Vulnerability Assessment of Groundwater to NO3 Contamination Using GIS, DRASTIC Model and Geostatistical Analysis

Adela Beauty Adu Agyemang
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Vulnerability Assessment of Groundwater to NO₃ Contamination Using GIS, DRASTIC Model and Geostatistical Analysis

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by

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ABSTRACT

Vulnerability Assessment of Groundwater to NO₃ Contamination Using GIS, DRASTIC Model and Geostatistical Analysis

by

Adela Beauty Adu Agyemang

The study employed Geographical Information System (GIS) technology to investigate the vulnerability of groundwater to NO₃ content in Buncombe County, North Carolina in two different approaches. In the first study, the spatial distribution of NO₃ contamination was analyzed in a GIS environment using Kriging Interpolation. Cokriging interpolation was used to establish how NO₃ relates to landcover types and depth to water table of wells in the county. The second study used DRASTIC model to assess the vulnerability of groundwater in Buncombe County to NO₃ contamination. To get an accurate vulnerability index, the DRASTIC parameters were modified to fit the hydrogeological settings of the county. A final vulnerability map was created using regression based DRASTIC, a statistic method to measure how NO₃ relates to each of the DRASTIC variables. Although the NO₃ concentration in the county didn’t exceed the USEPA standard limit (10mg/L), some areas had NO₃ as high as 8.5mg/L.
DEDICATION

I dedicate this thesis to my parents, my siblings, my daughter Michelle and my husband Maxwell. Your support, prayers and unconditional love made it possible for me to complete this thesis. I also want to dedicate this thesis to my advisor, Dr. Arpita Nandi; thank you for being the source of my inspiration. Your willingness to always give a helping hand is what made this dream a reality.
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CHAPTER 1
INTRODUCTION

Water plays a vital role in both human life and society. Both groundwater and surface water contribute to economic, social, health, recreational, and cultural activities and are critical in sustaining the environment and ecosystem (Anornu et al. 2012). Groundwater is the water present beneath Earth's surface in soil and rock pore spaces and in the fractures of rock formations, whereas surface water is the water found above the ground. Due to the rapid population growth, the volume and quality of surface water is diminishing with time leaving groundwater as the most reliable source of water in terms of its quality (Anornu et al. 2012). Challenges resulting from the effects of climate change and the contamination of surface water resulting from high population growth, industrialization, and irrigation practices have led to increased demand for groundwater (Anornu et al. 2012).

Groundwater is the most significant water resource on earth (Tirkey et al. 2013). In many arid and semi-arid areas in the world, it serves as the sole source of water for drinking, irrigation, and industrial purposes (Haris et al. 2011). Groundwater quality can be affected by residential, municipal, commercial, industrial, and agricultural activities particularly in relation to excessive application of fertilizers and unsanitary conditions (Ramakrishnaiah et al. 2009; Haris et al. 2011). Fertilizers contain nitrogen compounds which increase the productivity of crops. However, when nitrogen in fertilizer exceeds absorptive capacity of plants, the excess is carried into groundwater in the form of nitrates (NO$_3^-$) through infiltration of precipitation, irrigation, and other processes (Meisinger et al. 1991; Shamrukh et al. 2001). Even though a small amount of NO$_3^-$ in water can be harmless, high levels of NO$_3^-$ in water can affect human health. Greater amounts of NO$_3^-$ in the human body can cause methemoglobinemia, commonly called “blue baby syndrome”, in infants,
stomach cancer, birth malformation and other issues (Avery 1999; Majumdar and Gupta 2000; Addiscott and Benjamin 2004). Per US Environmental Protection Agency (EPA) standards, nitrate concentrations exceeding 10 milligrams per Liter (10mg/L) in drinking water can be harmful if ingested (EPA 1995).

Different methods have been used in several studies to assess groundwater’s vulnerability to nitrate contamination and other pollutants. These methods can be grouped into: Process-Based Methods, Statistical Methods, and Overlay and Index Methods (Tesoriero et al. 1998; Thirumalaivasan et al. 2003). Overlay and Index Methods overlay the layers of factors known to be controlling the movement of pollutants from the ground surface to the water strata to create a vulnerability index maps using specified vulnerability indices (Tirkey et al. 2013). Process Based Methods use a structured set of activities or processes designed to assess groundwater vulnerability, whereas statistical methods mainly use statistical analysis to establish the relationship between the spatial variables and existing pollutants in groundwater. One of the most widely used groundwater vulnerability mapping methods is the DRASTIC model, which falls within the Overlay and Index category (EPA 1993; Thirumalaivasan et al. 2003). DRASTIC model was developed by the EPA to assess groundwater vulnerability using hydrogeologic settings (Aller et al. 1987; Babiker et al. 2005; Al-Rawabdeh et al. 2013). DRASTIC is an acronym which stands for: Depth to water, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone and hydraulic Conductivity. According to Aller et al. (1987), the DRASTIC parameters play a vital role in transporting contaminants into ground water.
Previous Studies Involving Nitrate in Groundwater

Nitrate concentrations in groundwater has been studied in different areas worldwide. Power and Schepers (1989) associated nitrates in groundwater to non-point sources, like geological origins, point source septic tanks, improper use of animal manures, cultivation, precipitation, and fertilizers. A study by Burow et al. (2010) on NO₃ concentrations in groundwater in the United States revealed that, NO₃ is highest in shallow, oxygenated groundwater. Assaf and Saadeh (2009) identified a significant and persistent nitrate contamination of groundwater in Upper Litani Basin, Lebanon where most of the areas in the basin had nitrate concentrations exceeding the standard limit for drinking. Babiker et al. (2004) study of groundwater contamination by nitrate leaching from intensive vegetable cultivation indicated that, the landuse class “vegetable fields” was the principal source of nitrate contamination of groundwater in the Kakamigahara, Gifu Prefecture, central Japan.

In Konya, Turkey, the average concentration of nitrate for 1998 and 2001 was between 2.2 and 16.1 mg/L; these concentrations tended to increase towards the center of the city (Nas and Berktay 2006). The study of nitrogen balance and groundwater nitrate contamination in North China by Ju et al. (2006) showed that the groundwater in shallow wells (depth <15 m) was heavily contaminated with NO₃. Studies found that, about 4% of private wells in Iowa have nitrate concentration levels exceeding 10mg/L, the maximum contaminant level of NO₃ in drinking water (Kross et al. 1993). Ahn and Chon (1999) identified NO₃ as one of the principal groundwater pollutants in both Gurogu area, an industrial district and Asan area, an agricultural district of Seoul, Korea. A study by Tang et al. (2004) also indicated that NO₃ concentration in most wells with depth <40 m in Shijiazhuang region, China exceeds the drinking water standard set by the World Health Organization (WHO).
Previous Studies on Groundwater Vulnerability to Contamination Using DRASTIC Model

DRASTIC model has been employed in several studies to assess groundwater and aquifer vulnerability in various parts of the world. The model produces regional maps delineating areas of low, moderate, and high vulnerability which could be followed up with further site-specific studies. Kim and Hamm (1999), Rundquist et al. (1991), Lynch et al. (1997), and Pathak et al. (2009) used DRASTIC to evaluate the potential for groundwater contamination in the Cheongju city area, South Korea, Nebraska, South Africa, and Kathmandu Valley, Nepal, respectively. Babiker et al. (2005) assessed the aquifer vulnerability of Kakamigahara Heights Gifu Prefecture and Central Japan using DRASTIC model. Jamrah et al. (2008) also used the model in their study of groundwater vulnerability assessment in the coastal region of Oman. In Saidi et al. (2010) study of groundwater vulnerability and risk mapping of the Hajeb-jelma aquifer (Central Tunisia) using DRASTIC model, the risk map produced showed that, high risk areas in Hajeb-Jelma region were dependent on hydrogeological characteristics, land use, and human impacts.

Although the DRASTIC method usually gives satisfactory results in evaluating groundwater vulnerability to pollution, the model is rigid in assigning weights and rates to its parameters, which in some cases doesn’t give the desired result (Rupert, M. G. 2001 Javadi et al. 2011). However, to better address this issues, researchers have adopted several modifications of the original DRASTIC model for refined representation of a region’s specific hydrogeologic and land cover settings (Thirumalaivasan et al. 2003; Babiker et al. 2005). The modifications could be in the form of (i) incorporation of other parameters, (ii) removal of existing parameters, and (iii) manipulation of the assigned weights and ratings. Data sources such as groundwater flow, rate of groundwater flow, and source of groundwater recharge were used by Brown (1998) in addition to DRASTIC parameters in vulnerability assessment of Heretaunga plain aquifer, New Zealand (Thirumalaivasan et al. 2003).
Neshat et al. (2014) used modified DRASTIC in the form of manipulation of the assigned weights and rates in estimating groundwater vulnerability to pollution in Kerman agricultural area, Iran. Modified DRASTIC in the form of removal of existing parameters was used by Huan et al. (2012) in their study of the assessment and validation of groundwater vulnerability to NO₃ based on a modified DRASTIC model in Jilin City of northeastern China. Several other studies including Fritch et al. (2000), Meng et al. (2007), Javadi et al. (2010), Wang et al. (2012), and Sener et al. (2013) have used modified DRASTIC model to test for groundwater susceptibility to contamination.

**Geostatistical Analysis Methods Used in Groundwater Contamination Studies**

Geostatistics is a branch of statistical sciences used to analyze and predict values associated with spatial or spatiotemporal phenomenon (Chiles and Delfiner 2009; Bohling 2005). Geostatistics analyzes and interprets the uncertainties caused by limited sampling of a property under study by creating a continuous interpolated surface of the property to predict the unknown locations. Geostatistical analysis has been used in several studies to assess groundwater quality in different locations worldwide. Interpolation, a geostatistical analytical method, is mostly used to predict unknown data points based on a limited number of known points (Zhu et al. 2001; He and Jia 2004; Hu et al. 2005; Lui et al. 2006; Ahmadi and Sedghamiz 2007; Sanders et al. 2012).

Erxleben et al. (2002) used spatial interpolation methods to estimate snow distribution in the Colorado Rocky Mountains. A comprehensive archive of climate data was constructed in Australia using spatial interpolation to estimate for missing data (Jeffery et al. 2001). Spatial interpolation techniques were also used in China to develop monthly mean climate data (Hong et al. 2005). Kriging, an interpolation technique, was used by Nikroo et al. (2010) to determine groundwater depth and elevation in Mohr Basin of Fars province in Iran. Nas (2009) used Ordinary Kriging in
Turkey to predict the spatial patterns of water quality in rural areas. Ordinary kriging was also used by Sanders et al. (2012) and Hu et al. (2005) to determine the spatial distribution of arsenic in North Carolina groundwater and trace nitrate in groundwater in the North China plain. Mehrjardi et al. (2008) used Ordinary Kriging, Cokriging, and Inverse Distance Weighted (IDW) in Yazd-Ardakan Plain to predict the spatial distribution of groundwater quality and his results indicated that kriging and cokriging are superior to IDW in interpolating groundwater quality.

Eight spatial interpolation methods were used to evaluate groundwater level in an arid inland oasis, northwest China and three kriging interpolation methods (simple, universal and ordinary) produced the best fit model (Yao et al. 2014). Ahmadi and Sedghamiz (2008), applied kriging and cokriging methods to map groundwater depth in a plain with variable climatic conditions (normal, wet, dry) and in 2007 used geostatistical analysis to study the variations of groundwater levels. Ordinary kriging was used by Nas and Berktay (2010) to determine the spatial distribution of groundwater quality parameters such as pH, electrical conductivity, Cl\(^-\), SO\(_4\)\(^{2-}\), hardness, and NO\(_3\)\(^-\) concentrations in urban groundwater in Konya City, Turkey. Morio et al. (2010) estimated the spatial distribution of contaminant concentrations in groundwater using flow guided interpolation.

