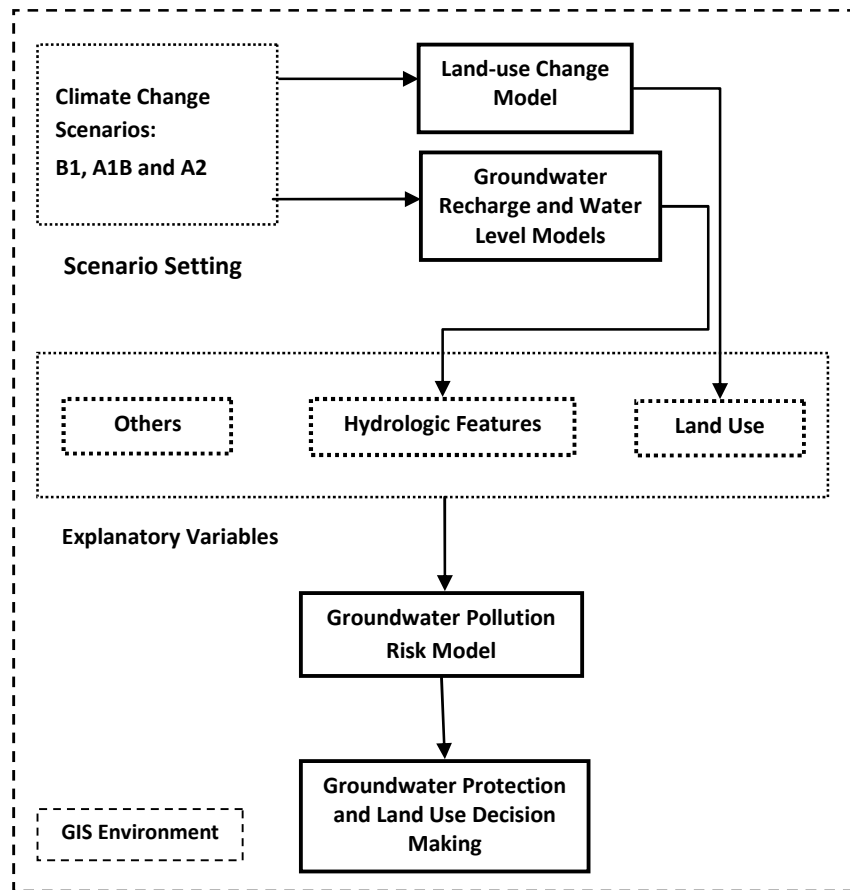
Figure 4.4 General modeling framework for model integration

alternative future demographic, social, economic, technological, and environmental developments (Figure 4.5), which can affect the projection of future greenhouse gas (GHG) emissions as well as global warming. The three specific scenarios employed in this study, B1, A2 and A1B, have been used with particular frequency by the climate change research community (Meehl and Hibbard, 2007):

- The B1 scenario envisions a future world having a high level of environmental and social consciousness combined with concerted global efforts towards sustainable development (Nakicenovic et al., 2000). This world use technology to achieve reductions in conventional energy usage, and exhibits increasing usage of

biofuels and wind energy. Under the B1 scenario, biofuel crops may expand rapidly to meet increasing demands for bioethanol and biodiesel fuels. Additionally, in this scenario demographic pressure is relatively low, and increases in food demands can be readily met by increasing productivity (Nakicenovic et al., 2000). Thus, more agricultural lands may be devoted to biofuel crops without affecting food safety. The B1 scenario represents the fastest pace of biofuels-related land use change.

- The A2 scenario is characterized by high demographic pressure, more limited environmental concerns, and high use of fossil fuels and nuclear energy. With rapid increase in population, arable lands are primarily used to produce food rather than biofuels. With the emphasis on food security, economic incentives for the biofuel industry are less likely to continue. Land use change driven by biofuels demands may diminish. The A2 scenario represents the slowest pace of biofuels-related land use change.

- The A1B scenario assumes a balance between conventional and new energy sources. It takes an intermediate position between the two extremes described by the respective storylines of the B1 and A2 scenarios (Nakicenovic et al., 2000). Thus, the A1B scenario represents a moderate pace of biofuels-related land use change.

It should be noted that the SRES scenarios exclude catastrophic futures, such as large scale economic and environmental collapse (Nakicenovic et al., 2000). In this research, the estimation of future biofuels-related land use is based on the three scenarios outlined above.

SRES Scenarios
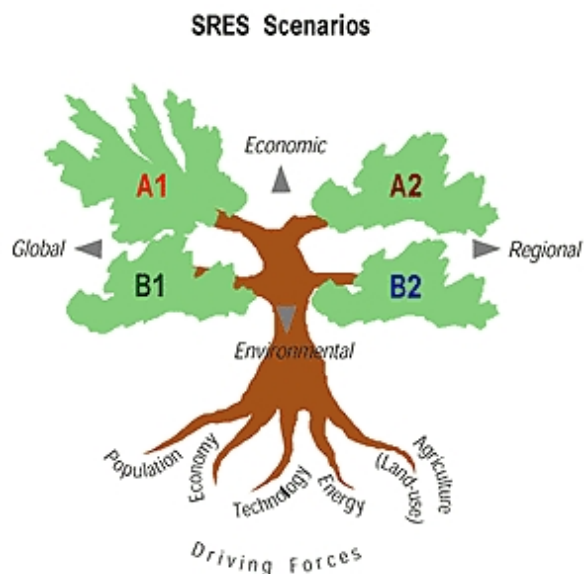
Figure 4.5 The schematic illustration of the four SRES storylines. The A1 and A2 families have a more economic focus than B1 and B2, which are more environmental, whilst the focus of A1 and B1 is more global compared to the more regional A2 and B2 (Nakicenovic et al., 2000)

4.3 Climate Change Scenarios

Apart from socio-economic, environmental and energy conditions, B1, A2 and A1B scenarios also assume different GHG emission levels, and hence differ in projections of surface temperatures. For example, A1B scenario forecasts the largest increase in global temperatures and B1 shows the least between about 2000-2060, while A2 exceeds A2b in global surface warming after 2060 (Figure 4.6). This is because the A1b scenario assumes higher GHG emission at the earlier period of the 21st Century. The IPCC SERS scenarios provide standard parameters for climate modelers to facilitate comparison of their projections.
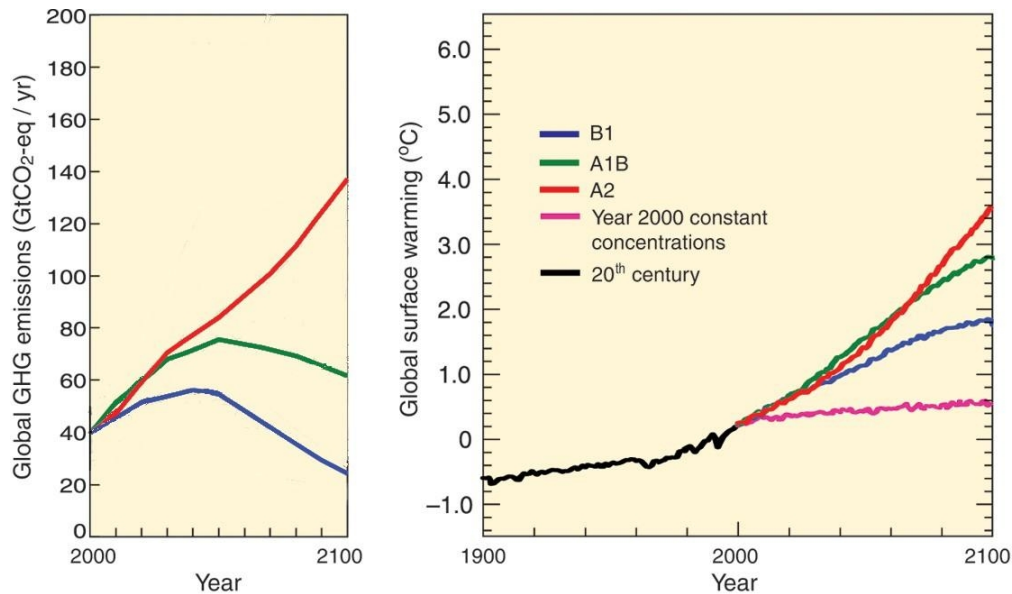
Figure 4.6 Atmosphere-Ocean General Circulation Model (AOGCM) projection of surface warming (the figure was reproduced based on IPCC, 2007)

The B1, A2 and A1B provided the foundation for the climate change projections in this study. An ensemble of statistically downscaled future climate change projections from 16 fully coupled atmosphere-ocean general circulation models (AOGCMs) such as CCSM3.0, GFDL_CM2.1, HadCM3.0, was obtained from Green Data Oasis (Maurer, et al., 2007). This archive contains a dataset of monthly temperature and precipitation projections during 1950-2099 over the contiguous United States at a 0.125-degree resolution. The original projections were generated from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset as referenced in the IPCC Fourth Assessment Report (Meehl et al., 2007). These data are typically produced and stored in netCDF or binary format, a format that cannot be directly utilized for spatial analysis in ArcGIS. It was, therefore, essential to convert these data into a GIS-compatible format for further analyses.

Average temperature and precipitation projection for the years 2010-2019, 2020-2029, 2030-2030, 2040-2049 and 2050-2059 were obtained from the Green Data Oasis in ASCII format. The ASCII data were converted to GeoTIFF format in batch by running Python programming codes in an OpenGIS framework (for the codes, see Appendix). These data were resampled at 1500 meters, a resolution consistent with the land use factor layer (see below).

To better reveal the spatiotemporal patterns of climate change over the Northern Great Plains, the future mean precipitation and temperature were visualized for North Dakota, South Dakota and Nebraska instead of North Dakota solely (Figure 4.7 and 4.8). These maps were produced by subtracting mean precipitation and temperature in 1970-2000 from those in different future periods. They portrayed the projected precipitation and temperature relative to a 30-year average for 1971-2000. As shown in Figure 4.7 and 4.8, most parts of the Northern Great Plains are predicted to exhibit increases in both precipitation and temperature, especially in the easternmost areas. In Figure 4.8, A1b showed higher warming trend than A2 in 2010-2059 because A1b shows greater warming tendency than A2 during this period, which is consistent with the general global warming trend shown in Figure 4.6.

