8-2017

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

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Vulnerability Assessment of Groundwater to NO_3 Contamination Using GIS, DRASTIC Model and Geostatistical Analysis

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A thesis

presented to

the Department of Geosciences

East Tennessee State University

In partial fulfillment

of the requirements for the degree:

Master of Science in Geosciences

Geospatial Analysis Concentration

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by

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August 2017

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Keywords: DRASTI Model, GIS, Kriging, Cokriging, NO_3, Groundwater, Spatial Statistics

ABSTRACT

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The study employed Geographical Information System (GIS) technology to investigate the vulnerability of groundwater to NO_3 content in Buncombe County, North Carolina in two different approaches. In the first study, the spatial distribution of NO_3 contamination was analyzed in a GIS environment using Kriging Interpolation. Cokriging interpolation was used to establish how NO_3 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 NO_3 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 NO_3 relates to each of the DRASTIC variables. Although the NO_3 concentration in the county didn't exceed the USEPA standard limit (10mg/L), some areas had NO_3 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.

ACKNOWLEDGEMENTS

I am grateful to the Almighty God for the gift of life, the strength, the wisdom and the opportunity given me to write this thesis. I could never have done it without Him.

My deepest gratitude goes to my committee members; Dr. Arpita Nandi, Dr. Ingrid Luffman, and Dr. Andrew Joyner for your patience, encouragement, valuable comments and mentoring. Special thanks to my committee chair and advisor, Dr. Arpita Nandi, God bless you for being a blessing to me. Your advice and words of encouragement has inspired me in all aspects of my life.

To all my friends and family, thank you for your constant prayers and support, and for helping me survive all the stress from graduate school. A big thank you to all the professors and students in ETSU Geosciences department. I am so blessed to be part of a family full of loving and supportive people.

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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: **D**epth to water, net **R**echarge, **A**quifer media, **S**oil media, **T**opography, **I**mpact of vadose zone and hydraulic **C**onductivity. 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 NO_3 concentrations in groundwater in the United States revealed that, NO_3 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 for1998 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 NO_3. Studies found that, about 4% of private wells in Iowa have nitrate concentration levels exceeding 10mg/L, the maximum contaminant level of NO_3 in drinking water (Kross et al. 1993). Ahn and Chon (1999) identified NO_3 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 NO_3 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 NO_3 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 a 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, andNO_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 μ 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;

$$Z1(s) = \mu 1 + \varepsilon 1(s)$$

$$Z2(s) = \mu 2 + \varepsilon 2(s)$$

$$Zn(s) = \mu n + \varepsilon n(s)$$

Where $\mu 1 \ldots \mu n$ are constants, $\varepsilon 1 \ldots \varepsilon n$ 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_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_3 in groundwater wells in Buncombe County, and (2) evaluate if the extent to which NO_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 8.5mg/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.

Keywords: *Nitrate concentration, Land cover, Depth to water table, Spatial analysis, Statistical analysis*

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 problem 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_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_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_3 concentration in groundwater and its health implications has raised concerns, resulting in the need for further research to locate areas with high NO_3. The objectives of this study are to: (1) analyze the spatial distribution of NO_3 in groundwater wells in Buncombe County, North Carolina, and (2) evaluate the extent to which NO_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.