**Kriging and Cokriging**

Geostatistical methods such as kriging are extensively used in spatial hydrogeology to predict the concentration of contaminants and heavy metals in groundwater (Gaus et al. 2003; Babiker et al. 2004; Nas and Berktay 2010). Kriging uses a statistical approach that requires a point map as input data and produces both a predicted interpolated raster map with an estimate of prediction uncertainty (Babiker et al. 2004). Kriging presumes that there is the existence of spatial autocorrelation among
measured data point and assign weight to unknown points based on the spatial arrangement and distance weight between known points. It draws on semi-variance to calculate weight and gives the measure of accuracy of the interpolated surface (Salih et al. 2002). Ordinary kriging, the most widely used of the kriging method. The method assumes that the constant mean is unknown. Ordinary kriging is established using the equation:

\[ Z(s) = \mu + \epsilon(s) \]

Where \( \mu \) is an unknown constant. A detailed explanation of the kriging method is given in literature (Cressie 1990; Oliver and Webster 1990; Stein 2012).

Cokriging is a multivariate extension of the kriging interpolation method. It uses autocorrelation and cross correlation to create a predicted interpolated surface using the same assumptions as kriging interpolation method. Ordinary cokriging uses the same method ordinary kriging in creating a predicted surface but incorporates a secondary variable in the model (Queiroz et al. 2008). The model assumes that; autocorrelation exist between the primary variable and the secondary variable. Cokriging model is created using the formula;

\[ Z_1(s) = \mu_1 + \epsilon_1(s) \]

\[ Z_2(s) = \mu_2 + \epsilon_2(s) \]

\[ Z_n(s) = \mu_n + \epsilon_n(s) \]

Where \( \mu_1 \ldots \mu_n \) are constants, \( \epsilon_1 \ldots \epsilon_n \) are the random errors at individual locations. The accuracy of a predicted surface (kriging) can be improved using cokriging.

The performance of an interpolated surface can be assessed using cross validation or validation method. Cross-validation uses the entire dataset estimate the accuracy of a model. It
removes each data one at a time, predicts the associated value using the remaining data and compares the predicted value to the observed value. Validation divides the data into two unequal subsets; the training data (most data), and the test data (least data). The training dataset is used to develop the autocorrelation model and the accuracy of the model is compared with the test data. The accuracy of the models produced from the subset data shows the accuracy of the overall model (Goovaerts 1997; Kitanidis 1997)

**Research Goals**

This research employed Geographical Information System (GIS) technology to investigate the vulnerability of groundwater to NO\textsubscript{3} content in Buncombe County, North Carolina. The research was conducted using two different approaches, separated into two different studies.

The first study investigates how nitrate concentrations in the county relate to landcover and depth to water. The objectives of the first study are to: (1) analyze the spatial distribution of NO\textsubscript{3} in groundwater wells in Buncombe County, and (2) evaluate if the extent to which NO\textsubscript{3} concentrations in groundwater relate to landcover type and depth to water table. The goals of the second study are to: (1) assess the vulnerability of groundwater to contamination using DRASTIC model parameters established by the US EPA and (2) improve the vulnerability model using land cover and nitrate concentrations in the groundwater through advanced geospatial analysis.
CHAPTER 2
PREDICTING GROUNDWATER NITRATE CONCENTRATIONS AND ITS RELATION TO
LAND USE AND WATER DEPTH IN BUNCOMBE COUNTY

Abstract
High concentrations of nitrate (NO$_3$) in groundwater can be harmful to human health if ingested, and may be the primary cause of blue baby syndrome, among other health impacts. In this study, the spatial distribution of NO$_3$ in groundwater for 610 private drinking water wells in Buncombe County, North Carolina was modeled. While NO$_3$ concentration in the sampled wells did not exceed the 10 mg/L limit established by the United States Environmental Protection Agency, some wells had NO$_3$ concentrations approaching this limit (as high as 8.5 mg/L). Kriging interpolation was implemented within a Geographic Information System to predict NO$_3$ concentrations across the county, and a cokriging model using land cover type and depth to water table as covariates was developed. Cross validation statistics of root mean square and root mean square standardized for both models were compared and the results showed that the predicted NO$_3$ layer was improved when land cover type was integrated into the model. The cokriging interpolated surface with land cover as a covariate had the lowest root mean square (0.979) when compared to the kriging interpolated surface (0.986), indicating a better fit for the co-kriging surface with land cover. The addition of depth to water table did not improve the cokriging surface as the landcover did. High NO$_3$ value of 2 mg/L and above were concentrated in hay/pasture land, developed open space, and deciduous forest containing 37%, 34%, and 29%, respectively. However, the study did not reveal any statistically significant difference in the presence of high NO$_3$ concentration between these landcover types, indicating they all contribute to high NO$_3$ content.
1.0 Introduction

Groundwater is the water present beneath Earth’s surface in soil pore spaces and in the fractures of rock formations. Groundwater provides about 80% of usable water storage in the world. The quality of groundwater is as important as that of its availability and quantity because it represents our main source of drinking water (Rahman, 2008). Groundwater is an important source of water supply because of its low susceptibility to pollution compared to surface water (EPA, 1985). Unfortunately, groundwater is vulnerable to pollution from underlying bedrock, human activities, and sewage discharge from industrial and agricultural sites (Babiker et al., 2005; Rahman, 2008). Nitrate (NO$_3$) is a widespread pollutant that enters the groundwater through the surface and is not naturally contained in the groundwater. Predicting areas that are likely to contain high levels of NO$_3$ may help to prevent the use of NO$_3$ contaminated water, and provide developers and planners with information about areas in need for additional testing.

1.1 Environmental and Health Concerns

Nitrogen is a primary component of fertilizers based on its ability to boost the productivity of crops. Global increase in the use of nitrogen fertilizer over the last few decades has led to increased NO$_3$ in groundwater, threatening water quality (Burow et al., 2010). When nitrogen in fertilizer exceeds the demand of plants and the ability of the soil to retain it, nitrogen leaches into groundwater in the form of NO$_3$ through infiltration of precipitation, irrigation, and other processes (Meisinger et
al., 1991; Shamrukh et al., 2001). Agricultural areas are susceptible to high levels of NO$_3$ concentrations due to the use of NO$_3$ rich fertilizers (Zhang et al., 1996; Thorburn, et al., 2003; Burow et al., 2008). Factors that affect NO$_3$ concentration in groundwater include land use operations, shallow water table, and subsurface clay thickness (Townsend and Young, 1995). Even though a small amount of NO$_3$ in water can be harmless, at high levels it can be damaging to human health. Increased concentration of NO$_3$ in groundwater may represent a loss of fertility in the overlying soil, cause eutrophication from the discharge of groundwater into surface water, and become a health hazard to animals and humans (McClay et al., 2001). Since groundwater serves as the primary source of drinking water, the presence of NO$_3$ in groundwater may cause health problems if ingested. Greater amounts of NO$_3$ in the body can cause methemoglobinemia, commonly called “blue baby syndrome” in infants, stomach cancer, birth malformation, and other issues (Addiscott and Benjamin, 2004; Avery, 1999; Majumdar and Gupta, 2000). Infants below the age of six months and pregnant women with low stomach acidity are most at risk (Messier et al, 2014). As such, the Environmental Protection Agency (EPA) has established a maximum contaminant level of 10 milligrams per Liter (10 mg/L) for NO$_3$ drinking water beyond which could be harmful to human health (EPA, 1995).

1.2 NO$_3$ concentrations in North Carolina

NO$_3$ concentrations in groundwater in the United States are highest in shallow, oxygenated groundwater (Burow et al 2010), most typically in areas beneath agricultural land with well-drained soils. In North Carolina, more than 25% of the population relies on private wells for drinking water, located outside municipal water supply systems. A state-wide study by North Carolina Health and Human Services between 1998-2010 reported concentrations of NO$_3$ in private well water that
ranged from 0.5 to 20mg/L (NCDHHS 2014). A study by Messier et al (2014) indicated that high levels of NO\textsubscript{3} concentrations in the southeastern plains of North Carolina are related to wastewater treatment residuals and localized animal feeding operations. Excess nutrient and fertilizer loadings in eastern North Carolina have degraded overall water quality (Luettich et al, 2000; Burkholder et al., 2006). A study by Harden and Spruill (2004) concluded that both agricultural and urban sites contributed to high percentages of NO\textsubscript{3} point sources in central and eastern North Carolina.

1.3 Study Objective

Nitrate concentration exceeding US EPA limit of 10mg/L may cause methemoglobinemia, stomach cancer and other issues when ingested. Excess NO\textsubscript{3} concentration in groundwater and its health implications has raised concerns, resulting in the need for further research to locate areas with high NO\textsubscript{3}. The objectives of this study are to: (1) analyze the spatial distribution of NO\textsubscript{3} in groundwater wells in Buncombe County, North Carolina, and (2) evaluate the extent to which NO\textsubscript{3} concentrations in groundwater relate to land cover type and depth to water table.

2.0 Study Area

This study was performed in Buncombe County, North Carolina (Fig 2.1). Buncombe County is located in western North Carolina in the Blue Ridge Physiographic province. The county is bordered to the north by Madison and Yancey counties, to the south by Henderson county, to the east by Rutherford and McDowell, and to the west by Haywood county. The county also shares a border with the Appalachian Mountains to the west and the Black Mountains to the east. The county covers a total area of 660 square miles, of which 657 square miles is land and 3.5 square miles is water (US Census Bureau, 2010). The average annual temperature of Buncombe County is 55.83°F, and average annual precipitation is 40.92 inches.
Physiographically, Buncombe County consists of high, smooth-rounded mountains surrounded by streams flowing in narrow valleys and underlain by bedrock consisting of igneous, meta-igneous, and sedimentary rocks (Aller et al. 1987). Aquifers in Buncombe County are mostly found in the crystalline metamorphic and igneous rocks (Trap and Horn 1997) where fractures in the crystalline bedrock serve as the primary storage for groundwater (Drever 1997). Wells located in valleys typically have shallow water tables and are more susceptible to contamination than wells located in hilly areas.
Fig 2.1 Map of Buncombe County, North Carolina, USA (Study Area)
3.0 Methods

The research methods used for the study were grouped into: database development and geocoding, exploratory non-spatial statistical analysis, exploratory spatial statistical analysis, and spatial statistical analysis. Fig 2.2 shows the methodology used for this study.

Fig 2.2 Methodology for predicting groundwater nitrate concentration and its relation to land use and water depth in Buncombe County
3.1 Data Development and Geocoding

Three different spatial variables were used in this study: NO$_3$ concentration in groundwater wells, depth to water table, and land cover/land use. Wells data were acquired from the North Carolina Division of Water Resources (NCDWR) in spreadsheet form. Data included well owner’s identification number, well permit number, first and last name, well location addresses (including city, state, zip code), GPS coordinates (longitude and latitude), and collection date. The forested areas, and the urban areas located in the central part of the county did not have records of private drinking wells. The data were divide into two groups: only wells with nitrate concentration data and the entire well data information for the purpose of depth to water table analysis. Well data containing no spatial information were discarded from the dataset.