4.4 Future Biofuels-related Land Use Change

In this study, corn and soybeans were considered to be "biofuels-related" LULC types because of their importance as bioethanol and biodiesel feedstocks (Horelik, 2008). Future change in biofuels-related LULC was modeled using linked "quantity" and spatial
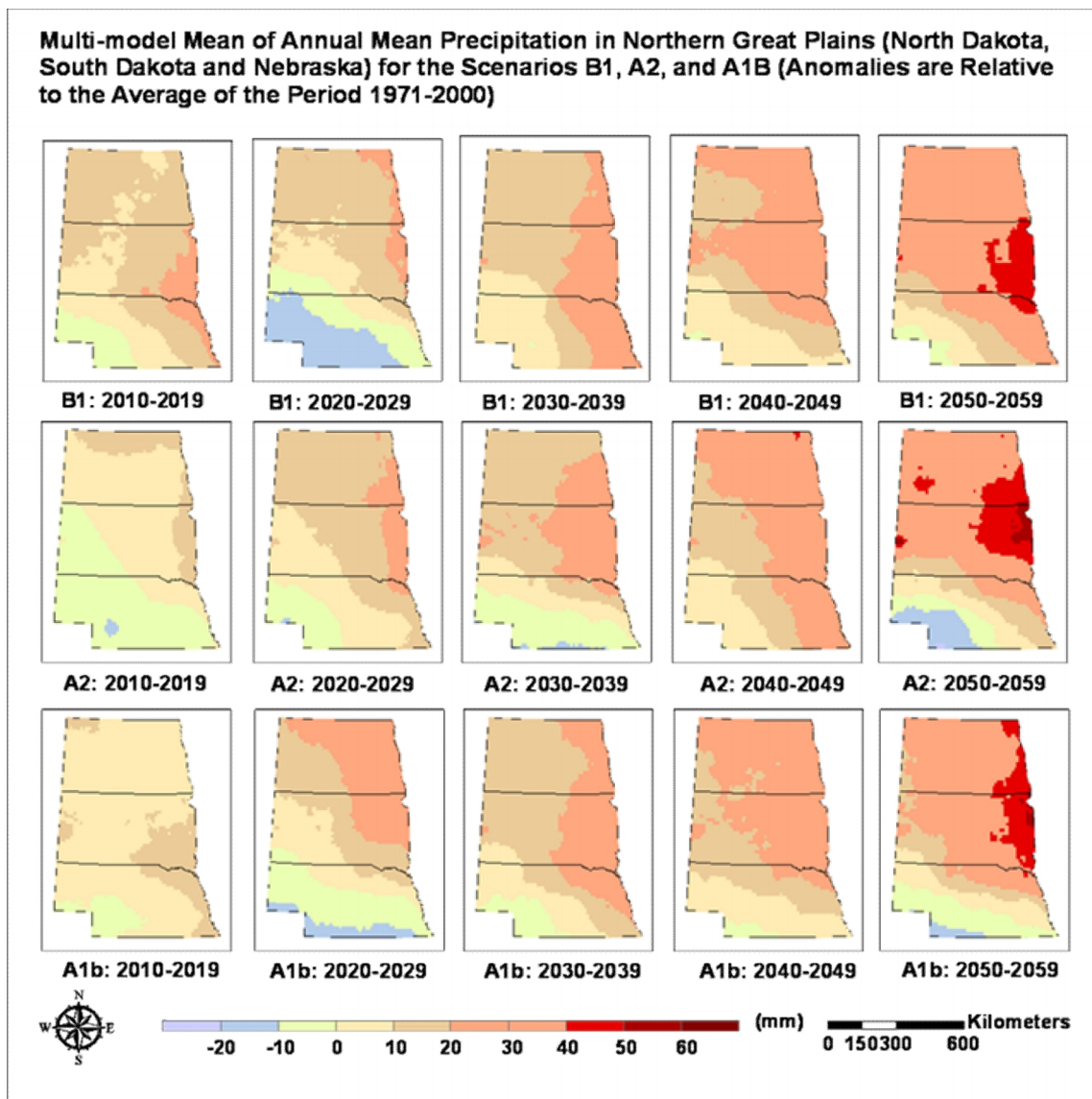
Figure 4.7 Changes in precipitation relative to the average period of 1971-2000 in the Northern Great Plains. The data were developed based on WCRP's CMIP3 multi-model dataset as referenced in the IPCC Fourth Assessment Report (Meehl et al., 2007)

allocation modules (Figure 4.9). The quantity module was employed to determine/ forecast the total amount of change in corn/soybean cropland (i.e., the number of cells of other LULC types to be transformed into corn/soybeans). The spatial allocation module
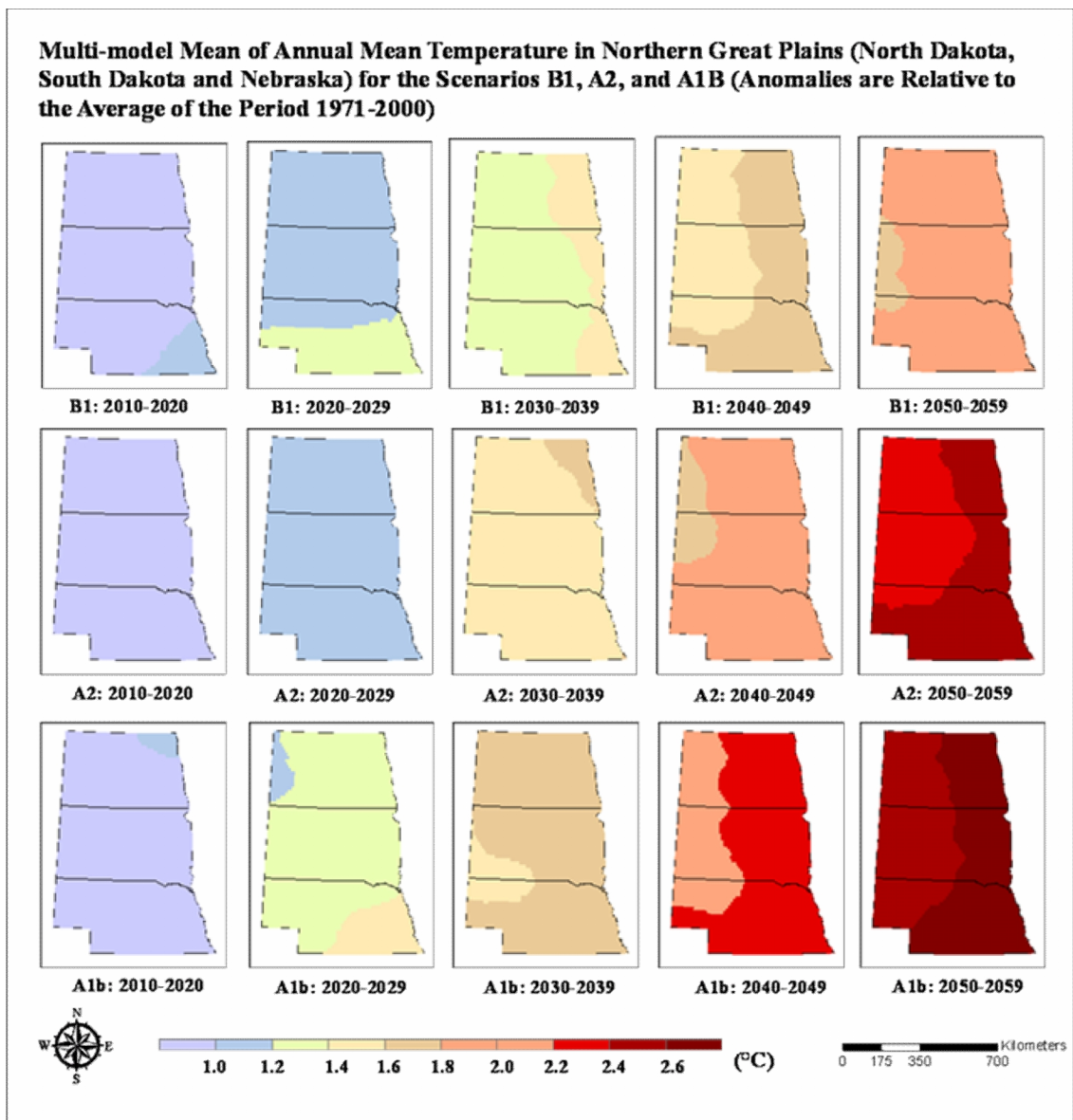
Figure 4.8 Changes in temperature relative to the average period of 1971-2000 in the Northern Great Plains. The data were developed based on WCRP's CMIP3 multi-model dataset as referenced in the IPCC Fourth Assessment Report (Meehl et al., 2007)

was then used to spatially distribute the projected changes (i.e., to determine which specific cells in the map grid to change from one LULC type to another).

It was assumed that future expansion of biofuel crops would occur first on lands having soils and climate most suitable for crop production and thereafter occur on lands less

suitable. The three SRES scenarios, described earlier, and corresponding climate change scenarios were used to guide modeling of future biofuels-related cropland change.
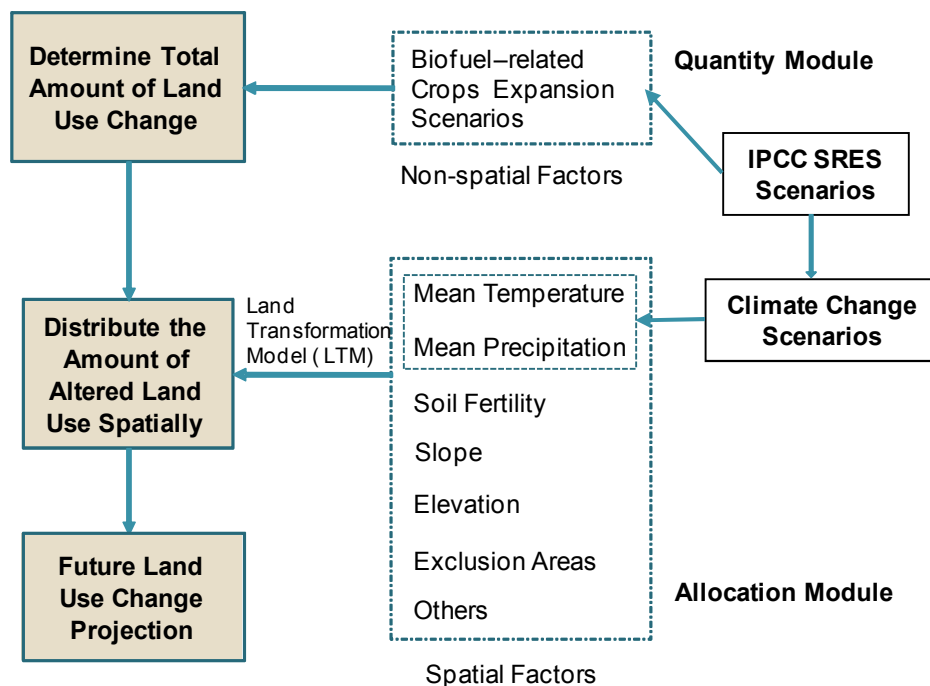
Figure 4.9 Framework to model biofuels-related land use change in response to different scenarios

Due to the qualitative nature of the SRES scenarios, they cannot be directly converted into quantitative data on biofuel crops. Estimates of future biofuels-related land use change were, therefore, made by combining the narrative descriptions of SRES scenarios (summarized above) with statistical extrapolation based on historical trends in crop acreages obtained from the National Agricultural Statistics Service (2010). It was assumed that the current high rate of increase in corn/soybean land will gradually slow due to factors such as increasing competitive use of corn/soybeans for food and biofuels (Horelik, 2008). S-shaped logistic growth models approximate the above growth pattern. Three logistic models, SLogistic1, SRichards1 and Five Parameter Logistic, were used to develop projections of future biofuels-related cropland (see http://www.originlab.com/

www/helponline/Origin/en/Category/Curve_Fitting_Functions.html). These logistic

functions provided areal estimates for the B1, A2 and A1B scenarios in the Year 2020

and Year 2050 (Figure 4.10).
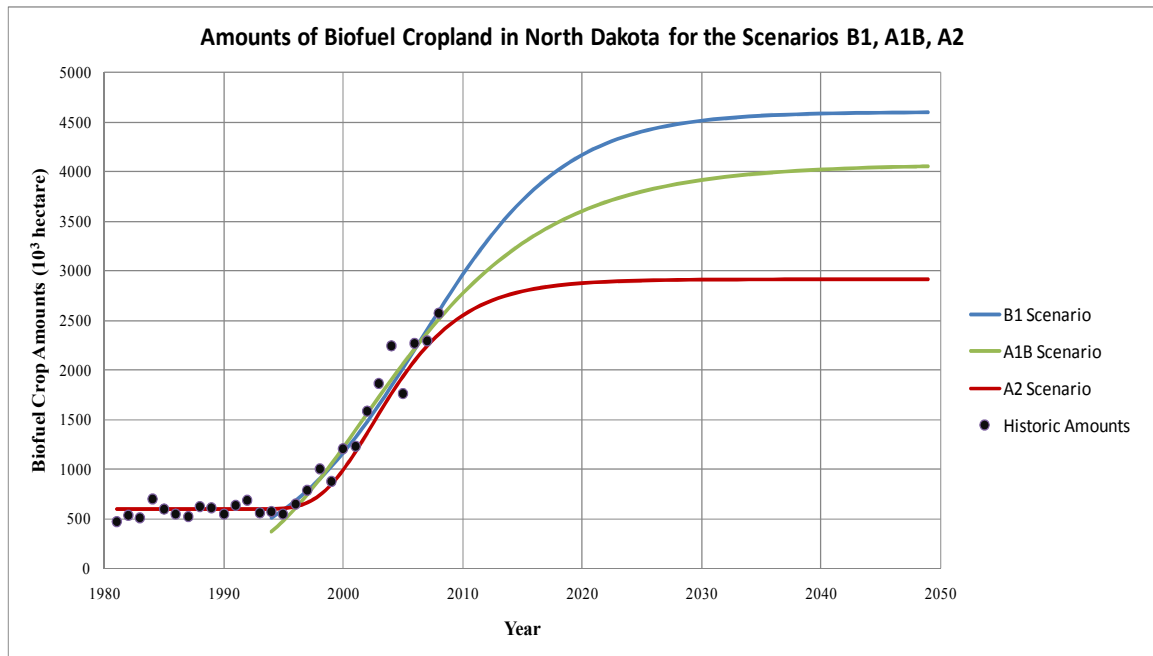
Figure 4.10 The amounts of biofuels-related cropland in North Dakota between 1980 and 2050. The figure was drafted based on agricultural statistical data from National Agricultural Statistics Service (2010)

The Land Transformation Model (LTM) was used to distribute the forecast LULC change

over the state of North Dakota. The LTM is a grid-based spatially explicit, well tested

and freely available model that integrates environmental and socio-economic drivers with

historic land use datasets to simulate LULCC (Pijanowski et al., 2002). The core of the

LTM is an Artificial Neural Network (ANN), which uses a machine learning approach

for modeling complex land use change. The ANN consists of an input layer comprised of

a set of nodes that represent driving factors, an output layer that represents the suitability

for biofuels-related cropland, and one or more hidden layers in between. The nodes

within adjacent layers are connected through Active Transfer Functions (ATFs). Through

a learning/calibration process using historical datasets, the LTM ANN adjusts the weights of ATFs to establish functional relationships between the driving factors and land use conversions. In other words, the ANN "learns" by acquiring knowledge based on the past history of land use change. Once trained, the ANN can be used to simulate land use change either retroactively, by attempting to replicate past observed changes, or to forecast future changes.

The model essentially generates a suitability map for croplands, and then selects the cells exhibiting the highest suitability to convert. Specifically, six steps were used to establish the model: (1) mapping historic cropland; (2) identifying driving factors; (3) preprocessing the raster layers for both land use and driving factors; (4) testing the model with all inputs; (5) calibrating and validating the model; and (6) identifying transitional cells to create possible scenarios of future land use. Six environmental variables were chosen as the driving factors for biofuel cropland modeling in North Dakota: terrain elevation, terrain slope, soil organic matter, Cation Exchange Capacity (CEC) of the soil, mean precipitation (1971-2000), and mean temperature (1971-2000). All are important to establishing the suitability of land for supporting crops (e.g., Bowen and Hollinger, 2002; Kravchenko and Bullock, 2000). U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Cropland Data Layers (CDLs) for North Dakota (www.nass.usda.gov/research/Cropland/SARS1a.htm) were used to map historic cropland change, because they provide specific cropland information for North Dakota over a relatively long time period (8-13 years). In addition, exclusionary zones (e.g. urban lands, wildlife protection areas, and water bodies) where future cropland growth

would be prohibited were established. It was assumed that other "non-agricultural" land use types remained relatively static during the modeled time period (2000-2050).

The model was calibrated and validated using 30m-resolution land use data obtained from the North Dakota CDLs for the years 1999, 2000, 2004. 2005, 2007 and 2008 (for details, see Chapter 3). Areal estimates of biofuel crops for the B1, A2 and A1B scenarios provided in the quantity module and corresponding climate change scenarios (i.e. precipitation and temperature) were then plugged into our calibrated model to calculate the future distributions of biofuel crops (Figure 4.9).

4.5 Future Groundwater Recharge Affected by Climate Change

A number of studies have indicated that climate change may affect groundwater recharge (Scibek and Allen, 2006; Holman, 2005; Eckhardt and Ulbrich, 2003). Increases in precipitation, for example, would generally be expected to produce greater aquifer recharge rates (Rosenzweig et al., 2007). Many modeling techniques have been used to determine the potential impacts of climate change on groundwater recharge. These include soil-water balance models (Toews and Allen, 2009; Scibek and Allen, 2006; Arnell, 1998), empirical models (Chen et al., 2002), and distributed models (Croley and Luukkonen, 2003; Eckhardt and Ulbrich, 2003). However, these methods are generally technically complex and unsuitable for large regional analyses since the data on key physical parameters are usually not available.

In this study, the percolation index (PI) method was used to estimate future average annual water flow through the soil (Hamza et al., 2007; Braun et al., 2003; Williams and

Kissel, 1991). The equation to calculate recharge is as follows. As noted below (Eq. 4.1), the model was originally formulated using English rather than the metric units.

Hydrologic Group	Equations
A	$PI = (P - 10.28)^2/(P + 15.43),$
B	$PI = (P - 15.05)^2/(P + 22.57),$
C	$PI = (P - 19.53)^2/(P + 29.29),$
D	$PI = (P - 22.67)^2/(P + 34.00),$

Eq. 4.1

Where PI is the percolation index (inches/year), P is the precipitation (inches/year), and A, B, C and D are hydrologic soil groups. In North Dakota, 99% of agricultural croplands are not irrigated (Jia et al., 2007); therefore irrigation was not considered in this research. Based on Eq. 4.1, future groundwater recharge was estimated using precipitation from the precipitation projection dataset (see Section 4.3) and hydrologic soil group. The spatial distribution of hydrologic soil groups was derived from the U.S. General Soil Map (STATSGO) using the Soil Data Viewer (http://soils.usda.gov/sdv/) developed by USDA. The ArcGIS Raster Calculator was used to implement the model.

4.6 Future DTW Conditions

Depth-to-water (DTW), defined as the distance from the ground surface to the groundwater table, impacts the time required for contaminants to reach the water table. As DTW increases, the probability of groundwater pollution generally decreases. DTW levels are controlled by the balance among recharge to, storage in, and discharge from an aquifer. Forecasting the DTW in response to climate change usually requires complex numerical modeling (Scibek and Allen, 2006; Yang and Xie, 2003), which also involves considerable uncertainties related to downscaled climate models, aquifer heterogeneity,

and other parameters (Scibek and Allen, 2006). Modeling can be complicated by groundwater pumping for irrigation as well as industrial and residential demands (Bates et al., 2008). In this study, changes in DTW were estimated using the water-table fluctuation (WTF) method, a method that relates changes in water-table level measured in unconfined aquifers with recharge water arriving at the water table (Rasmussen and Andreason, 1959). The method is implemented with an equation (Eq. 4.2) expressed as:

$$R(t_j) = S_y \times \Delta H(t_j) \qquad \textbf{Eq. 4.2}$$

where $R(t_j)$ is recharge occurring between initial time t_0 and ending time t_j, S_y is specific yield (dimensionless), and $H(t_j)$ is the peak water level rise attributed to the recharge period. It is assumed that long-term DTW fluctuations, over periods of decades, can be attributed to changes in recharges due to climate alteration. The water-table change in North Dakota was estimated using the projected increase of recharge (based on Section 4.5) and specific yield. The specific yield in North Dakota was estimated to be approximately 0.15 (Schuh and Patch, 2009; Burkart, 1981). The specific yield is defined as the ratio of the volume of water that will yield by gravity to the total volume of saturated soil or rock (a dimensionless value).

The DTW for the current period (t_0) was modeled using data extracted from, respectively, the USGS Active Groundwater Level Network and the North Dakota State Water Commission Surface and Ground Water Data Portal (http://www.swc.state.nd.us/4dlink2/ 4dcgi/wellsearchform/Map%20and%20Data%20Resources). The data were retrieved using a web query function of Microsoft Excel and stored in Excel spreadsheets. Locations of surface water features, such as major streams, lakes, wetlands, and springs were obtained from the USGS National Hydrography Dataset (NHD) and used to indicate

where the DTW approximates 0 (Snyder, 2008). ArcGIS was used to randomly plot

1,000 points (where the DTWs are 0) on these surface water features. The DTW surface

was estimated based on an integration of interpolated water table depth and water table

elevation, a method proposed by Snyder (2008) (for details, see Section 3.3.1, Chapter 2).

The DTW map for the year 2000 is shown in Figure 4.11.
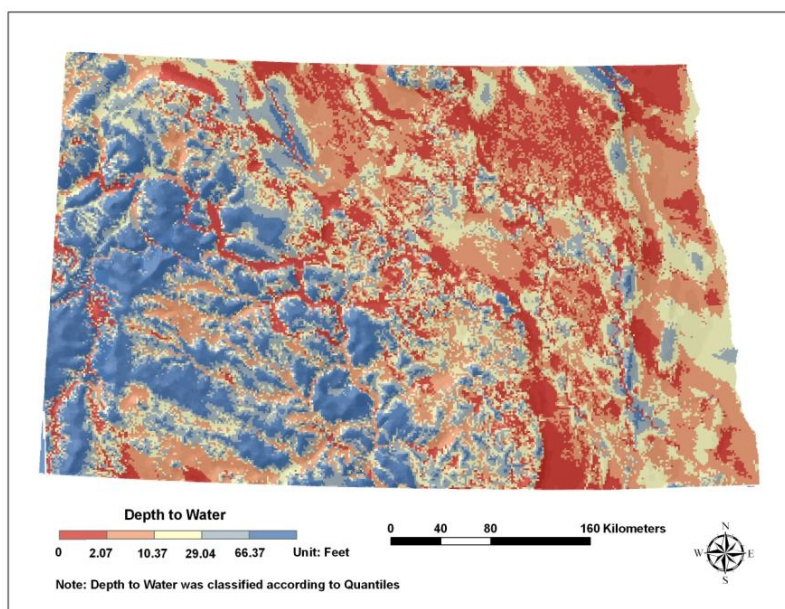
Figure 4.11 The DTW map for North Dakota for the year 2000

4.7 Other Factors

Several other factors were used to model groundwater pollution risk. These included soil,

topography (slope) and the characteristics of the vadose zone. These factors were

considered static in this study.

4.7.1 Soils Data Layer for North Dakota

Soils serve as the dominant sink for retention of nitrate (Barrett and Burke, 2002), and

impact the leaching of nitrate to deeper horizons. In this study, soils in North Dakota

were characterized according to their nitrate attenuation property. Five soil properties

(percentages of sand, silt and clay, saturated hydraulic conductivity (Ksat), and organic matter contents (OM)) were extracted from the U.S. General Soil Map (STATSGO) to represent the nitrate attenuation property. A factor analysis was conducted to reduce the collinearity among the soil characteristics (Ige et al., 2007), and produce a soil index reflecting this property. The first component was observed to account for most of the total variance (71%), and therefore this component was used to represent the composite soil characteristics in subsequent research (see Table 4.1).