The remaining dataset was geocoded using ArcGIS Online World Geocode Service to create a well location point map in ArcGIS 10.3. A total of 610 wells were matched during the geocoding process, and were subsequently used for kriging analysis. The entire dataset of geocoded wells (2948) was used to create a depth to water table data layer, that was further used as a covariate for cokriging. Additionally, the National Land Cover Dataset (WLCD), available from the Multi-Resolution Land Characteristics Consortium (MRLC) at a resolution of 30 m$^2$, was used as a covariate (Geospatial Data Gateway: https://datagateway.nrcs.usda.gov/). Fig 2.3 shows land cover types for Buncombe County. The county has over 60% of its land covered by deciduous forests followed by developed open space (14%) and hay/pasture (13%). Emergent herbaceous wetland is the least represented land cover type within the county.
3.2 Exploratory Non-Spatial Statistics

Per USEPA statistical protocol, all NO\textsubscript{3} concentration data below minimum detection limits (0.5 mg/L) were selected. Half of the values were kept at 0.5mg/L while the rest were assigned a concentration value of 0.25 mg/L. Descriptive statistics (mean, standard deviation, and range) were performed on the variables using Statistical Package for the Social Sciences, IBM SPSS statistics 23 (George and Mallery, 2016). Exploratory analysis was also conducted to test for normality and correlation among the variables: NO\textsubscript{3} concentration, land cover, and depth to water table.
To understand how NO$_3$ concentrations within each well compare with the different land cover types, a buffer radius surrounding the groundwater well was used to extract land cover data. Several studies have used different buffer radii ranging from 250 to 1000 m (Barringer et al., 1990). A buffer radius of 400 m was used by Babiker et al. (2004) in their study of groundwater contamination by NO$_3$ and land use. Eckhardt and Stackelberg (2005) chose a buffer radius of 800 m in their study of relationship groundwater quality to land use and McLay et al. (2001) selected a buffer radius of 500 m in studying groundwater NO$_3$ concentration in a region of mixed agricultural land use. The land cover in each well location within the 500 m buffer area was extracted using zonal histogram and the majority land cover was assigned to each well. Based on the test of normality, Spearman’s correlation coefficient was calculated to measure the statistical dependence of NO$_3$ on land cover and depth to water table. Histograms of the land cover data and depth to water table data were created to determine the percentages of the different land cover types and depth to water table in high NO$_3$ yielding wells. Additionally, one-way Analysis of Variance (ANOVA) was performed to compare the presence of high NO$_3$ content in different landcover types.

### 3.3 Exploratory Spatial Statistics using GeoDa

The existence of spatial dependency in the NO$_3$ and depth to water data was examined with GeoDa 1.8.14 (Anselin and Syabri, 2006). GeoDa is a software package used for spatial data analysis, data visualization, spatial autocorrelation, and spatial modeling. Spatial autocorrelation was examined in this study to check spatial dependency in the NO$_3$ and depth to water data. The result from this check served as the basis for further analysis in ArcGIS environment. The NO$_3$ data were imported into GeoDa and mapped. A spatial weight with a threshold distance of 15 miles was created using the spatial manager. The basis for choosing a threshold distance of 15 miles was to ensure that each well had at least one neighbor. Global and Local Moran’s I statistical tests were
then conducted to detect the presence of spatial autocorrelation in the NO₃ data. Global Moran’s I detects autocorrelation at the global level whereas Local Moran’s I detects autocorrelation at the local level and calculates the similarity among neighbors and their significance. These similarities are shown in a Local Indicators of Spatial Association (LISA) cluster map and grouped into low values near low values, high values near high values, low values near high values and high values near low values. The LISA significance maps also show the number of significant observations and their corresponding level of significance. Spatial autocorrelation in the depth to water data was tested using the same procedure as the NO₃ variable.

3.4 Spatial Statistics using Kriging and Cokriging

Kriging presumes that there is autocorrelation in the data, which was examined in the previous section (section 3.4). In this study, ordinary kriging interpolation was used, as the ordinary kriging method is simple and has satisfactory prediction accuracy in comparison to other kriging methods (Isaaks and Srivastava, 1989). The ordinary kriging interpolation created a predicted NO₃ concentration map from the NO₃ point data to examine the variation and spatial extent of NO₃ contamination in Buncombe County. Variogram was created for NO₃ using the NO₃ point map. The variogram measures the mean of variance between unknown values and a nearby data value, depicting autocorrelation at various distances (Kupfersberger et al, 1998; Robinson et al, 2006). Circular, exponential, and gaussian models with different parameters were examined to obtain the model which best fits the variogram. Ordinary kriging was also performed to predict the water table surface using the water table point data from well locations.

Land cover and depth to water table layers were used as covariates in a cokriging approach to further improve the NO₃ concentration prediction surface. The parameters used for the interpolation were kept the same for all created surfaces. A cross validation comparison was performed for the
kriged NO₃ surface and the cokriged NO₃ surfaces to select the best model. The comparison was done based on models diagnostics. The mean standardized error (ME), root mean square error (RMS), root mean square standardized error (RMSSE), and average standard error (ASE) of each interpolation were used to assess the model’s performance. A model is said to be best if it has a ME nearest to zero, a small RMS, an ASE closest to the RMS, and a RMSSE closest to one.

The NO₃ concentrations for the kriged/cokriged surface were grouped into six categories using quantile classification to make the maps comparable. Quantile classification gives the same number of data values to grouped features.

4.0 Results

4.1 Wells Location and Exploratory Non-Spatial Statistics

NO₃ contaminated wells in Buncombe County had concentration values ranging from 0.25 mg/L to 8.5 mg/L (Fig 2.4). The mean NO₃ concentration in the wells is 0.673 mg/L. These wells were distributed across the county except the northeastern corner, Biltmore, and the forest zones. There were 43 drinking water wells with concentrations of 2.0 mg/L and above, and these were in the northern, northwestern, central, and southeastern part of the county. The remaining wells with a concentration between 0.5mg/L to 2.0mg/L were also found closer to locations with high NO₃ (2.0 mg/L and above). Descriptive statistics of NO₃ and depth to water table are shown in Table 2.1. Depth to water table for county wells ranges from 0 to 1300 meters with a mean of 347.17m (Table 2.1). Distribution of the wells and their individual depth to water table are shown in Fig 2.5.
Fig 2.4 Nitrate contaminated wells in Buncombe County

Table 2.1 Descriptive statistics of NO₃ and depth to water table

<table>
<thead>
<tr>
<th></th>
<th>Nitrate (ppm)</th>
<th>Depth to water table (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.673</td>
<td>347.172</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.951</td>
<td>179.518</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>8.5</td>
<td>1300</td>
</tr>
</tbody>
</table>
Fig 2.5 Depth to water table of wells in Buncombe County

The Shapiro-Wilk Test of normality indicated that the NO$_3$ and depth to groundwater table were not normally distributed. While the overall NO$_3$ concentration did not show any correlation with landcover and depth to groundwater table, the wells with high NO$_3$ content (2.0 mg/L) indicated correlation with landcover data (Spearman’s rho = 0.24 at $p = 0.04$). No correlation was found between NO$_3$ and depth to water table data. Histogram analysis indicated that high level of NO$_3$ (2mg/L) were concentrated near hay and pasture land (37%), developed urban open space (34%), and deciduous forest (29%) (Table 2.2). ANOVA was performed to compare whether developed urban open space, deciduous forest, and hay and pasture land had significantly different...
levels of NO$_3$ in the county. The result did not find any significant difference in NO$_3$ content between the mentioned land cover types; hence Tukey post hoc tests were not performed.

Table 2.2 Percent landcover types in Buncombe County, and percent landcover type in/near high NO$_3$ area.

<table>
<thead>
<tr>
<th>Landcover type</th>
<th>Pixel count</th>
<th>% landcover in county</th>
<th>% landcover in high NO$_3$ area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open Water</td>
<td>7663</td>
<td>0.404</td>
<td></td>
</tr>
<tr>
<td>Developed Urban Open Space</td>
<td>264258</td>
<td>13.921</td>
<td>34.286</td>
</tr>
<tr>
<td>Developed low intensity</td>
<td>59816</td>
<td>3.151</td>
<td></td>
</tr>
<tr>
<td>Developed medium intensity</td>
<td>27313</td>
<td>1.439</td>
<td></td>
</tr>
<tr>
<td>Developed high intensity</td>
<td>8474</td>
<td>0.446</td>
<td></td>
</tr>
<tr>
<td>Barren land</td>
<td>1435</td>
<td>0.076</td>
<td></td>
</tr>
<tr>
<td>Deciduous forest</td>
<td>1149712</td>
<td>60.567</td>
<td>28.571</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>69504</td>
<td>3.661</td>
<td></td>
</tr>
<tr>
<td>Mixed forest</td>
<td>31100</td>
<td>1.638</td>
<td></td>
</tr>
<tr>
<td>Shrub/Scrub</td>
<td>11015</td>
<td>0.58</td>
<td></td>
</tr>
<tr>
<td>Herbaceous</td>
<td>22791</td>
<td>1.201</td>
<td></td>
</tr>
<tr>
<td>Hay/Pasture</td>
<td>237599</td>
<td>12.517</td>
<td>37.143</td>
</tr>
<tr>
<td>Cultivated crops</td>
<td>6041</td>
<td>0.318</td>
<td></td>
</tr>
<tr>
<td>Woody wetlands</td>
<td>1484</td>
<td>0.078</td>
<td></td>
</tr>
<tr>
<td>Emergent herbaceous wetland</td>
<td>45</td>
<td>0.002</td>
<td></td>
</tr>
</tbody>
</table>

4.2 Exploratory Spatial Statistics – GeoDa

The spatial autocorrelation test conducted using Global Moran’s I revealed that the nitrate concentration data were not spatially clustered at the global level. However, Local Moran’s I using LISA statistics identified 54 wells with high NO$_3$ values close to other high NO$_3$ values, and 79 wells with low NO$_3$ values close to other low NO$_3$ values. Clusters of low near low values were found in the northern part of the county whereas high values with other high values are scattered in the western and southeastern parts of the county (Fig 2.6)
The depth to water table data were significantly clustered at both the local and global level with Global Moran’s I = 0.017 (pseudo p value = 0.001 at 999 permutations). Locally, 1866 of the depth to water data were significant at $p = 0.001$, 366 at $p = 0.01$, and 192 at $p = 0.05$. Clusters of 437 deeper wells were located close to wells with high depth, and 988 shallow depth wells were located close to wells with shallow depth. Clusters of deep wells were found in the northern, northwestern, and western parts of the county, whereas clusters of shallow wells were found in the southern/southeastern part of the county (Fig 2.6). The results of the analysis using GeoDa (Fig 2.6) showed the existence of spatial autocorrelation in the NO$_3$ and depth to water variables and therefore provided the basis for further analysis with Kriging and Cokriging.
4.3 Spatial Statistics – Kriging and Cokriging

The cross-validation matrix for the kriging and cokriging were compared to determine the best model. All the models produced from cokriging were better in terms of models accuracy metrics compared to the kriging model (Fig 2.7 and 2.8). A summary of the accuracy metrics of NO$_3$ concentration from kriging/cokriging is given in Table 2.3. Nitrate/depth to water table had root mean square error (RMS) of 0.98 whiles the kriging model recorded the highest RMS (0.986). The cokriged nitrate/land cover and nitrate/land cover/depth to water table had the smallest RMS error (RMS = 0.979). As both RMS were 0.979, it was implied that adding depth to water table did not improve the nitrate/land cover/depth to water table model. For all models, mean error (ME) was
centered around zero with a range from -0.0044 to -0.0052. Nitrate/land cover however, had the smallest difference between RMS (0.979) and average standard error (ASE) (1.0941) and therefore, this model was considered the best model to predict nitrate concentration in groundwater for the study (Fig 2.8). A prediction standard error map was produced for the NO₃ kriging and NO₃/land cover cokriging interpolation maps (Fig 2.9 to 2.10). The cokriged interpolated surface had higher prediction errors at the extreme eastern/western and central part (around Asheville) of the county including the forested area. These parts of the county were the areas with missing data on well locations and NO₃ concentrations. The kriged NO₃ map on the other hand had high prediction errors in the same areas as the cokriged maps as well as areas around Candler, Biltmore Forest, Alexander, and Royal Pines.

**Table 2.3 Comparison of cross validation statistics of kriging and cokriging interpolated surfaces**

<table>
<thead>
<tr>
<th>Prediction errors</th>
<th>NO₃</th>
<th>NO₃ + Landcover</th>
<th>NO₃ + Depth to Water</th>
<th>NO₃ + Landcover + Depth to Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>-0.0044</td>
<td>-0.0047</td>
<td>-0.0048</td>
<td>-0.0052</td>
</tr>
<tr>
<td>RMS</td>
<td>0.986</td>
<td>0.979</td>
<td>0.980</td>
<td>0.979</td>
</tr>
<tr>
<td>RMSSE</td>
<td>0.9469</td>
<td>0.8956</td>
<td>0.8989</td>
<td>0.8975</td>
</tr>
<tr>
<td>ASE</td>
<td>1.0390</td>
<td>1.0941</td>
<td>1.0908</td>
<td>1.0919</td>
</tr>
</tbody>
</table>
Fig 2.7 Kriging interpolation map of NO$_3$ concentrations, Buncombe County
Fig 2.8 Prediction map of NO$_3$ concentrations cokriged with land cover
Fig 2.9 Prediction error map of NO₃ kriging interpolated surface
Fig 2.10 Prediction error map of NO cokriged with land cover

5.0 Discussion

5.1 Non-spatial Statistical Analysis

The non-spatial statistical analysis revealed that landcover type in the county was significantly correlated with high NO₃ content (0.24 at \( p = 0.04 \)), and high NO₃ concentrations were seen in developed urban open space, deciduous forest, and hay/pasture areas. The study did not reveal any statistically significant differences in the presence of high NO₃ concentration between these landcover types, indicating they all contribute to high NO₃ content. Previous studies correlated
high NO$_3$ content with urban areas where fertilizers were often applied to the lawns, parks, and golf courses (Nas and Berktay, 2006). Hay and pasture lands are known source of high NO$_3$ derived from animal manure and agricultural runoff (Hallberg and Keeney, 1993; Kross et al., 1993). In natural undisturbed forest the NO$_3$ content should be low, but studies have found that, high NO$_3$ content in forested areas are indicative of anthropogenic disturbance (Lowrance, 1992; Hallberg and Keeney, 1993; Nolan et al., 1997). This study did not show any correlation between NO$_3$ and depth to water table. Most wells found in Buncombe County have high depth ranging from 300m to 400m. Unlike shallow groundwaters less than 30m (McLay et al, 2001), which have a strong correlation with NO$_3$, deep groundwaters have a weak relationship with NO$_3$. This explains why NO$_3$ and depth to water table have no statistical correlation.

5.2 Spatial Statistical Analysis

This study indicated that nitrate concentration was not beyond the EPA limit, however some areas indicated higher NO$_3$ than other areas. The spatial distribution of NO$_3$ indicated that areas like Barnardsville, Biltmore Forest, Woodfin, and Black Mountain had very low NO$_3$ concentration below 0.5 mg/L. Swannanoa also had low NO$_3$ concentration levels above 0.5 mg/L but not exceeding 0.8 mg/L. High concentrations were recorded in Candler, Weaverville, Leicester Fairview, Arden, and some areas in Asheville. The study also examined land cover and depth to groundwater table, which have the potential to impact NO$_3$ concentration. Relating land cover type to the concentrations of NO$_3$ in groundwater in the county, evergreen forested areas had low concentrations whereas areas with hay/pasture land cover type had high concentration levels. National forest and incorporated areas did not have enough well samples and were excluded from the study. The predicted error also indicated the same, where low predicted error was indicated in the
N, NW, W, and SE parts of the study area. Moderate level of NO$_3$ concentrations (neither as low as forested areas or as high as hay/pasture) were found in areas with the following land cover types; developed open space, developed low intensity, medium intensity, and high intensity. Kriging interpolated surface (fig 2.7) and cokriging interpolated surfaces (fig 2.8) indicated that the NO$_3$ interpolated surface was improved when cokriged with land cover, confirming the results from non-spatial statistical analysis.

5.3 Study Limitations and Future Research

Although the study objectives were accomplished, there were some unavoidable limitations. First of all, data on private drinking wells were not available for the National Forest areas and the incorporated urban areas. This affected the prediction errors from the kriging / cokriging interpolated maps. Secondly, nitrate data were available for only 610 wells and out of 623. Other private drinking wells not included in the data may have very high nitrate concentrations which could have impacted the results and findings of this study. There were private drinking wells with missing information on depth to water table as well. All this information could have helped to improve the accuracy of the predicted models.

Despite the limitations, future studies can be conducted using this study as the basis to perform more site-specific study in high nitrate areas to monitor the wells located in those areas and detect the cause of the high nitrate content. It is recommended that further research be done especially in deciduous forested areas and developed open space landcover areas to find out why nitrate content is high in those regions. Further, this study also serves as a guide for estate planners and developers on choice of site and how vulnerable the area may be to contamination.
6.0 Conclusion

Land cover type used in cokriging with the NO₃ point map influenced the level of NO₃ concentrations in parts of the county. NO₃ cokriged with land cover produced the model which best represented the NO₃ concentrations in the county. The evergreen forested areas, developed intensity (low, medium, high), barren land, and wetlands had very low NO₃ concentrations, whereas hay/pasture, developed open urban space, and deciduous forest areas had high NO₃ concentration.

The eastern part of Buncombe County (mountainous areas) recorded very low concentrations of NO₃ in groundwater compared to the central, northern, and southern parts. Nearly half of the county had NO₃ concentration of 0.5 mg/L or below. The level of nitrate concentrations within the whole county ranged from 0.25 mg/L to 8.5 mg/L. Even though higher NO₃ concentrations were found in some regions, none of the regions’ NO₃ concentrations exceeded the maximum concentration level set by the US EPA (10 mg/L), beyond which is considered to be harmful to human health.
7.0 References


Rahman, A. (2008), A GIS based DRASTIC model for assessing ground water vulnerability in shallow aquifer in Aligarh, India Applied Geography 28, 32–53


CHAPTER 3

A GIS BASED DRASTIC MODEL FOR VULNERABILITY ASSESSMENT OF GROUNDWATER TO NITRATE CONTAMINATION IN BUNCOMBE COUNTY, NC

Abstract

High concentrations of nitrate (NO$_3$) in groundwater can be harmful to human health if ingested, and may be the primary cause of blue baby syndrome, among other health impacts. This study employed Geographical Information System (GIS) technology to investigate the vulnerability of groundwater to NO$_3$ content in Buncombe County, North Carolina. The study used DRASTIC model established by the United States Environmental Protection Agency (USEPA) to assess the vulnerability of groundwater in Buncombe County to NO$_3$ contamination. To get an accurate vulnerability index for the County, the DRASTIC model was modified to fit the hydrogeological settings of the county. A third vulnerability map was created using regression-based DRASTIC, a statistical method, to measure how NO$_3$ relates to each of the DRASTIC variables. The study resulted in three vulnerability index maps indicating areas with very low to very high vulnerability potential and the spatial distribution of NO$_3$ concentrations in the county. Comparison of the three models indicated that the regression-based DRASTIC model best depicted the spatial distribution of NO$_3$ concentrations in the county. Although the NO$_3$ concentrations in groundwater did not exceed the USEPA standard limit for drinking water (10 mg/L), some areas in the county had NO$_3$ as high as 8.5 mg/L.

**Keywords:** EPA DRASTIC Model, Modified DRASTIC model, Regression-based DRASTIC model, GIS, Kriging, NO$_3$, Groundwater
1.0 Introduction

Water plays a vital role in human life and society as a whole. Both groundwater and surface water contribute to economic, social, health, recreational, and cultural activities and are critical in sustaining the environment and ecosystem (Anornu et al., 2012). Groundwater is the water present beneath Earth's surface in soil and rock pore spaces and in the fractures of rock formations, whereas surface water is the water found above the ground. Due to rapid population growth, the volume and quality of surface water with time is diminishing leaving groundwater as the most reliable source of water in terms of quality (Anornu et al., 2012). Challenges resulting from the effects of climate change and the contamination of surface water resulting from high population growth, industrialization, and irrigation practices, have led to increased demand for groundwater (Anornu et al., 2012).

Groundwater is the most significant water resource on earth (Tirkey et al., 2013). It provides about 80% of usable global water storage and contributes immensely to agricultural, industrial, and other municipal uses, especially in areas lacking other sources of water (Shirazi et al., 2012). The quality of groundwater is as important as its availability and quantity because it represents the primary source of drinking water worldwide (Rahman, 2008). According to Kemper (2004), about two billion people around the world depend on groundwater for their day to day activities. Groundwater is an important source of water supply because of its low susceptibility to pollution compared to surface water (EPA, 1985). Unfortunately, groundwater is vulnerable to pollution, which may be caused by underlying bedrock, human activities, and sewage discharge from industrial and agricultural sites (Babiker et al., 2005). Groundwater vulnerability refers to the tendency for contaminants released onto the ground surface or in the aquifer’s uppermost layer to transport into the groundwater system (National Research Center, 1993; Javadi et al., 2010; Shirazi et al., 2012).
The study of groundwater per Tirkey et al. (2013) is based on the idea that groundwater vulnerability to contamination is related to land use activities and varies with land areas. Any activity whereby chemicals or wastes may be released into the environment has the potential to pollute groundwater. Due to high population growth and industrialization, substantial amounts of domestic, industrial, and agricultural sewage are released into the environment as runoff leading to groundwater pollution (Rahman, 2008). Compared to surface water pollution, groundwater pollution is difficult to detect and even more difficult to treat. After detection, treatment of polluted groundwater may take years, decades, or even centuries (Todd, 1980; Rahman, 2008).

Groundwater contamination caused by excess nitrate (NO$_3^-$) concentrations is a worldwide problem and is usually identified with sources such as intensive agriculture, high density housing with unsewered sanitation, and liquid manure spreading onto land through irrigation (Keeney, 1986; Eckhardt and Stackelburg, 1995; Spalding and Exner, 1993). Groundwater is contaminated by nitrate when nitrogen released onto the earth’s surface infiltrates into the ground. Nitrogen increases the productivity of crops and is consistently and extensively used in fertilizers. However, when nitrogen in fertilizer exceeds the demand of plants and the absorptive capacity of the soil to absorb, it gets carried into groundwater in the form of NO$_3^-$ through infiltration of precipitation, irrigation and other processes (Meisinger et al., 1991; Shamrukh et al., 2001). Increased concentration of NO$_3^-$ in groundwater may represent a loss of fertility in the overlying soil, cause eutrophication from the discharge of groundwater into surface water at springs and become a health hazard to animals and humans (McClay et al., 2001). Even though a small amount of NO$_3^-$ in water can be harmless, high levels of NO$_3^-$ in water can affect human health. Since groundwater serves as the main source of drinking water, the presence of NO$_3^-$ in groundwater in excess may cause health problem when ingested. Greater amounts of NO$_3^-$ in the body can cause methemoglobinemia, commonly called
“blue baby syndrome”. Infants below the age of six months and pregnant women with low stomach acidity are most at risk from methemoglobinemia (Messier et al., 2014). As such, the Environmental Protection Agency (EPA) has established a maximum NO₃ contaminant level of 10 milligrams per Liter (10 mg/L) for drinking water, beyond which NO₃ in groundwater could be harmful (EPA, 1995).

Several methods have been developed to assess the potential for groundwater to be contaminated by NO₃ or other pollutants. These methods can be grouped into three categories: Overlay and Index Methods, Process Based Methods, and Statistical Methods (Tesoriero et al., 1998; Thirumalaivasan et al., 2003). Overlay and Index methods overlay the layers of factors known to influence the movement of pollutants from the ground surface to the water table to create a vulnerability index map using specified vulnerability indices (Tirkey et al, 2013). Process Based Methods use a structured set of activities or processes designed to assess groundwater vulnerability, whereas Statistical Methods mainly use statistical analysis to establish the relationship between the spatial variables and existing pollutants in groundwater. One of the most widely used groundwater vulnerability mapping methods is the “DRASTIC” model, which falls under the Overlay and Index category (EPA, 1993; Thirumalaivasan et al., 2003).