Table 4.1 Component Score Coefficient Matrix

	Component
	1
Sand	-.294
Clay	.262
Silt	.256
Ksat	-.257
OM	.138

The index is positively correlated with contents of organic matter and percentage of silt and clay, but negatively associated with the saturated hydraulic conductivity and the percentage of sand. This index is indicative of the groundwater pollution attenuation property of the soil.

$$Soil\_Index = -0.294 Sand + 0.262 Clay + 0.138 OM - 0.257 Ksat \quad \textbf{Eq. 4.3}$$

Finally, based on Eq. 4.3, a map layer of the soil index was developed (Figure 4.12). A higher index value indicates higher nitrate attenuation potential, and vice versa.
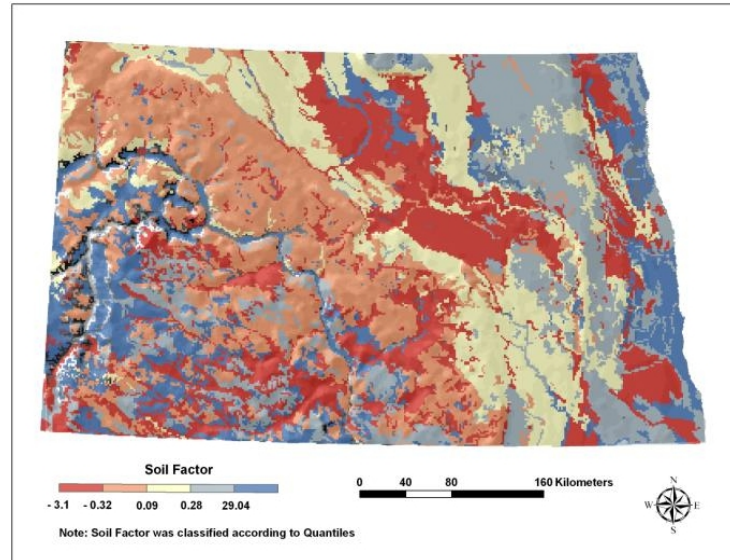
Figure 4.12 The soil factor map for North Dakota

4.7.2 Slope Data Layer for North Dakota

Slope affects the likelihood that a contaminant deposited on the land surface will infiltrate the soil. As slopes become increasingly steep, pollutants are more likely to runoff than to seep into the subsurface (Aller et al., 1985). Slopes were derived from the 30m National Elevation Dataset (http://seamless.usgs.gov/) using the slope program in ArcGIS (Figure 4.13).

4.7.3 Impact-of-the-Vadose-Zone Data Layer for North Dakota

Characteristics of the vadose zone media, the unsaturated area below the soil profile and above the unconfined water table, are important for assessing nitrate attenuation processes such as biodegradation, chemical reaction, volatilization, and dispersion. Silt and clay in the vadose zone can increase the time and opportunities for attenuation. The thickness of silt and clay in the vadose zone media was used as an indicator of the impact of the vadose zone on nitrate attenuation. This factor was derived from lithologic records
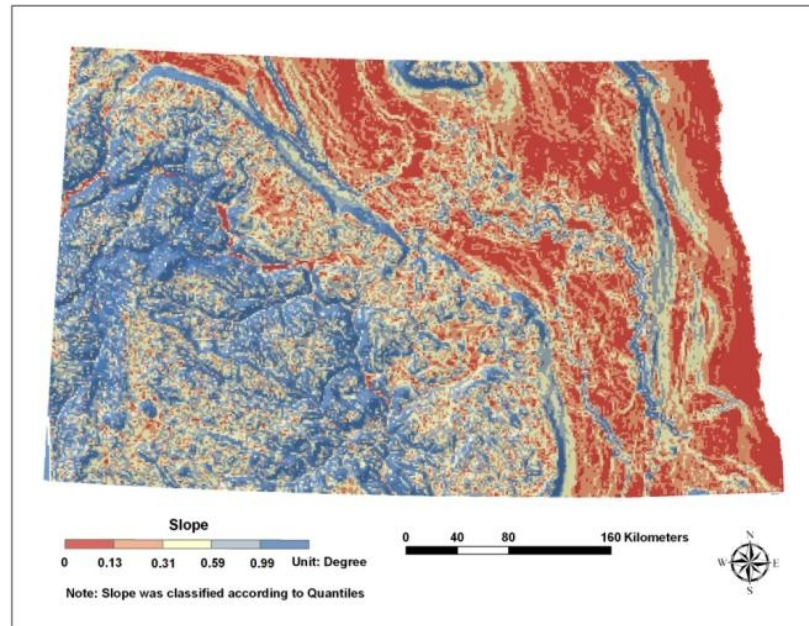
Figure 4.13 The slope map for North Dakota

in the Surface and Ground Water Data Portal administered by the North Dakota State Water Commission. Lithologic descriptions for each record were reclassified into one of six groups: silt/clay, sand/gravel, sand/silt/clay, sandstone/limestone, bedrock and other hard materials (such as shale and lignite). The percentage of silt/clay was computed by dividing the accumulated thickness of silt/clay above the water table by the DTW in each test hole. The DTW in each test-hole location was queried from the DTW map layer. The percentages of silt/clay in test holes were interpolated using kriging to a surface for the study area. Finally, the thickness of silt/clay in VZM was generated by multiplying the layers of silt/clay percentage in the VZM and DTW using the ArcGIS Raster Calculator (Figure 4.14).
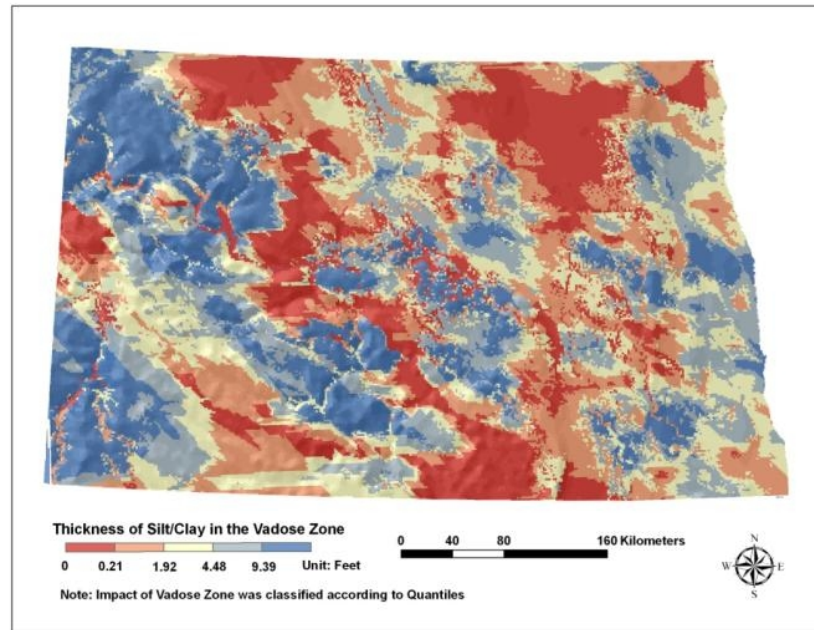
Figure 4.14 The impact-of-the-vadose-zone map for North Dakota

4.8 Groundwater Vulnerability Modeling

A revised DRASTIC model, DRSTIL (Eq. 4.4), was employed to model groundwater vulnerability. Each of the DRSTIL factors (**D**epth-to-water table, **R**echarge (net),**S**oil media, **T**opography, **I**mpact of the vadose zone, **L**and use) was assigned ratings and a numerical weighting to reflect its relative importance in estimating groundwater pollution potential. Ratings are intended to reflect the relative significance of data values (mapped "classes") within each factor (Merchant, 1994). For example, locations where the water table is deep below the surface are assumed to be less vulnerable to pollution than locations where the water table is shallow because, all other things being equal, the greater depth-to-water should indicate lower likelihood of contaminants reaching an aquifer. Therefore, areas having greater depth-to-water are assigned a lower numerical rating than locations with a shallower water table. All factors were assigned ratings on this basis (see Aller et al., 1985). The ratings for the land use factor were assigned based

on the nitrate fertilizer application guide recommended for different crops in North Dakota (Franzen, 2009) (Table 4.2). A departure from the standard approach to assignment of ratings was adopted for this research. The ratings for each factor layer (in the ESRI Grid format) were assigned by normalizing the grid values of the layer to a 0-1 scale. For factors with larger values indicating higher pollution potentials (e.g. recharge and land use), the ratings were calculated using the following approach: (V − min V)/(max V − min V), where V, min V and max V represent the values, maximum value and minimum value of the factor in the original dataset. For factors with smaller values corresponding to higher pollution potentials (e.g. DTW, soil, topography and impact-of-vadose-zone), the ratings were normalized as: (max V −V)/(max V − min V). This approach allows variables to have different means and standard deviations but equal ranges.

$$\textbf{Groundwater Vulnerability Score} = \mathbf{D_R D_w + R_R R_w + S_R S_w + T_R T_w + I_R I_w + L_R L_w}$$

Where

  R: Rating
  W: Weight

D Depth to Water
R (Net)Recharge
S Soil Media
T Topography (Slope)
I Impact of the Vadose Zone
L Land Use

Eq. 4.4

Weights were assigned to each factor following guidelines given in the DRASTIC documentation (Aller et al., 1985). Aller (et al., 1985) proposed two approaches for weighting the factors in DRASTIC: a pesticide and a general version. Pesticide weights were designed to reflect the processes that most affect pesticide transport into the subsurface with particular focus on soil (Frederick, 1991; Aller et al., 1985). General

Table 4.2 Ratings for different land use and land cover types

Crop Type	Soil Nitrate plus Fertilizer Nitrate Required (pound/acre)	Ratings
Alfalfa	0	0
Barley	160	0.68
Canola	150	0.64
Corn	235	1
Dry Edible Beans	80	0.34
Pasture/Range	50	0.21
Potatoes	200	0.85
Sorghum	132	0.56
Soybeans*	0	1
Sugar Beets	130	0.55
Sunflower	125	0.53
Spring and Drum Wheat	50	0.21
Safflower	100	0.43
Water/Wetlands	0	0
Urban/Barren	0	0
Woodland/Shrubland	0	0

*Corn and soybeans, typically grown in rotational cycles, present similar or even higher contaminant leaching potentials to continuous corn (Zhu and Fox, 2003; Klocke et al., 1999; Randall et al., 1997), although soybeans can fix nitrogen and do not require fertilizer input. Continuous corn production may create smaller annual percolation below the root zone when compared corn-soybeans rotations (Thomas et al., 2009).

DRASTIC weights were recommended for use in studying other potential pollutants such as application of fertilizers (Frederick, 1991). Since the focus of this research is on the vulnerability of groundwater to pollution from nitrates, the weightings for each factor were derived from those developed for the general DRASTIC (Table 4.3). Although land use was not included in the original DRASTIC model, it was assigned the largest weight due to its direct relationship with nitrate pollutant loadings.