1.1 Background Information

The DRASTIC model was developed in the United States with the support of the EPA as a tool to assess aquifer vulnerability in multiple hydrogeologic settings based on a vulnerability index (Aller et al., 1987; Babiker et al., 2005; Al-Rawabdeh et al., 2013). A hydrogeologic setting is a composite description of all main geologic and hydrologic factors that affect the movement of groundwater into, through, and out of a zone or region. DRASTIC is one of the most widely used
models to assess groundwater vulnerability to potential contaminants (Al-Rawabdeh et al., 2013). It is a weight-and-rating based model that integrates several factors to produce the desired vulnerability index map of a chosen region. DRASTIC uses a seven parametric system consisting of Depth to water (D), net Recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of vadose zone (I), and hydraulic Conductivity (C) to create the vulnerability map. Table 3.1 gives the detailed description of each parameter.

**Table 3.1 Description of DRASTIC model parameters**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>D</strong></td>
<td>Depth to water is the depth from the ground surface to the water table or to the confining layer of a confined aquifer.</td>
</tr>
<tr>
<td><strong>R</strong></td>
<td>Net recharge is the amount of water released onto the ground surface that infiltrates and reaches the aquifer.</td>
</tr>
<tr>
<td><strong>A</strong></td>
<td>Aquifer media refers to the type of underlying rock that serves as the aquifer.</td>
</tr>
<tr>
<td><strong>S</strong></td>
<td>Soil media is the uppermost portion of the vadose zone and describes soil cover characteristics.</td>
</tr>
<tr>
<td><strong>T</strong></td>
<td>Topography is the slope variability of the land surface.</td>
</tr>
<tr>
<td><strong>I</strong></td>
<td>Impact on vadose zone refers to the unsaturated zone above the water table.</td>
</tr>
<tr>
<td><strong>C</strong></td>
<td>Hydraulic conductivity describes the ability of water to flow within the aquifer material.</td>
</tr>
</tbody>
</table>

Constant weights are assigned to these parameters based on their pollution potentials and a variable rating based on ranges or significance of the media type. DRASTIC model has been used by several researchers for groundwater and aquifer vulnerability assessment worldwide (Saidi et al., 2010; Secunda et al., 1998; Neshat et al., 2014). Fritch et al. (2000) used DRASTIC to assess the Paluxy aquifer’s vulnerability to contamination in central Texas, USA. Babiker et al. (2005) used DRASTIC model to assess aquifer vulnerability of Kakamigahara Heights Gifu Prefecture and Central Japan. Jamrah et al (2008) also used the model in their study of groundwater vulnerability assessment in the coastal region of Oman. DRASTIC models produce regional maps delineating
areas of low, moderate, and high vulnerability, which could be followed up with further site specific studies.

DRASTIC model is, however, rigid in assigning weights and rates to its parameters, which in some cases does not result in accurate assessments (Rupert, 2001). Researchers have indicated some disadvantages, where the influence of regional topography, geology, and land cover characteristics are not considered in the model computation, as such the same weights and rating values are used everywhere (Javadi et al., 2011). However, to better address this issue, researchers have adapted to several modifications of the original DRASTIC model have been adopted to refine the representation of a region’s specific hydrogeologic and land cover settings (Thirumalaivasan et al., 2003; Babiker et al., 2005). The modifications could be in the form of (i) incorporation of other parameters, (ii) removal of existing parameters, and (iii) manipulation of the assigned weights and ratings. Data sources such as groundwater flow, rate of groundwater flow, and source of groundwater recharge were used by Brown (1998) in addition to DRASTIC parameters in the study of vulnerability assessment of the Heretaunga plain aquifer in New Zealand (Thirumalaivasan et al., 2003). Neshat et al. (2014) used a modified DRASTIC by manipulating the assigned weights and rates in estimating groundwater vulnerability to pollution in the Kerman Agricultural Area of Iran. A modified DRASTIC was also implemented by removing existing parameters in a nitrate based study in Jilin City of northeastern China (Huan et al., 2012). Several other studies including Wang et al., (2012), Sener et al., (2013), Fritch et al., (2000), Meng et al., (2007), and Javadi et al., (2010) have used modified DRASTIC models to test for groundwater susceptibility to contamination. Several studies indicated that DRASTIC model results could be used to detect nitrate pollution in groundwater (Javadi, et al., 2010; Huan et al., 2012; Remesan and Panda, 2008). A study by Antonakos and Lambrakis (2006) focused on the development and testing of three hybrid methods
for the assessment of aquifer vulnerability to nitrates based on DRASTIC modeling in NE Korinthia, Greece. Similar studies by Al-Adamat et al. (2003), Neshat et al. (2014), and Javadi et al. (2010) also revealed that modified DRASTIC models using nitrate could be effectively used to predict groundwater vulnerability.

1.2 Study Objective

The main objectives of this study are to (i) assess the vulnerability of groundwater to contamination using DRASTIC parameters established by the US EPA and (ii) improve the vulnerability model using land cover and nitrate concentrations in the groundwater through advanced geospatial analyses.

2.0 Study Area

Buncombe County, North Carolina was selected as a case study to demonstrate the applicability of the proposed method (Fig 3.1). Buncombe County is located in the western North Carolina in the Blue Ridge Physiographic province. The county is bordered to the north by Madison and Yancey counties, to the south by Henderson County, to the east by Rutherford and McDowell counties and to the west by Haywood County. Buncombe County is also bordered to the west by the Appalachian Mountains and to the east by Black Mountains. The county covers a total area of 660 mi², of which 657 mi² is land and 3.5 mi² is water (US Census Bureau, 2010). The average annual temperature of Buncombe County is 55.83°F, and the average annual precipitation is 40.92in.

Buncombe County consists of high, smooth-rounded mountains surrounded by streams flowing in narrow valleys and is underlain by bedrock consisting of igneous, meta-igneous, and sedimentary rocks (Aller et al., 1987). Aquifers in Buncombe County are mostly found in the
crystalline metamorphic and igneous rocks (Trap and Horn, 1997) where fractures serve as the primary storage for groundwater (Drever, 1997). Wells located in valleys typically have shallow water tables and are more susceptible to contamination than wells located in hilly areas (Burow et al., 2010).
Fig 3.1 Map of Buncombe County, North Carolina, USA (Study Area)
3.0 Method of study

The methods of consisted of three steps: (1) Input Data Collection, (2) Vulnerability Model Preparation, and (3) Model calibration and Preparation of Final Vulnerability Map. The flowchart represents a step-by-step research plan (fig 3.2).

**Fig. 3.2 Methodology for groundwater vulnerability assessment using DRASTIC Model in GIS**
3.1 Input Data Collection

DRASTIC parameters used in the study include Depth to water, net Recharge, Aquifer media, Soil media, Topography (percent slope), Impact of vadose zone, and hydraulic Conductivity. Additional parameters used are land cover and nitrate concentrations in private drinking water wells. Data used for this study were obtained from the Geospatial Data Gateway (Geospatial Data Gateway: https://datagateway.nrcs.usda.gov/) and North Carolina Department of Natural Resources Center. The following sections explain each parameter in detail.

**Depth to water table (D):** The depth to water table data obtained from the North Carolina Department of Natural Resources Center was geocoded in ArcMap using the ArcGIS Online Geocoding Service to create a point map. The Geostatistical Analyst (GA) tool in ArcMap was then used to create a continuous predicted depth water table surface (using ordinary kriging interpolation) then converted into a raster file for further analysis. The depth to water table map was then classified into ranges with ratings ranging from 1 for deeper water tables (lowest impact on vulnerability) to 10 for shallow water tables (highest impact on vulnerability) assigned to each class. The depth to water map is given in Fig 3.3A.

**Net Recharge (R):** In this study, average annual precipitation recorded in inches was used as the major source of recharge. The recharge map was classified using the class ranges provided by EPA’s DRASTIC model from 1 for low recharge value (lowest impact on vulnerability) to 10 for high recharge value (highest impact on vulnerability) (Table 3.1). Ratings were then assigned to the individual classes. The net recharge map of the area is given in Fig 3.3A.

**Aquifer media (A):** The map for the aquifer media layer was prepared from Buncombe County’s geology map. Several rock types are present in the county including Ashe Metamorphic Suite and Tallulah Falls Formation (Muscovite-biotite gneiss), Brevard Fault Zone, Amphibolite, Meta-
ultramafic Rock, Great Smokey Group, Henderson Gneiss, and Biotite Gneiss and Schist. Weights and ratings were assigned to the aquifer media based on the type of rock formation and the degree of permeability. Metamorphic rock/Serpentine, which is the most vulnerable to contamination due to its high permeability, was given a rating of 8. The least vulnerable aquifer media; granite gneiss with amphibolite, was assigned the lowest rating value of 2 due to its low permeability rate. The types of aquifer media within the county are given in Fig 3.3A.

**Soil media (S):** Hydrologic soil group data in Buncombe County were used to create the soil media layer (Fig 3.3A). Soils are classified into hydrologic groups based on their runoff potentials. In the hydrologic soil group, A represents soil with high infiltration rates which consist mainly of deep, well-drained to excessively drained sands or gravelly sands. Group B represents soil with moderate infiltration rates which consist of well-drained soils that have moderately fine to moderately coarse texture. This soil group has a moderate rate of water transmission. The group C soil group has low infiltration rates and is made up of soils that retard the downward movement of water. D is the soil group with the lowest infiltration rate and mainly consist of clay. Some areas in the county also had mixed hydrogeologic soil groups such as A/D, B/D and C/D. These soil groups were rated according to their rate of infiltration. Higher ratings were assigned to the group with the highest infiltration rate and lower ratings were assigned to the group with the lowest infiltration rate.

**Topography (T):** For the topography map, a digital elevation model (DEM) at a resolution of 3 m² was used to create the percent slope of the area. Hilly areas were assigned low rating values and lowlands were given high rating values. The topography map of the study area is given in Fig 3.3B.

**Impact of vadose zone (I):** In this study, percent sand was used as the vadose zone since sand is the medium through which water can easily penetrate. High percent sand shows high infiltration rates, hence high vulnerability, whereas low percent sand shows low infiltration rates, hence low
vulnerability. Rating was assigned from 10 (high percent sand) to 1 (low percent) sand. Fig 3.3B represents the vadose zone of the study area.

**Hydraulic Conductivity (C):** Hydraulic conductivity of the aquifer is determined by the amount and connectivity of void spaces within the aquifer which may occur as a result of factors like fracturing and bedding planes. The hydraulic conductivity of the area varied from 0 to $9.2 \times 10^{-5}$ m/s. Rating was assigned to the hydraulic conductivity layer based on the rate of movement of water in the soil. High values were assigned high ratings, whereas low values were assigned low rating values. Buncombe County’s hydraulic conductivity is given in Fig 3.3B

**Land cover (LC):** Land cover refers to the physical material such as grass, trees, bare ground, developed open space, hay/pasture, and forest found on the surface of the earth. Land cover within a zone tends to have impact on groundwater depending on the type of land cover present. The most vulnerably landcover types in Buncombe County are hay/pasture and developed open spaces while the least vulnerable land cover types are the forested zones. In the modified DRASTIC, Buncombe County’s land cover (Fig 3.3B) was incorporated into the model. Land cover data were obtained from the Geospatial Data Gateway. Parameters included in the modified DRASTIC and the assigned weight for the individual parameters are shown in table 3.2.

**Nitrate data**

Data on nitrate concentrations in 623 groundwater wells in Buncombe County were acquired from the North Carolina Division of Water Resources. Each well data record contained information on address location or latitude and longitude from a cartesian coordinate system. The dataset was geocoded using the ArcGIS Online World Geocode Service to create a nitrate concentration location point map in ArcGIS 10.3. A total of 610 nitrate concentrated wells were
matched during the geocoding process and was used for further analysis. The point map created was used to generate a continuous predicted nitrate surface with the Geostatistical Analyst tool in ArcMap using ordinary kriging interpolation.

Fig 3.3: Parameters used in EPA vulnerability analysis: Depth to water (A), Net recharge (B), Aquifer media (C), and Soil media (D)
Fig 3.4: Parameters used in EPA vulnerability analysis: Topography (A), Impact of vadose zone (B), Hydraulic conductivity (C) and Land cover types (D)
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Range</th>
<th>Rating</th>
<th>EPA based weight (DRASTIC)</th>
<th>weight (Modified DRASTIC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth to water table (D) in (meters)</td>
<td>99-1300</td>
<td>1</td>
<td>5</td>
<td>-</td>
</tr>
<tr>
<td>Net recharge (R) in (inches)</td>
<td>36-69</td>
<td>10</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>
| Aquifer media (A)                | metamorphic rock/ serpentine schist/ phylonite
metasedimentary rock/ mica schist
amphibolite/ metasedimentary rock
biotite gneiss/ amphibolite
gneiss/ mica schist
granitic gneiss/ amphibolite      | 8                   | 7       | 6                         | 5                        |
|                                  | metamorphic rock/ serpentine schist/ phylonite
mica schist/amphibolite          | 5                   | 4       | 3                         | 2                        |
| Soil media (S)                   | A                      | 10      | 8                         | 6                        |
|                                  | B                      |         |                           |                          |
|                                  | C                      |         |                           |                          |
|                                  | A/D                    |         |                           |                          |
|                                  | B/D                    |         |                           |                          |
|                                  | C/D                    |         |                           |                          |
| Topography (T) in (Percent Slope) | 0-2                    | 10      | 9                         | 8                        |
|                                  | 2-6                    |         |                           |                          |
|                                  | 6-12                   |         |                           |                          |
|                                  | 12-18                  |         |                           |                          |
|                                  | >18                    |         |                           |                          |
| Impact of vadose zone (I)        | 1-36                   | 2       |                           | 5                        |
|                                  | 37-45                  |         |                           |                          |
|                                  | 46-51                  |         |                           |                          |
|                                  | 52-58                  |         |                           |                          |
|                                  | 59-61                  |         |                           |                          |
|                                  | 62-63                  |         |                           |                          |
|                                  | 64-68                  |         |                           |                          |
|                                  | 66-76                  |         |                           |                          |
|                                  | 77-98                  |         |                           |                          |
| Hydraulic Conductivity (C) in (micrometer/sec) | 1-5                    | 2       |                           | 3                        |
|                                  | 6-9                    |         |                           | 2                        |
|                                  | 10-12                  |         |                           |                          |
|                                  | 13-14                  |         |                           |                          |
|                                  | 15-17                  |         |                           |                          |
|                                  | 18-20                  |         |                           |                          |
|                                  | 21-24                  |         |                           |                          |
|                                  | 25-31                  |         |                           |                          |
|                                  | 32-92                  |         |                           |                          |
| Land Cover (LC)                  | Hay/Pasture            | 10      |                           |                          |
|                                  | Developed, Open Space  | 9       |                           |                          |
|                                  | Developed, Low Intensity/Cultivated Crops | 8     |                           |                          |
|                                  | Developed, Medium Intensity | 7     |                           |                          |
|                                  | Developed, High Intensity | 6    |                           |                          |
|                                  | Barren Land            | 5       |                           |                          |
|                                  | Shrub/Scrub            | 4       |                           |                          |
|                                  | Deciduous Forest/Evergreen Forest/Mixed Forest/Herbaceous | 3     |                           |                          |
|                                  | Woody Wetlands         | 2       |                           |                          |
|                                  | Open Water/Emergent Herbaceous | 1 |                           |                          |
3.2 Vulnerability Model Preparation

The input parameter layers were grouped using ranges proposed by EPA and ratings on a scale of 1 to 10 were assigned to each range based on its pollution potential (Table 3.2). All the factors were assigned weights proposed by the US EPA, based on the significance of each factor in transporting contaminants. Raster calculator was then used to calculate the DRASTIC index vulnerability model using the following equation:

\[
\text{Drastic index} = D_r D_w + R_r R_w + A_r A_w + S_r S_w + T_r T_w + I_r I_w + C_r C_w
\]

Where D, R, A, S, T, I, and C represent the seven parameters and the r and w subscripts represent the ratings and assigned weights of each of the parameters. The model yielded a numeric vulnerability index map. Higher values depicted areas with high vulnerability and lower values depicted areas with low vulnerability. Using quantile classification, the vulnerability index map was regrouped into no risk, low, moderate, high, and very high pollution potential areas.

Modified DRASTIC: To better represent the groundwater vulnerability of Buncombe County, based on regional hydrogeology, topography, and land cover distribution, a knowledge-based heuristic method was adopted. Rating values for the DRASTIC parameters were maintained while the weights of the EPA DRASTIC model were modified (Table 3.2). The modification, included (a) reduction in weights of depth to water table and aquifer media as deep seated groundwater in crystalline bedrock are less likely to get contaminated (Lindsey and Bickford, 1999); (b) increase in weights of the surficial deposits or soil media, as for deeper aquifers, the contaminant loading from the surface may play an important role in groundwater vulnerability; (c) increase in weights of topographic slope, as in a mountainous region the valleys become more vulnerable to contaminants, due to water accumulation from increased runoff; (d) finally addition of a land cover layer for analysis, as land cover is a known source of contamination in North Carolina.
The modified DRASTIC vulnerability index was calculated using the equation:

\[ \text{Drastic index} = R_r R_w + S_r S_w + T_r T_w + C_r C_w + L C_r L C_w \]

The vulnerability index map produced was grouped into very low vulnerability zones, low vulnerability zones, medium vulnerability zones, high vulnerability and very high vulnerability zones using quantile classification.

**Regression DRASTIC Model**

A data-driven approach was taken to assign weights to each DRASTIC layer and land cover. In this approach, the distribution of high nitrate content greater than 1mg/L was used, where 70% data were used to train the DRASTIC model, and 30% were left for model validation. The Ordinary Least Square (OLS) regression, Spatial Lag, and Spatial Error models were considered to predict the groundwater vulnerability using nitrate as the dependent variable and the individual DRASTIC layers and landcover layer as independent variables.

The relationship between the variables were modeled using the equation:

\[ Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots \ldots \ldots + \beta_n X_n + \varepsilon_i \]

Where 1, 2, \ldots, n are number of variables, Y is nitrate, \(X_1, X_2, \ldots, X_p\) are the DRASTIC and land cover parameters, and \(\beta_1, \beta_2, \ldots, \beta_p\) are regression coefficients, i.e., the weights used in the model. The regression equation was then used in ArcMap to calculate the regression DRASTIC index map. The vulnerability index map was classified using quantile into very low vulnerability zones, low vulnerability zones, medium vulnerability zones, high vulnerability and very high vulnerability zones.
4.0 Results

4.1 Descriptive Statistics

Gneiss coupled with mica schist represents the most dominant aquifer type in Buncombe County, followed by metasedimentary/mica schist, whereas the least dominant aquifer type is amphibolite/metasedimentary. Land cover type, conversely, is highly dominated by deciduous forest, followed by hay/pasture and developed open space. The least dominant of the land cover type in the county is emergent herbaceous wetland. Buncombe County’s terrain elevation ranges from 395.53m (lowest area) to 1939.44m (highest area) with a percent rise (% slope) from 0 to 730. Almost all the areas in Buncombe County fall within 0 to 120% with just a few above the 120% rise. Hydrologic soil group B is the most dominant soil group in the county, followed by group A, while the least dominant soil type is group C/D. Table 3.3 summarizes the descriptive statistics for depth to water table (D), net recharge (R), impact of vadose zone (i.e., % sand), and the hydraulic conductivity (C) of the aquifers in the county.

Table 3.3 Descriptive statistics of Depth to water, net Recharge, Impact of vadose zone, and hydraulic Conductivity parameters

<table>
<thead>
<tr>
<th></th>
<th>D (m)</th>
<th>R (ln)</th>
<th>l (%)</th>
<th>C (µm/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>347.172</td>
<td>52.5</td>
<td>50.38168</td>
<td>17.25516</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>179.5178</td>
<td>9.9582</td>
<td>15.41168</td>
<td>10.74713</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>36</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>1300</td>
<td>69</td>
<td>97.9</td>
<td>92</td>
</tr>
<tr>
<td>Range</td>
<td>1300</td>
<td>33</td>
<td>97.9</td>
<td>92</td>
</tr>
</tbody>
</table>
4.2 EPA DRASTIC model

The DRASTIC index model calculated per EPA weighting and rating system provided a numerical range of values where higher DRASTIC values equate to greater potential of groundwater vulnerability within the study area. The computed DRASTIC index values varied from 62 to 170 and were categorized into five groups: very low (62-93), low (94-102), moderate (103-110), high (111-122) and very high (123-170) vulnerability (Table 3.4). The results showed that, out of the total area of the county, 418.41 km² (24.57%) of the area fell in the very low vulnerability zone with the DRASTIC index ranging from 62 to 93. A total area of 276.2 km² (16.22%) was found within low vulnerability zones with a DRASTIC index value from 94 to 102. Moderate and high vulnerability zones covered by 324.32 km² and 312.2 km², representing 19.04% and 18.33% of the total area with DRASTIC index ranging from 103 to 110 and 111 to 122, respectively. The DRASTIC vulnerability map showed that 371.8 km² (21.83%) of the study area was classified as having a very high pollution potential with DRASTIC index values ranging from 123 to 170.

<table>
<thead>
<tr>
<th>DRASTIC index value</th>
<th>Vulnerability Zone</th>
<th>Area (km²)</th>
<th>% Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>62 – 93</td>
<td>Very low</td>
<td>418.41</td>
<td>24.57</td>
</tr>
<tr>
<td>94 – 102</td>
<td>Low</td>
<td>276.20</td>
<td>16.22</td>
</tr>
<tr>
<td>103 – 110</td>
<td>Moderate</td>
<td>324.32</td>
<td>19.04</td>
</tr>
<tr>
<td>111 – 122</td>
<td>High</td>
<td>312.20</td>
<td>18.33</td>
</tr>
<tr>
<td>123 – 170</td>
<td>Very high</td>
<td>371.80</td>
<td>21.83</td>
</tr>
</tbody>
</table>
Based on the vulnerability map, a color scheme ranging from green to red was applied to the individual vulnerability zones with green representing the least vulnerable zone and red the most vulnerable zone. The high vulnerable zone areas were distributed across the county, mostly in the eastern part, and some near the western boundary of the county. Very low to low vulnerability areas were concentrated in the central part of the county. Asheville, which is one of the most populated areas, lies in a low vulnerability zone together with other cities like Leicester, Alexander, Candler, and Woodfin.

Fig 3.5 EPA DRASTIC index vulnerability map of Buncombe County, NC
4.3 Modified DRASTIC model

The DRASTIC index provided vulnerability values ranging from 24 to 150. The vulnerability map was categorized into five classes using natural breaks: no risk vulnerability (24-65), low (66-80), moderate (81-96), high (97-111), and very high vulnerability (112-150) (Table 3.5). The results showed that, out of the total area, 379.85 km² (22.31%) lies in the no risk vulnerability zone with DRASTIC index ranging from 24 to 59. An area of 599.46 km² (35.2%) was assigned to the low vulnerability zone with DRASTIC index values from 66 to 80. A moderate and high vulnerability zone within the county was covered by 321.29 km² and 224 km² representing 18.87%, and 13.15%, with DRASTIC index values from 81 to 96, and 97 to 111, respectively.

Table 3.5 Modified DRASTIC index values and their respective vulnerability zones and areas covered within the zones.