Table 4.3 Weights of the DRSTIL Factors

Factor	Weight
Depth-to-Water	5
Recharge	4
Soil	2
Topography	1
Impact of the Vadose Zone	5
Land Use	5

5 Modeling Results

5.1 Future Land Use Scenarios

Areas planted to corn and soybeans, crops often used for biofuels, are projected to expand northward and northwestward under all future scenarios (see Fig 5.15 and 4.16). Table 4.4 shows the areal differences in the biofuels-related cropland between different SRES scenarios and ecoregions in North Dakota. In general, the B1, A2 and A1B scenarios all suggest expansion of biofuels-related cropland between the years 2020 and 2050 in the Lake Agassiz Plain and Northwestern Glaciated Plains. In the Northern Glaciated Plains, while B1 and A1B scenarios indicate expanding trend of biofuels-related cropland between the years 2020 and 2050, a reduction of biofuels–related cropland is observed under the A2 scenario (Table 4.4). This apparent anomaly may be attributed to potentially reduced land suitability for biofuels-related crops affected by future climate change. In the Northwestern Great Plains, no biofuels–related cropland was projected to distribute in this region for the year 2020 and 2050.
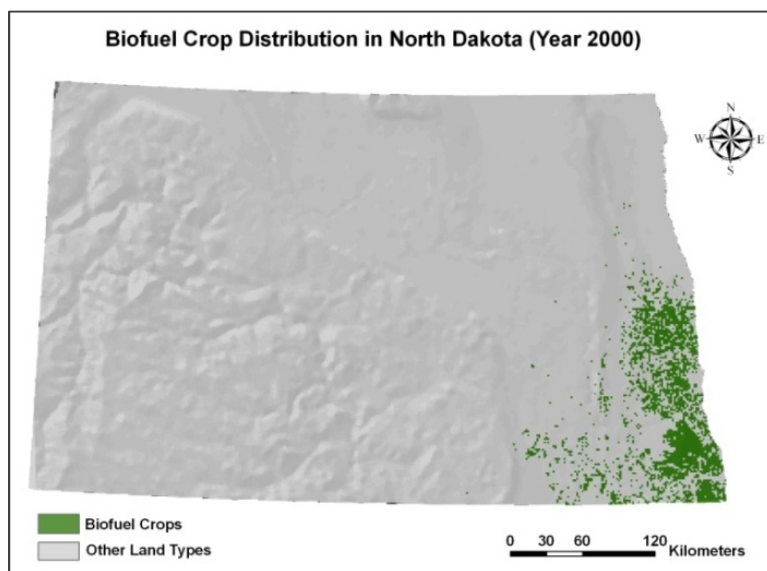
Figure 4.15 biofuels-related land use for the year 2000 in North Dakota
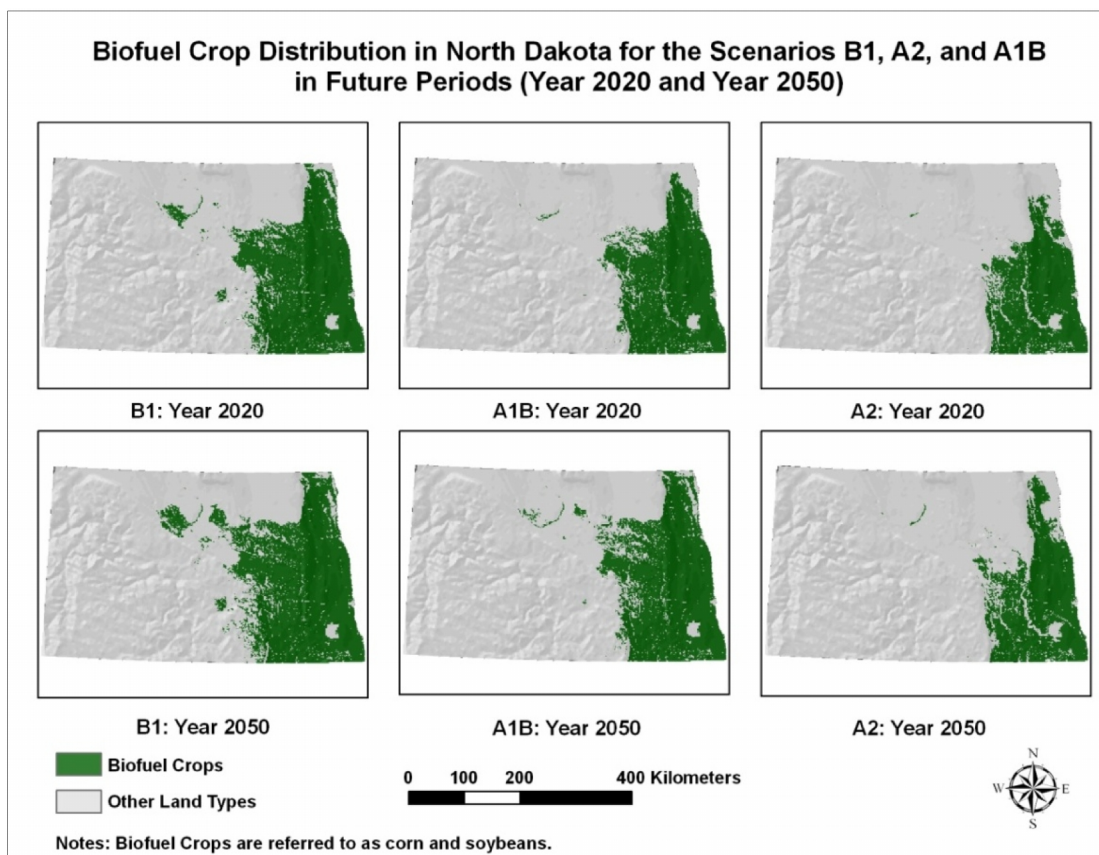
Figure 4.16 Projected biofuels-related land use Change in North Dakota

Table 4.4 Areas of biofuels-related crops in North Dakota (10^3 hectares)

Ecoregion \ Scenarios	Lake Agassiz Plain	Northern Glaciated Plains	Northwestern Glaciated Plains	Northwestern Great Plains
B1: Year 2020	1547.33	2745.90	227.25	0.00
A1B: Year 2020	1512.00	2333.93	67.50	0.00
A2: Year 2020	1156.95	1757.03	14.40	0.00
B1: Year 2050	1590.53	3150.90	319.05	0.00
A1B: Year 2050	1573.88	2727.00	78.30	0.00
A2: Year 2050	1296.00	1652.40	17.78	0.00
B1: Changes during 2020-2050	43.20	405.00	91.80	0.00
A1B: Changes during 2020-2050	61.88	393.07	10.80	0.00
A2: Changes during 2020-2050	139.05	-104.63	3.38	0

The greatest increases in biofuel cropland are projected to occur in the Lake Agassiz Plain and Northern Glaciated Plains ecoregions (Table 4.4). Compared with other regions of North Dakota, these two ecoregions feature fertile soil, lower elevation, flat topography, warmer temperature and abundant precipitation, and thus present the highest suitability for the cultivation of biofuel crops. The largest area of cropland development is projected to occur under the B1 scenario, while the A2 scenario shows the fewest hectares of LULC change. This difference can be attributed to the differing assumptions of future demands for cleaner energy described in the basic scenarios. Under the B1 scenario, high demands for cleaner energy, especially biofuels, would tend to favor expansion of lands devoted to corn and soybean production. By contrast, under the A2 scenario, the socio-economic priority is to meet food demands of an increasing population rather than demands for cleaner energy. Therefore, LULC change would tend

to result in additional areas devoted to food crops such as wheat rather than to biofuel crops alone; thus, the area of corn and soybeans under the A2 scenario would likely be lower than under the B1 scenario.

5.2 Future Recharge Scenarios

Figure 4.17 shows higher changes in groundwater recharge affected by climate change in southeastern North Dakota than in other regions. In general, 0.25-0.5 inches of changes in recharge may occur in southeastern North Dakota for most of the future scenarios. According to Eq. 4.1, projected future precipitation patterns are critical to the differences in recharge changes among B1, A2 and A1B scenarios. For example, highest changes in recharge have been projected to occur for A1B scenario in 2020 and for A2 scenario in 2050, because A1B and A2 scenario correspond to the largest increase in precipitation during these two periods respectively (Figure 4.7). This difference may be explained by Figure 4.6: A1B scenario is associated with the highest warming trend at the earlier period of the 21st Century, but then A2 scenario supersede A1B scenario afterward.

5.3 Future DTW Scenarios

Most parts of Eastern North Dakota are projected to increase 1-5 inches in 2020 and 2050 under all scenarios. In 2020, A1B scenario shows largest increase in groundwater level in response to highest increase in groundwater recharge (see Figure 4.18). While, A2 scenario presents largest increase in groundwater level in 2050 because groundwater recharge is greatest under A2 scenario in the same period (Figure 4.18). Similar to groundwater recharge, the differences of changes in DTW among B1, A2 and A1B scenarios can be explained by the differing projected future precipitation patterns.

Increases (or decreases) in precipitation can enhance (or reduce) water recharged to the aquifer, and hence elevate (or diminish) groundwater levels.
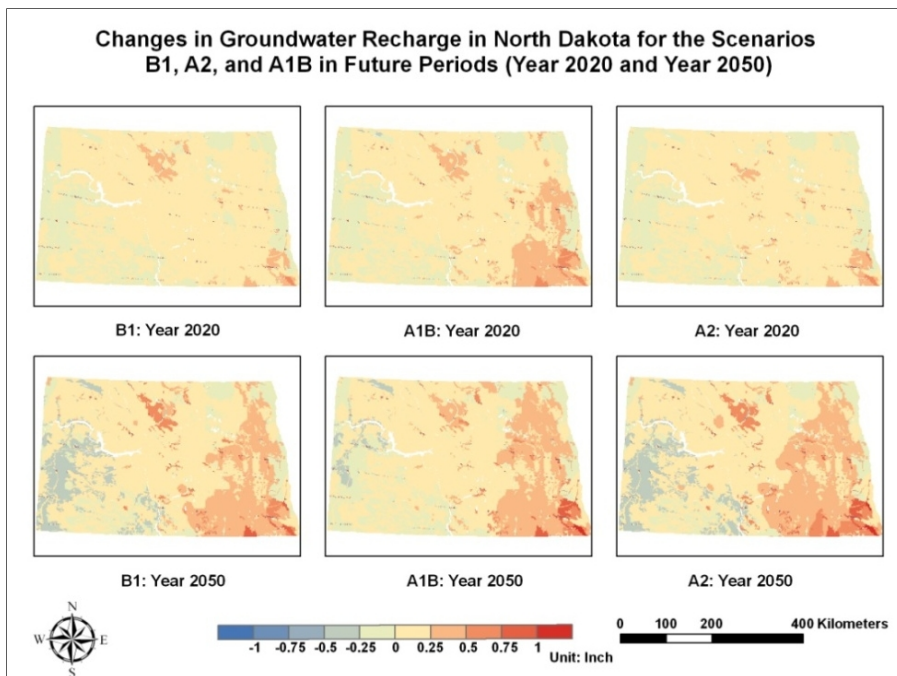
Figure 4.17 Projected groundwater recharge change in North Dakota (the changes are relative to the average period of 1971-2000)
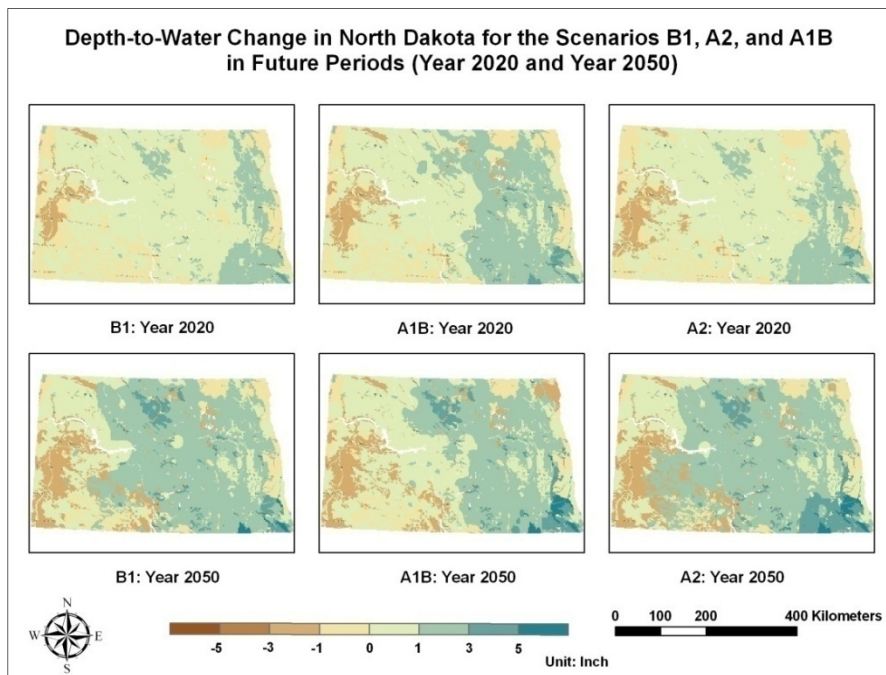
Figure 4.18 Projected DTW change in North Dakota

5.4 Modeled Current and Future Groundwater Vulnerability Patterns

Both current and future groundwater vulnerability maps were developed as described above (Section 4.8 and Figures 4.19 and 4.20). For the current period (Year 2000), the areas with the highest groundwater vulnerability were primarily in southeastern North Dakota. However, groundwater vulnerability patterns are expected to shift significantly under all future scenarios. The greatest increases in groundwater pollution potential are projected to occur in the Lake Agassiz Plain and Northern Glaciated Plains ecoregions. Thus, Eastern North Dakota may face higher groundwater pollution risk in the near future.

Groundwater pollution potential shows the greatest increase under the B1 scenario. This is most likely attributable to expanded cultivation of corn and soybeans that is associated with higher fertilizer inputs and nitrate leaching potentials. The A2 scenario shows somewhat lower groundwater pollution risks overall, perhaps primarily due to lesser expansion of corn and soybeans. The observed similarities between patterns of groundwater vulnerability and biofuels-related land use (Figure 4.16 and 4.20) may be explained by the high weights assigned to the land use factor, because land use is directly related to nitrate pollutant loadings. For B1, A2 and A1B scenarios respectively, the increase in groundwater vulnerability between 2020 and 2050 may not be as significant as that between 2020 and 2050, because biofuels-related cropland in North Dakota is projected to increase most rapidly from 2000 to around 2020, and then slow down and approach to its expanding capacity after 2020 (Figure 4.10).
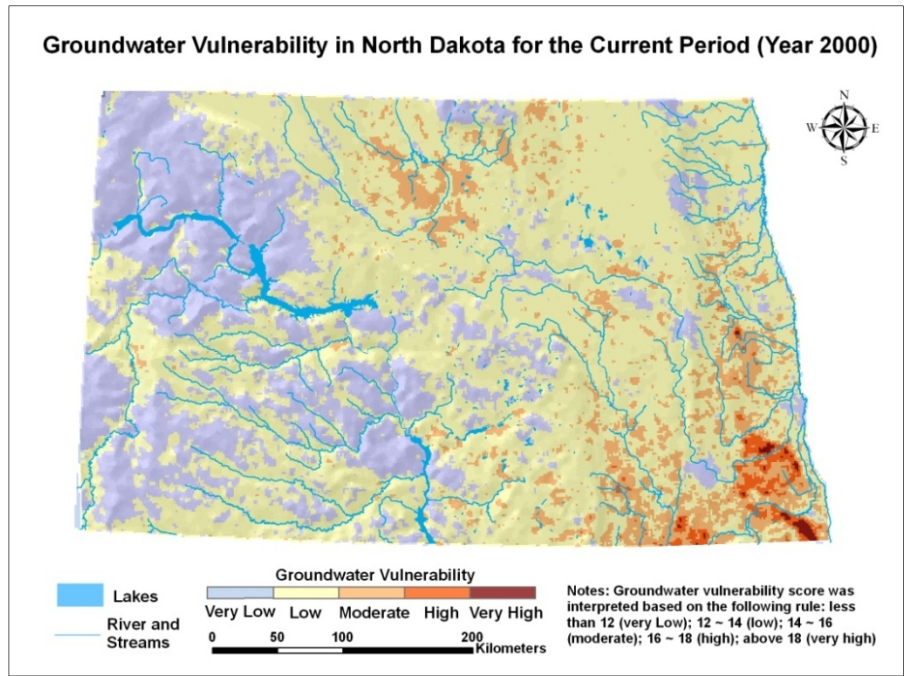
Figure 4.19 Groundwater vulnerability in North Dakota for the current period (current period)
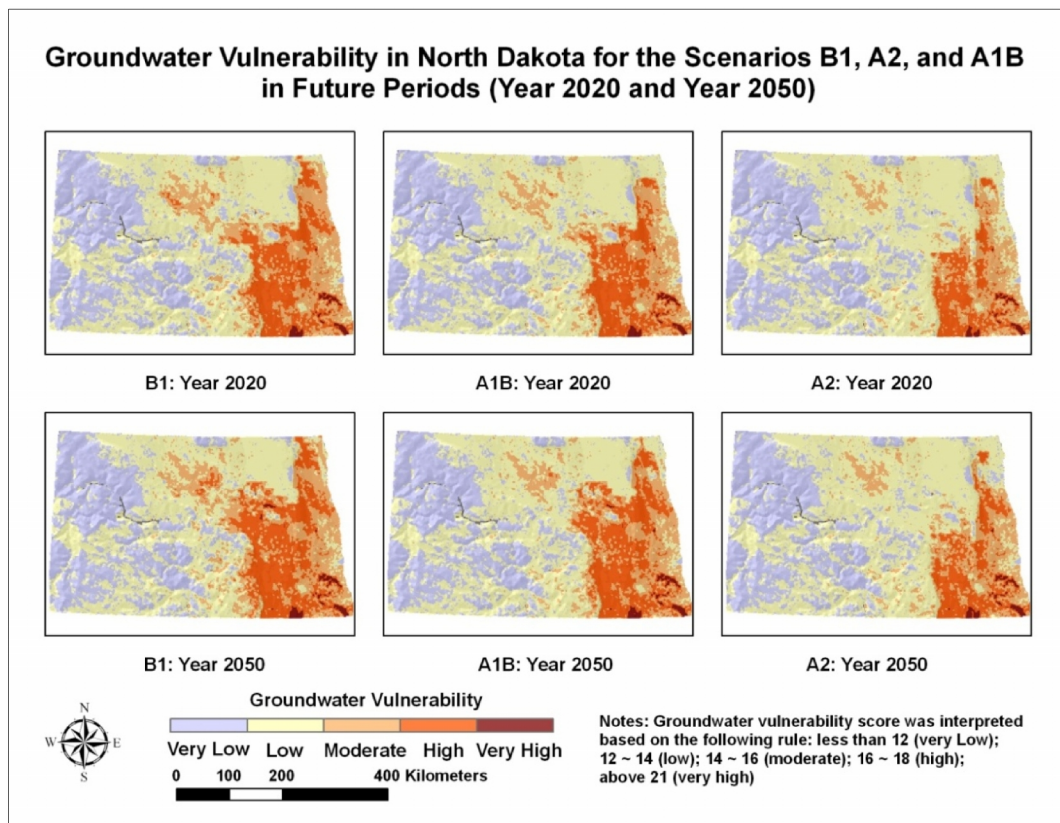
Figure 4.20 Projected groundwater vulnerability in North Dakota

Ideally, the results of the groundwater pollution modeling should be validated by comparing them to observed nitrate concentrations from groundwater quality monitoring wells (Figure 4.21). Unfortunately, the groundwater quality monitoring wells are highly clustered and sparsely distributed, and thus the validation was not possible using this methodology. As an alternative, results of modeling were assessed by comparing a national risk map of groundwater contamination by nitrate (Figure 4.22) and the year 2000 map of Pesticide DRASTIC Map for North Dakota developed by the North Dakota Health Department (Radig, 1997) (Figure 4.23). Generally, Figure 4.22 shows a close pattern of groundwater vulnerability to nitrate to our modeled current groundwater vulnerability (Figure 4.19). While the map was developed at the national scale, it clearly indicates that areas with highest vulnerability occur in the southeastern part of the state. Although the pesticide map (Figure 4.23) was developed using a somewhat different model formulation, it also shows similar groundwater vulnerability patterns (Figure 4.19).
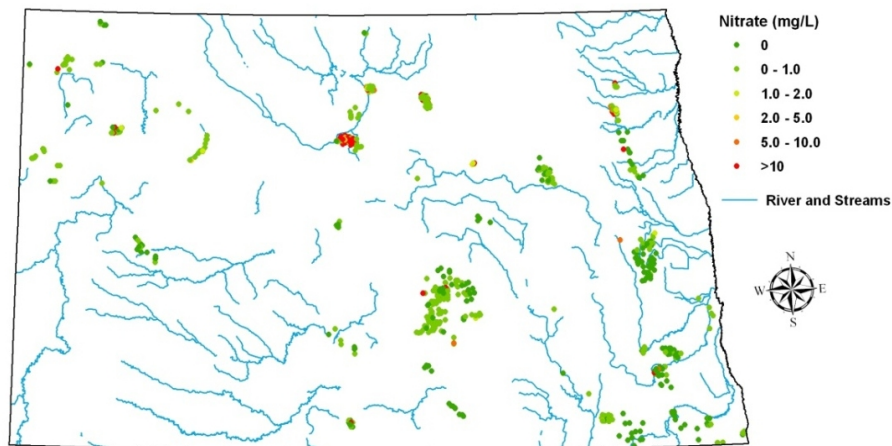
Figure 4.21 Groundwater sampling well for nitrate in North Dakota (data retrieved from North Dakota State Water Commission Surface and Ground Water Data Portal between 2000 and 2009)
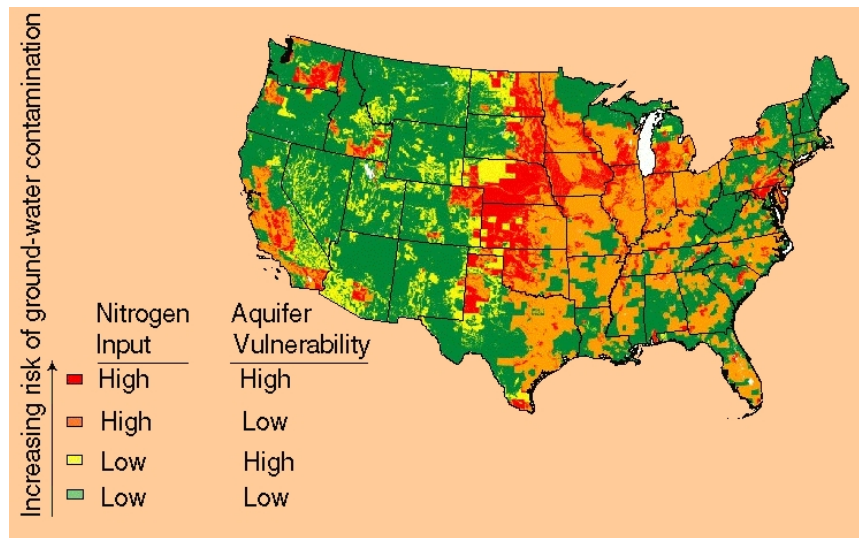
Figure 4.22 A national map showing groundwater vulnerability to nitrate (Nolan et al., 1988)
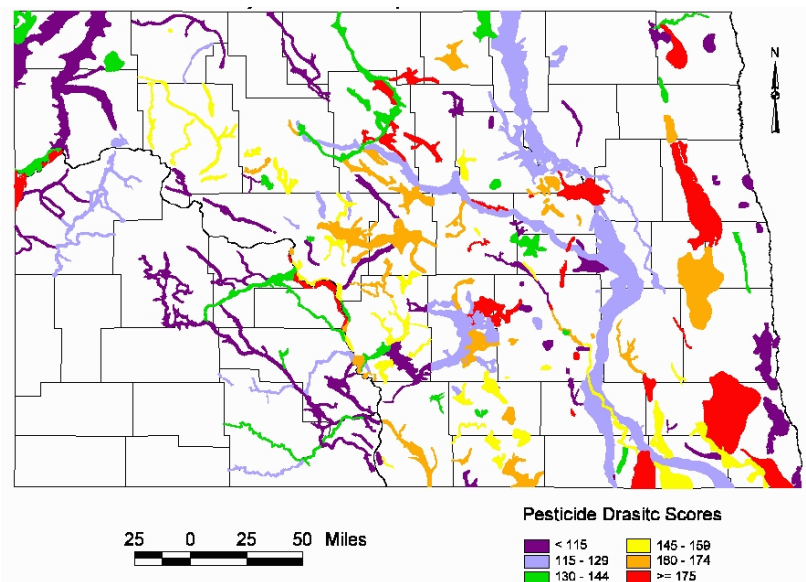
Figure 4.23 Pesticide DRASTIC scores for major glacial drift aquifers in North Dakota (Radig, 1997)

6 Discussion

6.1 Implications of the Results

This research has shown that, under all future scenarios examined, most parts of eastern North Dakota will be increasingly vulnerable to groundwater contamination from nitrates. The results indicate that the largest increase in groundwater pollution risk will occur under the B1 scenario, while under the A2 scenario pollution risks will increase

least. Note that under the B1 scenario, a quality environment and clean energy are highly preferred, and expansion of biofuel crops for bioethanol and biodiesel could be expected as a response to encourage reduction of carbon dioxide. Although the A2 scenario assumes high demographic pressure and high fossil fuel usage, lower demands for biofuel crops tend to discourage fast expansion of corn and soybeans, thus reducing nitrate pollution stemming from fertilizers.