<table>
<thead>
<tr>
<th>DRASTIC index value</th>
<th>Vulnerability Zone</th>
<th>Area (km²)</th>
<th>% Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>24 - 65</td>
<td>Very low</td>
<td>379.85</td>
<td>22.31</td>
</tr>
<tr>
<td>66 - 80</td>
<td>Low</td>
<td>599.46</td>
<td>35.20</td>
</tr>
<tr>
<td>81 - 96</td>
<td>Moderate</td>
<td>321.29</td>
<td>18.87</td>
</tr>
<tr>
<td>97 - 111</td>
<td>High</td>
<td>224</td>
<td>13.15</td>
</tr>
<tr>
<td>112 - 150</td>
<td>Very high</td>
<td>178.21</td>
<td>10.47</td>
</tr>
</tbody>
</table>

The DRASTIC vulnerability map showed that about 10.47% of the area was classified as being very highly vulnerable with DRASTIC index values ranging between 112 and 150, covering about 178.21 km² of the study area. Similarly, a color scheme ranging from green to red was applied to the individual vulnerability zones with green representing the least vulnerable zone and red the most vulnerable zone. High vulnerability areas were found mainly in the central and western part of the county as well as some areas in the eastern side. No to low groundwater vulnerability were
identified in the eastern/northeastern part and along the western boundary. Moderate and high vulnerability zones were distributed across the county with most of those areas centered in the central part of the county. Most of Asheville lies in moderate to very high vulnerable zones together with other cities like Leicester, Alexander, Candler and Woodfin.

Fig 3.6 Modified DRASTIC index vulnerability map of Buncombe County, NC
4.4 Regression based DRASTIC model

Out of the seven DRASTIC parameters, only topography (0.395 at $p<0.09$), hydraulic conductivity (0.306 at $p<0.049$) and land cover (0.309 at $p<0.046$) indicated significant correlation with the nitrate data.

Using 70% of the NO$_3$ concentration data as dependent variable and the corresponding DRASTIC, and landcover as independent variables a regression-based model was created to predict groundwater vulnerability. The combined DRASTIC and landcover model accounted for 27% of the variability (adjusted $R^2 = 0.27$, $p = 0.015$). The analyses of individual independent variables are summarized in Table 3.6, and indicate that topography, hydraulic conductivity, and land cover significantly contribute to groundwater vulnerability. After removing the variables with high $p$ values, the adjusted $R^2$ value did not change. The residuals were normally distributed, satisfying the criteria for evaluating a linear relationship (Fig 3.7). A test for spatial autocorrelation was performed, but neither spatial lag nor spatial error models were significant, so an OLS regression model using the significant variables was used to prepare a regression DRASTIC index. The coefficients of the independent variables were assigned as weights in ArcMap with raster calculator using the equation:

$$Y(\text{NO}_3) = 0.69 + 0.23T + 0.45C + 0.22\text{LC}$$

Where $Y$ is the dependent variable (nitrate), and the independent variables are topography ($T$), hydraulic conductivity ($C$), and land cover ($\text{LC}$) respectively.
### Table: 3.6 Regression model result using all variables and only significant variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Variables</th>
<th></th>
<th>Significant Variables</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Probability</td>
<td>Coefficient</td>
<td>Probability</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>2.09</td>
<td>0.38</td>
<td>0.69</td>
<td>0.27</td>
</tr>
<tr>
<td>Water_depth</td>
<td>0.18</td>
<td>0.29</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Net_Recharge</td>
<td>0.16</td>
<td>0.65</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Aquifer_media</td>
<td>-0.21</td>
<td>0.19</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Soil_media</td>
<td>-0.04</td>
<td>0.77</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Topography</td>
<td>0.26</td>
<td>0.07</td>
<td>0.23</td>
<td>0.05</td>
</tr>
<tr>
<td>Impact_vz</td>
<td>0.12</td>
<td>0.32</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>H_Conductivity</td>
<td>0.59</td>
<td>0.01</td>
<td>0.45</td>
<td>0.02</td>
</tr>
<tr>
<td>Land Cover</td>
<td>0.21</td>
<td>0.04</td>
<td>0.22</td>
<td>0.02</td>
</tr>
</tbody>
</table>

**Normal Q-Q Plot of residuals**

**Fig 3.7 Relationship between observed and expected normal values of nitrate concentrations**

The regression DRASTIC index vulnerability map (Fig 3.8) yielded values ranging from 2.97 to 10.7. The index values were categorized into a very low risk zone: 2.974–4.313, which covers 27.18% of the county, a low risk zone: 4.314–5.095(28.33%), a medium risk zone: 5.096–
5.865(19.25%), and high and very high vulnerability risk zones: 5.866–6.774(13.22%) and 6.775–10.705(12.01%) respectively. Table 3.7 summarizes the vulnerability category of the regression-based DRASTIC model and the area covered by each category.

**Fig 3.8 Regression DRASTIC index vulnerability map of Buncombe County, NC**
Table 3.7 Modified DRASTIC index values and their respective vulnerability zones and areas covered within the zones.

<table>
<thead>
<tr>
<th>DRASTIC index value</th>
<th>Vulnerability Zone</th>
<th>Area (km²)</th>
<th>% Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.974 – 4.313</td>
<td>Very low</td>
<td>463.62</td>
<td>27.18</td>
</tr>
<tr>
<td>4.314 – 5.095</td>
<td>Low</td>
<td>483.23</td>
<td>28.33</td>
</tr>
<tr>
<td>5.096 – 5.865</td>
<td>Moderate</td>
<td>328.38</td>
<td>19.25</td>
</tr>
<tr>
<td>5.866 – 6.774</td>
<td>High</td>
<td>225.40</td>
<td>13.22</td>
</tr>
<tr>
<td>6.775 – 10.705</td>
<td>Very high</td>
<td>204.91</td>
<td>12.01</td>
</tr>
</tbody>
</table>

4.5 Model Validation

All three vulnerability maps were overlaid with the interpolated nitrate concentration surface to visually compare the spatial distribution of nitrate concentration with respect to the three vulnerability index maps (Fig. 3.9). In the regression-based DRASTIC model, high nitrate concentrations were mostly seen in high vulnerability areas with few appearing in medium to low vulnerability zones. Unlike the regression DRASTIC, the EPA DRASTIC index vulnerability map did not accurately represent the nitrate concentrations within the county. Most of the high nitrate concentrations fell within no and low vulnerability zones with only a few located in medium to high vulnerability zones. Even though modified DRASTIC did not provide the best result in terms of representing nitrate concentration within the county, it provided a better result when compared to the EPA DRASTIC model.

Additionally, using 30% of the data set aside for model validation, percentages of high nitrate concentrations (>1ppm/L) within each vulnerability category of the three DRASTIC maps were compared in table 3.8. The regression DRASTIC model correctly plotted 34.4% of high nitrate concentration values in medium to very high vulnerability categories when compared to the EPA and
Modified DRASTIC models, which plotted 11.9% and 14.3%, respectively. The visual and quantitative validation result showed that the regression DRASTIC model best represented the groundwater vulnerability to pollutants in Buncombe County using nitrate concentrations as a reference.

Table 3.8 Percentage of high nitrate within the vulnerability category for EPA, Modified and Regression DRASTIC models.

<table>
<thead>
<tr>
<th>Nitrate Conc (ppm/L)</th>
<th>Vulnerability Category</th>
<th>EPA DRASTIC (% of Nitrate)</th>
<th>Modified DRASTIC (% of Nitrate)</th>
<th>Regression DRASTIC (% of Nitrate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.0 – 3.4</td>
<td>Medium</td>
<td>9.5</td>
<td>7.1</td>
<td>21.4</td>
</tr>
<tr>
<td>3.4-5.6</td>
<td>High</td>
<td>0</td>
<td>4.8</td>
<td>4.8</td>
</tr>
<tr>
<td>5.6-8.5</td>
<td>Very High</td>
<td>2.4</td>
<td>2.4</td>
<td>7.1</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>11.9</td>
<td>14.3</td>
<td>34.4</td>
</tr>
</tbody>
</table>
Fig 3.9 Comparison of EPA DRASTIC, Modified DRASTIC and Regression DRASTIC index vulnerability map

5.0 Discussion

5.1 Model Comparison

The EPA-recommended DRASTIC method has been used by several researchers to assess aquifer vulnerability in different areas. Though the EPA DRASTIC model usually provides reasonable results for vulnerability assessment of shallow groundwater areas, the accuracy of the models often depends on the area’s regional hydrogeological setting. Often EPA DRASTIC models are modified to not only include specific intrinsic hydrogeological properties (hydraulic
conductivity, porosity), but also to take account of the proximity of contaminant sources and their particular characteristics (location, chemical interaction with surface water) that could impact the quality of groundwater (Meng et al., 2007; Javadi et al., 2010). Since nitrate is not normally present in groundwater under natural conditions, it is often used as a good indicator of contaminant movement based on land cover type (e.g., agricultural lands, hay and pasture fields, urban areas with high use of fertilizers, etc). In this study, an experience-based modified DRASTIC method was used where the assigned weight for DRASTIC parameters were adjusted, and land cover data were added to represent the current source of potential nitrate contaminant. Similar studies conducted using experience-based approaches revealed that the method works well for regional scale vulnerability assessment, however due to the use of relative weights based on the expert opinion, it lacks a more rigorous data-driven methodology (Gupta, 2014; Wang et al., 2012, Sener et al., 2013). To overcome the limitations of a relative weight based approach, this study also used a data-driven statistical approach (Regression DRASTIC). High nitrate concentration data from private drinking water wells were used as a dependent variable to model the groundwater vulnerability using DRASTIC variables and landcover as independent variables. Several studies used the linear regression approach and found successful improvement in groundwater vulnerability prediction (Saha and Alam, 2014; Chenini and Khemiri, 2009; Muthulakshmi et al., 2013).

In the present study, all three different types of DRASTIC models identified areas vulnerable to groundwater contamination in relation to other areas. In the EPA DRASTIC model, very low to low vulnerability were seen in valleys around the central and extreme western part of the county, whereas medium to high vulnerability were located in the eastern, northeastern, and southeastern parts of county in the ridges with some traces of low vulnerability. This output was not realistic as areas of low elevation indicated no to low vulnerable zone, where in reality, most groundwater
pollution is generally accumulated in the valley region from surface runoff, agricultural practice, and presence of hay and pasture land in valley region on Buncombe County. Unlike the EPA, the modified and the regression-based DRASTIC models provided a reversed result in terms of vulnerability categories and their location. Medium to high vulnerability were located in the central, southern (valley areas), and some areas in the northern part of the county for both the modified and regression-based DRASTIC models. Very low to low vulnerability areas were situated in the eastern and extreme western part of the county, mostly in the ridges. Both outputs are realistic in terms of presence of pollutants, especially Nitrates. Cities like Alexander, Swannanoa, Candler Royal Pines, and Arden were located within medium to high vulnerability zones. However, when the models were overlaid with the nitrate concentration map, the regression-based DRASTIC model best depicted areas with high nitrate (2 mg/L and above). These areas were found in the medium and high vulnerability zones.

5.2 Model Parameters

In the Modified DRASTIC model topography, hydraulic conductivity of soil, landcover, soil media, and net recharge were considered, while depth of water table, aquifer media, and impact of vadose zone were eliminated from the model input. Depth to water table is an important factor in shallow aquifers, but there is the tendency for natural attenuation to occur as the contaminants percolate through aquifer with a deeper water table (Al-Zabet, 2002; Gupta, 2014). All wells located in Buncombe County are deep wells with an average depth of 347m. Therefore, the depth of water table was not incorporated in the modified model. Aquifer media controls the route and path of contaminant transport. In the study area, the crystalline deep fractured aquifers are mainly made up of metasedimentary rocks, and did not influence the aquifer vulnerability model based on an agricultural contaminant like nitrate. A study from Lindsey and Bickford (1999) examining
crystalline rocks of Pennsylvania, indicated that crystalline aquifers are less susceptible to agricultural and landuse contaminants. The impact of vadose zone is difficult to estimate and regional vadose zone maps are generally not available for planning purposes (Li and Zhao, 2011), and were not available for Buncombe County, NC. Often impact of vadose zone is estimated from soil texture, thickness, and hydraulic conductivity (Bartzas et al., 2015). In this study, soil texture in terms of hydrologic soil group, and hydraulic conductivity were used, thus impact of vadose zone layer was eliminated from the modified DRASTIC model.