The results also suggest that biofuel crops, traditionally regarded as climate friendly (Powlson et al., 2005), may act as a double-edged sword to the environment. With biofuel crops displacing other crops such as wheat and alfalfa in North Dakota, there may be a significant increase in fertilizer inputs to the farm lands. A field study conducted in southeastern North Dakota has proved that increases in nitrate application rates can notably elevate nitrate concentrations in the shallow groundwater in this area (Derby et al., 2009). Thus, increasing risks of groundwater pollution may be associated with the expansion of biofuel crops. Apart from local groundwater deterioration, nutrients losses from biofuel crops also pose detrimental effects to the quality of surface water (Costello et al., 2009), although this is not the focus of this study.

The results of this study indicate potential profound changes in groundwater quality (for nitrates) under future climate and LULC changes in the Northern Great Plains. However, few studies have been found to confirm or related to our results. Most global change studies usually focused on issues such as biofuel crops affecting surface water quality (Dominguez-Faus et al., 2009; Foley et al., 2004) and climate change impacting groundwater quantity (Jyrkama and Sykes, 2007; Scibek and Allen, 2006; Holman, 2005). The paucity of related literature can be attributed to the complexity of the

groundwater system and interaction between groundwater, climate and land use systems. The residence time of groundwater can range from days to tens of thousands of years, which delays or disperses the effects of climate and related LULC change (Chen et al., 2004). Our results can work as a starting point for more long-term groundwater quality studies in this area.

6.2 Sensitivity Analysis

Sensitivity analysis was carried out to assess how DTW, recharge and land use could affect modeled groundwater pollution risk. The analysis evaluated overall model responsiveness to a specific factor using the following equation.

$$V\% = \frac{V(x) - V}{V} \times 100\% \qquad \text{Eq. 4.5}$$

Where V% is the variation of groundwater vulnerability expressed as a percentage, V(x) stands for the vulnerability affected by changes in specific factor x (e.g. DTW, recharge), and V is the vulnerability computed before any change.

Table 4.5 shows the statistical summary of changes in groundwater vulnerability due to changes in DTW, recharge and land use under the B1, A1B and A2 scenarios for 2020 and 2050. *Mean, minimum, maximum* and *Standard Deviation* indicate the average, smallest, largest values and standard deviation of groundwater vulnerability variations over the entire study areas by varying DTW, recharge and land use in order. Overall, variations of groundwater vulnerability caused by changes in land use are much more significant than those did by changes in DTW and recharge. The effects of changes in DTW are greater than changes in recharge on variations in groundwater vulnerability. Since changes in DTW and recharge reflect the climate conditions and land use change is

mainly attributable to anthropogenic activities, this sensitivity analysis also indicates that human factors may dominate the changes in groundwater vulnerability in North Dakota compared with climate change. This is consistent with the finding that impact of LULCC on the hydrologic system may surpass that of recent or anticipated climate change at least over decadal time scales (Vorosmarty et al., 2004).

Table 4.5 Statistics of sensitivity analysis for the model prediction

Parameters / Variation		Mean	Minimum	Maximum	Standard Deviation
B1 2020	DTW	-1.4%	-14.7%	10%	0.003
	Recharge	0.1%	-4.0%	5.6%	0.006
	Land use	5.5%	-40.4%	78.7%	0.134
A1B 2020	DTW	-1.4%	-14.7%	10%	0.003
	Recharge	0.3%	-4.0%	6.3%	0.007
	Land use	4.5%	-40.4%	78.7%	0.125
A2 2020	DTW	-1.4%	-14.7%	10%	0.003
	Recharge	0.1%	-4.1%	5.4%	0.006
	Land use	3.2%	-40.4%	78.7%	0.113
B1 2050	DTW	-1.4%	-14.6%	10%	0.003
	Recharge	0.6%	-6.4%	9.1%	0.014
	Land use	6.4%	-40.4%	78.7%	0.140
A1B 2050	DTW	-1.4%	-14.7%	10%	0.003
	Recharge	0.5%	-4.5%	7.1%	0.010
	Land use	5.3%	-40.4%	78.7%	0.132
A2 2050	DTW	-1.4%	-14.6%	10%	0.003
	Recharge	0.6%	-5.5%	7.6%	0.013
	Land use	3.2%	-40.4%	78.7%	0.113

Therefore, the accuracy and reliability of the land use modeling results are more influential than those of DTW and recharge on the predicted future groundwater vulnerability in North Dakota. Greater emphasis should be placed on the modeling of biofuels-related land use change in a study of future groundwater vulnerability in response to future climate and land use change. This also justifies that an entire chapter (Chapter 3) was devoted to the biofuels-related land use change modeling.

6.3 Limitations

In this study, future changes in groundwater vulnerability were modeled as the effects of a combination of climate-related socio-economic scenarios, climate change, and biofuels-related cropland change. These factors were linearly combined to model the changes in groundwater vulnerability. However, the actual physical process of groundwater contamination may not be linear itself. The whole process involves complex mechanisms such as pollutant transport and dilution, adsorption on soil particles, chemical and biological degradation, any of which may be non-linear. Thus, the actual vulnerability may be over- or under-estimated compared with the modeling results. But the linear modeling approach features a significant advantage: a simplification of the complex groundwater contamination processes. It can provide a quick evaluation of a large area for future scenarios based on a group of well-recognized key hydrogeologic factors. This evaluation can be very difficult using physical models which typically require complex parameterization of hydrologic processes and considerable computing resources. Besides, the relationships between predictive factors and modeled groundwater vulnerability also follow valid hydrogeologic principles, e.g. smaller DTW indicating higher chance of contaminants reaching the groundwater. Furthermore, the linear modeling scheme can

readily be implemented in a GIS framework. This research does not establish if we do not assume valid linear relationships between groundwater vulnerability and predictive factors such as DTW, recharge and soil. Furthermore, it should be noted that the groundwater vulnerability maps developed for this research may not be used to interpret incidences of local groundwater contamination caused by site-specific factors such as hydraulic fracturing for shale oil in western North Dakota, which may cause drinking water contamination (Mayda, 2011).

The results can be affected significantly by uncertainties related to climate change projections. Impacts of climate change on the fate and transport of pollutant tend to be highly variable and difficult to predict because of the uncertainties associated with the climate predictions (Bloomfield et al., 2006). Discrepancies between projections of climate change models (e.g., regarding future precipitation and temperature patterns) can vary significantly, especially in the Northern Great Plains. Figure 4.24 shows considerably different precipitation patterns predicted by different climate change models under the A1B scenario. The line of zero change (i.e. the boundary where no change in precipitation occurs over the modeling periods) is oriented more or less west-to-east in this region (Christensen et al., 2007) for different models. The study area is predicted to be drier by some models (e.g. MIROC3.2.medres), while wetter by some other models (e.g. CGCM3.1.T63). The multi-model mean of climate projections (Figure 4.7, 4.8) used in this study may vary its spatial pattern, depending on the number of climate projections included for averaging. Therefore, great variability in climate projections is inherent in this study, and may affect the final groundwater vulnerability patterns.

In addition, the study did not consider climate variability over short periods, which may also be critical to groundwater contamination. Variations in temperature and precipitation association with ENSO (El Niño Southern Oscillation) and PDO (Pacific Decadal Oscillation) over short periods can influence the amount of water that recharges aquifers (Toews and Allen, 2009). The variability may result in greater climate extremes and considerable shifts to the mean climate conditions, and hence add more uncertainties to the projections of biofuels-related land use, recharge, DTW and groundwater vulnerability. But these climate cycles, due to their high unpredictability, were not considered in current climate change projections.

In addition to climate change, uncertainties associated with biofuels-related cropland modeling, groundwater level and recharge modeling may also be crucial to the results. For example, biofuels-related cropland change (Figure 4.11) is modeled cell-by-cell under the assumption that such cells have at least 40% of their area in cultivated corn and/or soybeans. When assigning rating and weighting values, these cells are treated as if they were 100% corn and/or soybeans. Thus, the vulnerability scores of some cells are almost certainly overestimated. The uncertainties of estimated future recharge and DTW exist for the study area, largely due to uncertainty in input parameters including future precipitation projections and the specific yield (no spatially detailed data). Nonetheless, these uncertainties related to recharge and DTW projections may not be as significant as those associated with land use change to the groundwater vulnerability modeling, because the modeled groundwater vulnerability were found less sensitive to the changes in recharge and DTW (Table 4.5).

Annual Mean Precip Response (%)

Figure 4.24 The annual mean precipitation response in North America in 21 IPCC Assessment Report 4 (AR4) Models. Shown is the percent change in precipitation from the Years 1980-1999 to 2080-2099 for different models under the A1B Scenario (Christensen et al., 2007)

7 Summary and Conclusions

Changes in groundwater vulnerability patterns are the result of human-environment-climate interactions across a range of spatial and temporal scales. In this study, climate change scenarios, a land use change model, a recharge estimation model, and a groundwater vulnerability model were integrated in a GIS framework to map future groundwater vulnerability patterns in North Dakota. The "backbone" of this framework is DRSTIL (a modified DRASTIC model). The modeling approach used here appears well-suited for linking groundwater vulnerability with climate and land use change at the regional scale.

This research suggests that groundwater vulnerability in the northern Great Plains will be impacted by projected climate change and biofuels-related land use change. The modeling results indicate that eastern North Dakota will exhibit the greatest risks of groundwater contamination. Natural resources managers will likely need to target protection strategies and measures such as regulating application of farm chemicals and installing monitoring wells in areas prone to high groundwater pollution risk. Although this research was conducted in North Dakota, it clearly could be adapted and applied in other similar agricultural regions undergoing significant climate change and rapid land use change.

Future research should include testing this modeling approach in other locales. In addition, it is recommended that the narrative descriptions of SRES scenarios and statistical extrapolation of historical cropland data be augmented by information on biofuel policies and food security.

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Chapter V

Summary and Conclusions

1 Summary

The overarching goal of this research is to develop and evaluate a regional pollution risk assessment procedure that will provide natural resource managers with information required to protect potentially-threatened groundwater resources. Previous chapters present detailed accounts of the research background and objectives, a groundwater vulnerability model, models for projecting biofuels-related land use change, and the model integration.

Chapter 1 provided the general background, research questions, objectives, dissertation structure and significance of the research. It introduces the core hypothesis that patterns of groundwater pollution risk will change in response to future climate change and biofuels-related land use changes. The objective is to test this hypothesis in the Northern Great Plains under different future scenarios. This chapter also provides readers a general overview of the modeling framework and the importance of this research in groundwater quality management.

Chapter 2 presented a groundwater vulnerability model, DRSTIL, which can be implemented over large regions in the Northern Great Plains. The techniques for developing factor layers were designed using national or statewide datasets to make sure the techniques transferable to other places in the Northern Great Plains. The model was developed and tested in the Elkhorn River Basin, Nebraska. It was found that there is a

general consistency between the modeled groundwater vulnerability and observed nitrate contamination in the study area. Compared with the DRASTIC model (Aller et al., 1985), DRSTIL drops aquifer and hydraulic conductivity factors from the DRASTIC model, and adds a new land use factor. Aquifer characteristics and conductivity were dropped because this research focuses on groundwater vulnerability at the water table. A land use factor was added to reflect the contaminant loadings associated with land use. The groundwater vulnerability model presented in this chapter was subsequently applied to North Dakota in Chapter 4.

Chapter 3 presented a model to forecast future biofuels-related land use, a key factor in accessing future groundwater vulnerability patterns. The research focused on the modeling of corn and soybean cropland expansions in North Dakota using geographic information systems (GIS) and the Land Transformation Model (LTM). The USDA Cropland Data Layers (CDLs) were used to generate a series of biofuel cropland maps. These historical cropland data, together with a variety of environmental factors (i.e., topography, soil fertility, and climate), were used to calibrate the neural network that is embedded in the LTM. Validation analysis showed the calibrated LTM was able to yield fairly accurate simulation results. Compared with previous works (Smeets et al., 2006; de la Torre Ugarte and Ray, 2000) related to biofuel crops modeling, the modeling approach is grid-based, location-specific and capable of distinguishing long-term regional trends in land use and land cover change (LULCC) from frequent short-term changes (e.g., crop rotations) in cropping practices.

Chapter 4 integrated groundwater vulnerability model (in Chapter 2), land use change model (in Chapter 3) and climate change scenarios within a GIS environment to forecast

groundwater vulnerability conditions under different climate and land use change scenarios in North Dakota. Traditionally, the methodologies used to evaluate groundwater pollution risk have been based on a "static" assumption that groundwater systems do not change significantly over time (Butscher and Huggenberger, 2009). This study incorporates the climate and land use dynamics into the modeling framework. The results showed that areas with high vulnerability will expand northward and/or northwestward in eastern North Dakota under different scenarios. It confirms the hypothesis of this dissertation that patterns of groundwater pollution risk will change in response to future climate change and biofuels-related land use changes. Modeling that accounts for future changes in climate and land use can help decision makers identify potential future threats to groundwater quality, and take early steps to protect this critical resource.

2 Conclusions

The modeling results confirm the major hypothesis of this research that global warming and accelerating demands for biofuels will influence land managers to plant more area to corn and soybeans, and such changes in climate and land use will increase risks of groundwater pollution. The groundwater vulnerability modeling conducted in North Dakota demonstrates that under all future scenarios examined most parts of eastern North Dakota will be increasingly vulnerable to groundwater contamination from nitrates. The increase in groundwater vulnerability is mainly associated with the rapidly-expanding biofuel crops, which generally require higher fertilizer application rates and have high leaching potentials to the underground. Climate change may also contribute to increased groundwater pollution potentials by enhancing groundwater recharge and raising

groundwater tables in the area. Many places in the Northern Great Plains may face greater challenges in groundwater quality protection in the future.

In areas of groundwater vulnerability, this research is unique in that it views groundwater as a dynamic rather than static concept, and presents a modeling framework, which employs four sub-models linked within a GIS environment, to evaluate the groundwater pollution risks under future climate and land use changes. It broadens the horizon of current groundwater vulnerability studies in this regard. In addition, this study proposes a groundwater vulnerability model, DRSTIL, which can potentially be applied in most areas of the Northern Great Plains using national or statewide datasets. It can potentially help promote the efficiency of groundwater vulnerability assessment in this region.

In areas of climate change impacts, this research reveals how climate change may affect the distribution of biofuel crops and groundwater quality in the future. Rises in temperature may make the Northern Great Plains, especially North Dakota, increasingly suitable for biofuel crops cultivation, while high biofuel demands may lead more land to be devoted to biofuel crops (associated with high fertilizer application rates)by farmers. Increases in precipitation enhance groundwater recharge and elevate the groundwater level, making groundwater more susceptible to ground contaminants such as farm chemicals. Assuming all other factors such as soil and topography constant, changes in land use, groundwater recharge and water table will consequently alter current patterns of groundwater vulnerability.

In areas of land use change, this research illustrates a grid-based biofuel-crop model that was adapted based on the LTM model. It is the first spatially-explicit land use model

developed to simulate the distribution of biofuel crops in North Dakota. Compared with traditional models for biofuel crops, this model features two major advantages: (1) the modeling approach is location specific on a grid basis, enabling the modeling results readily applicable to other environmental models such as a groundwater vulnerability model, and (2) The model is capable of distinguishing long-term regional trends in LULCC from frequent short-term changes (e.g., crop rotations) in cropping practices.

3 Recommendations

This research could, perhaps, benefit the groundwater quality management in the context of potential climate and land use change, aiding in selecting and prioritizing sites for future groundwater monitoring and protection. Monitoring of groundwater quality and clean-up of pollutants are often technically complex and cost-prohibitive. Water quality management strategies, therefore, need to be targeted so that limited staff, funds and technology can be focused upon those areas most threatened in order to provide the greatest benefit for a given investment. But targeting must be based upon reliable forecasts of the risk of groundwater pollution under a variety of possible future climate/socio-economic/land use scenarios (Twarakavi and Kaluarachchi, 2006). Thus, the results of this study may be used by resource protection agencies to focus groundwater sampling and pollution prevention programs on areas of greatest potential for future contamination occurrence (Rupert, 1999).

For the areas predicted to have elevated groundwater pollution risks, appropriate agricultural policies/practices may be imperative to prevent groundwater contamination. There are many ways to reduce the potential loss of fertilizers to groundwater. North

Dakota State University Extension Service recommended several agricultural practices (Weston and Seelig, 1994)

- Testing soil to identify nutrient additions necessary to meet crop needs;

- Avoiding fall nitrogen application on coarse-textured soils;

- Planning a topdressing program for soils with high nitrate leaching susceptibility;

- Delaying fall anhydrous ammonia and urea applications as long as possible; and

- Follow strict irrigation scheduling and fertilizer recommendations for irrigated crops

The results from this research may also help promote dialogue and improve decision making on biofuels incentives, polices and laws. In a national pursuit of biofuel energy for global warming mitigation, economic benefits and energy independence (Koshel et al., 2010), the potential negative environmental impacts of the so-called "New Gold Rush" (Simpson et al., 2008) may be largely overlooked. The modeled fast expansion of corn and soybeans acreage may result in a sequence of unintended negative environmental and ecological consequences (Kennedy, 2007; de Oliveira et al., 2005). A typical example is the potential loss of critical wildlife habitats, such as native prairies and pothole wetlands in the Northern Great Plains (Brook et al., 2009). Expansion of corn fields can also significantly affect the quality of both surface water and groundwater, because corn fields generally require more fertilizers input compared with other crop types, and the amount of excess fertilizers may move into water bodies or leach into the ground (Dams et al., 2007; Thomas et al., 2009). The deterioration of water quality accompanying land use conversion may become a major threat to human health. Thus, it

will be extremely beneficial to incorporate some environmental concerns in the biofuels-related policy making.

The modeling framework presented in this study has the potential to be applied in other regions where groundwater is at risk from LULCC. However, the groundwater vulnerability maps developed in this study should be used with caution. Groundwater vulnerability is not equivalent to groundwater contamination occurrence. In addition, it should be noted that the results of regional studies such as that carried out here cannot be used in place of site specific assessment. Whether a specific site will have groundwater pollution problems depends on many site-specific factors such as the type, characteristics and quantities of applied farm chemicals, and detailed hydrogeologic parameters (such as subsurface redox conditions and preferential flow), which may not be mappable at the regional level.

Future research should include the following:

1) Incorporation of spatio-temporal dynamics into the biofuel crops modeling. The current model assumes a steady-state behavior of the artificial neural network (ANN) where inputs are either static in time or periodically varying. But it does not include explicit topological or spatial structure and temporal properties (Ermentrout, 1998), and thus cannot model the land use change progressively in response to climate variations. Furthermore, the current model assumes one-way relationships between the driving factors and LULCC (climate affecting the land use), and it would be useful to integrate the dynamic interactions between land use change and regional climate. Future research should involve revision of models to address such issues.

2) Inclusion of more scenarios in the modeling framework. In this dissertation, biofuels-related land use scenarios focused on the future distribution of corn (source of bioethanol) and soybeans (source of biodiesel). But with growing popularity of cellulose-based ethanol and potentially reducing production cost (Tyner, 2008), perennial herbaceous plants such as switchgrass (Panicumvirgatum L.) may gradually replace corn as the major source of bioethanol and lead to a shift of the current land use patterns. Thus, future research will be directed towards modeling the potential distribution of switchgrass and corresponding outlook of groundwater vulnerability in the Northern Great Plains.

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Appendix

The following python scripts were used to convert the climate projection data (i.e. temperature and precipitation) in ASCII format to GeoTIFF format in an OpenGIS framework. The example codes were originally written for future precipitation under A1b scenario, and they are adaptable for data conversion of temperature and precipitation projection under other scenarios.

_____

```
try:
fromosgeo import gdal, gdalconst, ogr
except:
importgdal, gdalconst, ogr
importos, sys, string, Numeric, osr
# Access to the shapefilesites.shp
os.chdir("Y:\\geog498\\s-rli2\\climatedata") #Run the program in local drive. Net drive will be problematic
# #############Below is to generate new files for Year 2010-2059################
# Access to the ASCII files
inFilename = "A1b.txt"
txtFile = open(inFilename, "r")
lines = txtFile.readlines()
newList = []
for line in lines:
dataList = line.lstrip().rstrip().split(" ")
fori in range(len(dataList)):
ifdataList[i] <> '':
newList.append(dataList[i])
iflen(newList)>3:
```

```
        ## print newList

outFilename = "A1b_"+newList[2]+".txt"

outFile = open(outFilename, "a")

outFile.write(newList[0]+" "+newList[1]+" "+newList[2]+" "+newList[3]+" "+newList[4]+"\n")

outFile.close()

newList = []

txtFile.close()


# #############Below is to generate new image############################

# create New image driver

imgDriver = gdal.GetDriverByName('Gtiff')

imgDriver.Register()

nCols = int((104.1875-95.1875)*8+1)

nRows = int((49.1875-39.8125)*8+1)

print "nCols= "+str(nCols), " nRows="+str(nRows)

# get the georeference info.

originX = -104.25

originY = 49.25

# the Lat/long represent the center of each pixel

pixelWidth = 0.125

pixelHeight = -0.125

fori in range(2010, 2060):

   # set the image driver and source; array settings

outImage = "A1b_"+str(i)+".tif"

outDS = imgDriver.Create(outImage, nCols, nRows, 1, \

                  gdalconst.GDT_Float32)

outBand = outDS.GetRasterBand(1)

outBand.SetNoDataValue(-999)

outArray= Numeric.zeros((nRows, nCols), Numeric.Float)

outArray = outArray - 999
```

```
    # Read file from Year 2010-2059

fileName = "A1b_"+str(i)+".txt"

    File = open(fileName, "r")

fileLines = File.readlines()

forfileLine in fileLines:

        List = fileLine.rstrip().split(" ")

        ## print List

xOffset = int((float(List[0]) - originX) / pixelWidth)

yOffset = int((float(List[1]) - originY) / pixelHeight)

        # Be careful with the order of xoffset and yoffset for the Block.

outArray[yOffset][xOffset] = float(List[4])

outBand.WriteArray(outArray, 0, 0)

File.close()

deloutArray

    GeoRef = [-104.25, 0.125, 0.0, 49.25, 0.0, -0.125]

outSR = osr.SpatialReference()

outSR.ImportFromProj4("+proj=longlat +ellps=GRS80 +datum=NAD83 +no_defs")

outWkt = outSR.ExportToWkt()

outDS.SetGeoTransform(GeoRef)

outDS.SetProjection(outWkt)

outBand = None

outDS = None
```