The Regression DRASTIC model further refined the association between groundwater vulnerability and the related variables. The topography, soil hydraulic conductivity, and land cover indicated positive significant correlation with nitrate concentrations, as a representation to groundwater vulnerability. Different studies also found that hydraulic conductivity, topography, and land cover positively relate to groundwater vulnerability (Saha and Alam, 2014; Muhammad et al., 2015; Colins et al., 2016). Topography refers to slope variability of the land surface. The degree of slope determines the likelihood of a pollutant to run off or remain on the ground surface long enough to infiltrate into the ground. Steep slope terrain has high runoff, hence low vulnerability, whereas shallow slope terrain has low runoff, hence high vulnerability to water quality. The central part of the county had lower elevations while the eastern part and the extreme west had higher elevations. In the study, the lowlands indicated areas of high groundwater vulnerability. The rate of groundwater movement in the soil and fractured crystalline aquifer is controlled by hydraulic conductivity, and the average hydraulic conductivity was 1.7 X10⁻⁵ m/s, indicative of a high hydraulic conductivity media. Land cover in Buncombe County included deciduous and evergreen forest, bare ground, developed open space, hay/pasture, and croplands. The dominance of agricultural land, hay/pasture area, developed open spaces, and possibly urban parks or golf courses has influenced the
nitrate content, and consequently groundwater vulnerability. Additionally, the regression DRASTIC model showed high vulnerable areas along drainage lines, which might indicate possible surface water-groundwater interaction through fractured bedrock. Further study is required to examine the potential of possible surface water-groundwater interaction.

5.3 Study Limitations and Future Research

Most of the residents located in the urban jurisdictions are provided with municipal drinking water and therefore do not depend on groundwater for drinking supplies. Such residents might not be directly affected by the existence of contaminants in groundwater even though those areas were highly vulnerable. Another limitation was the use of only nitrate concentrations as a check to groundwater vulnerability in the county. Using other chemicals mostly found in water in addition to nitrate could have yielded a more reliable vulnerability result. The nitrate data had missing information on wells in the central and forested areas in the county which could have affected the accuracy of the interpolated surface for nitrate concentrations (underestimation/overestimation of nitrate concentration in those areas). Overlaying this map on the three DRASTIC models to compare the distribution of nitrate concentration with respect to the DRASTIC maps may not lead to a completely transparent comparison.

Although the study had some limitations, future research should still be conducted using this study as the basis to perform more site-specific studies, especially in areas within medium to high vulnerability zones. Since this study points out areas with very low vulnerability to high vulnerability, it could serve as the baseline for estimating water quality in Buncombe County and can be used in further research to assess the kind of contaminants that may impact the groundwater within the area. Eventually, measures can be put in place to treat the contaminants. This study also
serves as a guide to estate planners and developers on site selection and how vulnerable the area is to contamination.

6.0 Conclusion

This research aimed to assess groundwater vulnerability to nitrate pollution in Buncombe County, NC located in Blue Ridge Physiographic Province. Assessment of groundwater vulnerability in the study area has been achieved by using EPA recommended DRASTIC model, experience based heuristic DRASTIC model using landcover, and statistical based regression DRASTIC model using landcover and nitrate concentration in groundwater. The study delineated areas with low, medium, high and very high, vulnerability using all three different methods.

- High groundwater vulnerable areas were mostly concentrated in the central part of the county along lowland and valleys where hay and pasture land, and development are more dominant. High vulnerable areas were also found along drainage lines, which indicate possible surface water-groundwater interaction via bedrock fault and fracture systems in the Blue Ridge Province.

- Nitrate concentration in the study area correlated significantly with topography, soil hydraulic conductivity, and landcover. Depth to water table, net recharge, aquifer media, soil media and impact of vadose zone were not significantly correlated with nitrate concentrations.

- Regression DRASTIC plotted 34.4% of known high nitrate concentration values in medium to very high vulnerability categories when compared to 11.9% for EPA and 14.3% for Modified DRASTIC.
The Regression DRASTIC model was used to create the final groundwater vulnerability map and could explain 27% of the variability of the independent variables including topography, soil hydraulic conductivity, and landcover.

The final groundwater vulnerability map can be useful in determining the most vulnerable areas that need detailed site specific investigation and monitoring, especially in terms of delineating vulnerable zones due to nitrate concentrations. Additionally, groundwater vulnerability maps using this approach can be useful for policy makers and developers during groundwater management and protection especially in urban, agricultural, and pasture lands. Finally, with efficiency in GIS environment, DRASTIC is an established and effective tool for analyzing groundwater vulnerability.
7.0 References


CHAPTER 4
DISCUSSION AND MAJOR FINDINGS

The first study predicted groundwater nitrate concentrations and its relation to land use and depth to water table in Buncombe County, NC using spatial and non-spatial statistical data analysis methods such as exploratory descriptive statistics, exploratory spatial data analysis, kriging and cokriging.

The study presented some major finding which are:

1. Nitrate contaminated wells in Buncombe County had concentrations ranging from 0.25 mg/L to 8.5 mg/L. Even though none of the concentrations exceeded the 10 mg/L standard limit set by the USEPA, some areas had NO$_3$ concentrations approaching the EPA limit. The nitrate contaminated wells were distributed across the county except for the northeastern corner, Biltmore, urban areas, and forested areas.

2. The Shapiro-Wilk Test of normality revealed that NO$_3$ concentrations and the depth to water table were not normally distributed. Wells with high NO$_3$ content (2.0mg/L) were positively correlated with landcover data (Spearman’s rho=0.24 at p=0.04).

3. Histogram analysis conducted revealed that 37.14% of high NO$_3$ concentration wells were located near hay and pasture land, 34.29% near developed urban open space, and 28.57% near deciduous forest. ANOVA test however indicated there is no significant difference in NO$_3$ content between hay and pasture, developed urban open space, and deciduous forest land cover types.

4. The spatial autocorrelation test using Moran’s I showed a significant cluster in the depth to water table data at both the local and global levels. Global Moran’s I had a value of 0.017, which was significant (pseudo p value = 0.001) at 999 permutations. Clusters of shallow
wells were located near wells with shallow depths and deep wells were located near other deep wells. The NO₃ data conversely were spatially clustered only at the global level of Moran’s I. The existence of autocorrelation in both data provided the basis for further analysis with kriging and cokriging.

5. Kriging interpolation method was used to create a predicted spatial distribution map of NO₃ concentrations in Buncombe County groundwater.

6. Cokriging interpolation was used to evaluate the effect of landcover and depth to water table on the spatial distribution of NO₃ concentrations across the county. The cross-validation matrix of the interpolated surfaces (kriging and cokriging) indicated that NO₃ cokriged with landcover provided the best model in terms of accuracy metrics.

7. The spatial distribution map of NO₃ concentrations in Buncombe County indicated that areas like Barnardsville, Biltmore Forest, Woodfin, and Black Mountain had very low NO₃ concentrations (below 0.5 mg/L). Swannanoa had low NO₃ concentration level above 0.5 mg/L but not exceeding 0.8 mg/L. High NO₃ content were present in Candler, Weaverville, Leicester Fairview, Arden, and some areas in Asheville.

The second study assessed groundwater vulnerability to NO₃ contamination in Buncombe County using EPA, Modified, and Regression-based DRASTIC methods. The parameters used in this study were Depth to water table (D), Net recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of vadose zone (I), hydraulic conductivity (C), and Landcover (LC).

The major findings from this study are as follows:

1. EPA DRASTIC model was prepared using D, R, A, S, T, I, C. The vulnerability index model calculated per the USEPA weighting and rating system provided a numerical range of values (62-170) where high values represent high vulnerability and low values represent low
vulnerability. The EPA DRASTIC index values were categories into very low vulnerability zone: 62-95 which covers (29.25%) of the county, low risk zone: 96-109 (28.62%), medium risk zone: 110-123 (20.73%), high and very high vulnerability risk zones: 124-139 (19.63%) and 140-170 (1.65%).

2. Modified DRASTIC model was created using R, S, T, C, LC parameters. The model’s vulnerability index provided values ranging from 24 to 150. The vulnerability map showed that, 21.07% of the county’s total area lies in the “very low vulnerability zone” with DRASTIC index value: 24 to 59. An area of 549 km² (32.24%) was found within low vulnerability zones with DRASTIC index values from 60 to 78. A moderate and high vulnerability zone within the county was covered by 389km² and 267 km², representing 22.85% and 15.67% with DRASTIC index values from 79 to 95, and 96 to 114, respectively. About 8.15% (139km²) of the county was classified as very high vulnerability potential area with DRASTIC index values ranging between 115 and 150.

3. Correlation analysis conducted showed the existence of significant correlation between T, C, and LC and the nitrate data. These parameters were used as independent variables to predict NO₃ (dependent variable) in groundwater and the results indicated that the DRASTIC and landcover accounted for 27% variability (adjusted R²=0.27, p = 0.015). OLS regression model with the significant variables (T, C, LC) was used to prepare a regression-based DRASTIC index and the coefficients of each parameter was assigned as DRASTIC weights. The vulnerability map created using regression yielded a numeric range of values which varied from 2.97 to 10.7. The index map indicated that, 36.16% of the county’s total area with index value ranging from 2.974 to 4.867 lay in a very low vulnerability zone, 37.99%
(4.688-5.804) lay in a low vulnerability zone, 15.43% (5.805-6.900) in medium vulnerability, 7.21% (6.901-8.145) and 3.21% (8.146-10.7) in high and very high vulnerability zones.

4. The spatial distribution of nitrate concentration with respect to EPA, Modified, and Regression-based vulnerability index maps indicated that, the regression based vulnerability map best represented the spatial distribution of NO₃ concentrations in Buncombe County. High NO₃ concentrations were mostly seen in high vulnerability areas with few appearing in medium to low vulnerability zones. Modified DRASTIC provided a better representation of NO₃ concentrations whereas EPA DRASTIC on the other hand showed a reverse result: most of the high nitrate concentrations fell within very low and low vulnerability zones with only few located in medium to high vulnerability zones.

Study Limitations and Future Research for Study 1

Although the study objectives were accomplished, there were some unavoidable limitations. First of all, data on private drinking wells were not available for the National Forest areas and the incorporated urban areas. This affected the prediction errors from the kriging / cokriging interpolated maps. Secondly, nitrate data were available for only 610 wells and there may be other private drinking wells not included in the data. These wells may have very high nitrate concentrations which could have impacted the results and findings of this study. Private drinking wells with missing information on depth to water table were excluded from the study. All this information could have helped to improve the accuracy of the predicted models.

Despite the limitations, future studies can be conducted using this study as the basis to perform more site-specific research in high nitrate areas to monitor the wells located in those areas and detect the cause of the high nitrate content. It is recommended that further research be done
especially in deciduous forested areas and developed open space landcover areas to find out why nitrate content is high in those regions.

**Study Limitations and Future Research for Study 2**

Most of the residents located in the urban jurisdictions are provided with municipal drinking water and therefore do not depend on groundwater for drinking supplies. Such residents might not be directly affected by the existence of contaminants in groundwater even though those areas may be highly vulnerable. Another limitation was the use of only nitrate concentrations as a check to groundwater vulnerability in the county. Using other chemicals mostly found in water in addition to nitrate could have yielded a more reliable vulnerability result. The nitrate data had missing information on wells in the central and forested areas in the county which could have affected the accuracy of the interpolated surface for nitrate concentrations (underestimation/overestimation of nitrate concentration in those areas). Overlaying this map on the three DRASTIC models to compare the distribution of nitrate concentrations with respect to the DRASTIC maps may not lead to a completely transparent comparison.

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