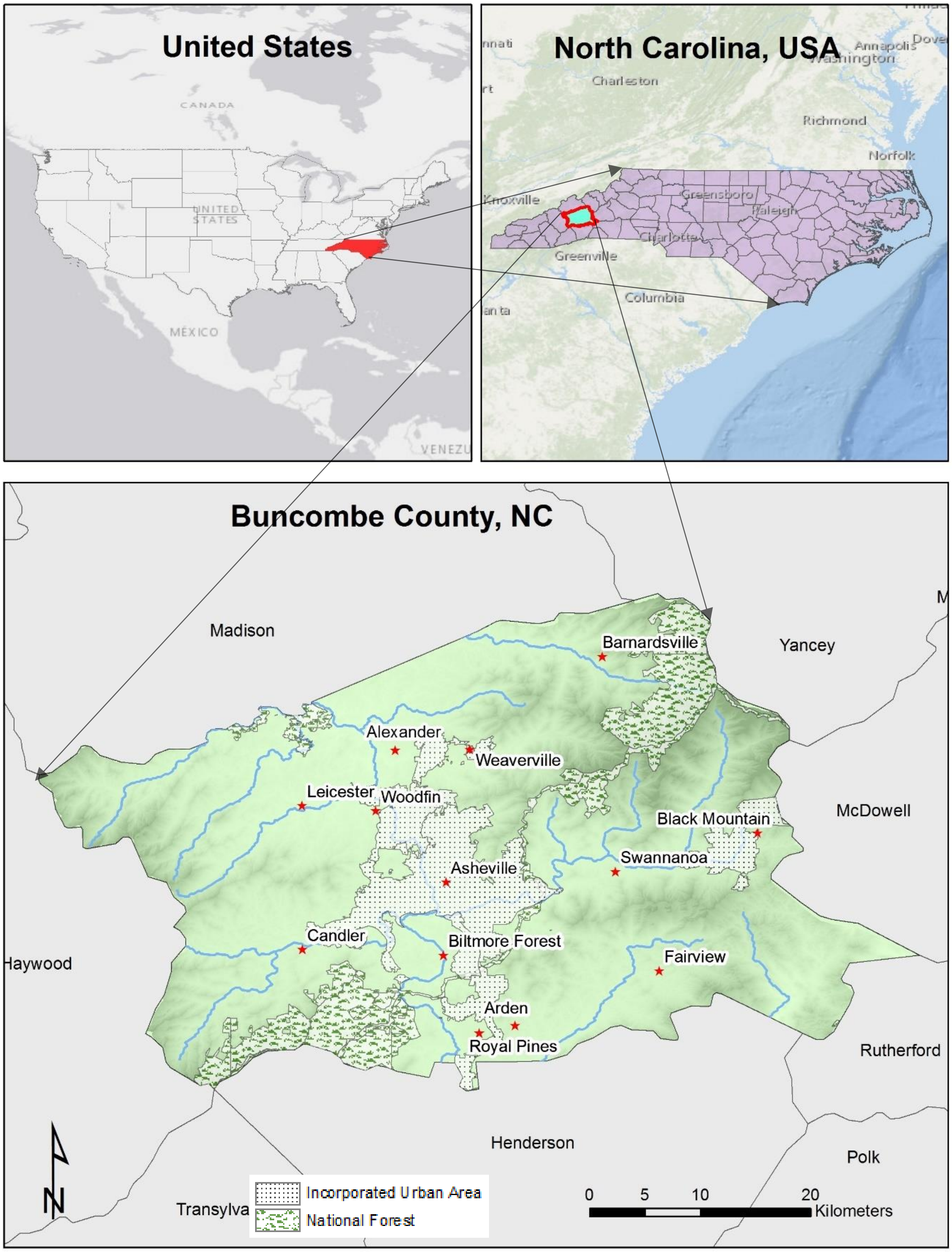

Fig 2.1 Map of Buncombe County, North Carolina, USA (Study Area)

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.

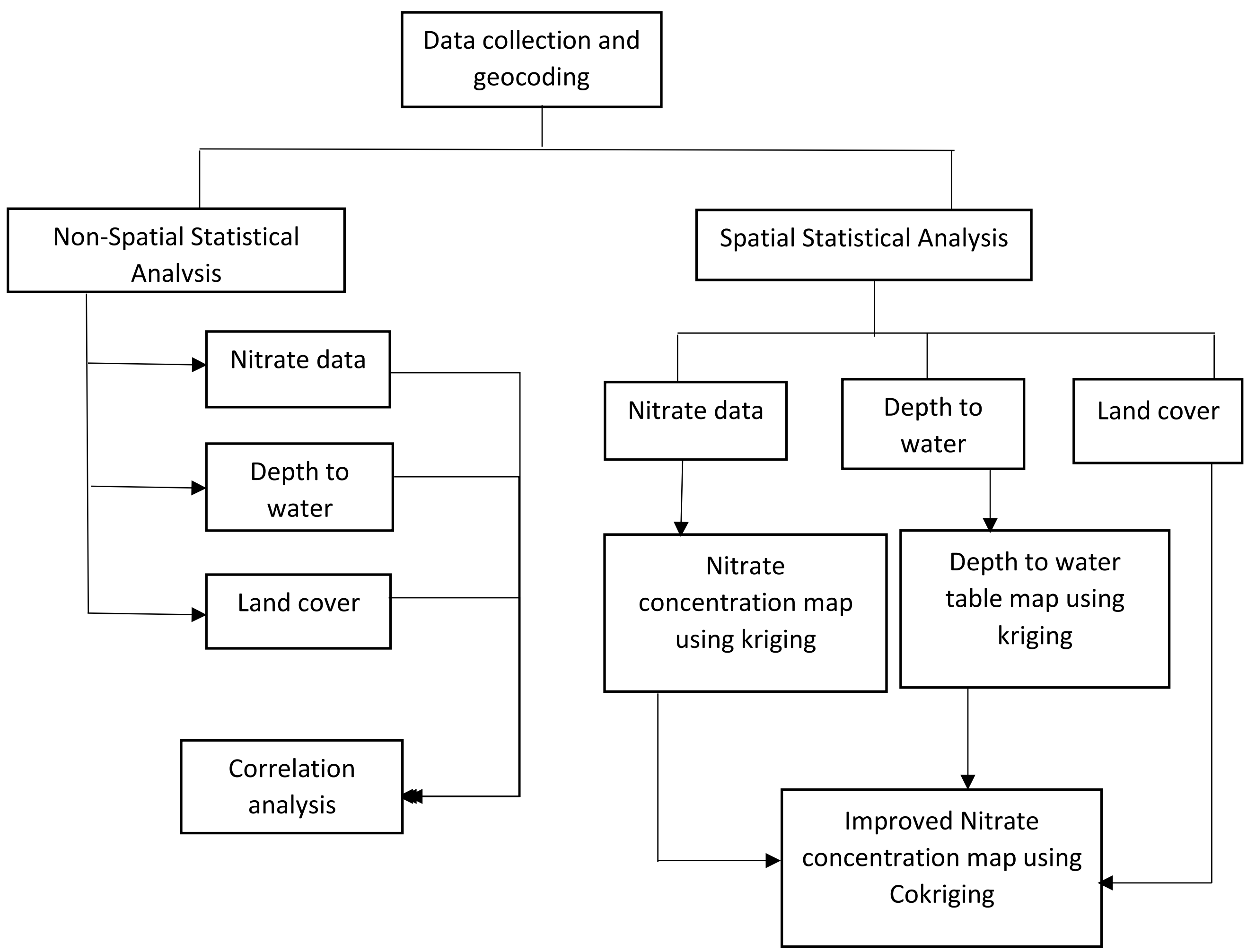

Fig 2.2 Methodology for predicting groundwater nitrate concentration and its relation to land use and water depth in Buncombe County

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.

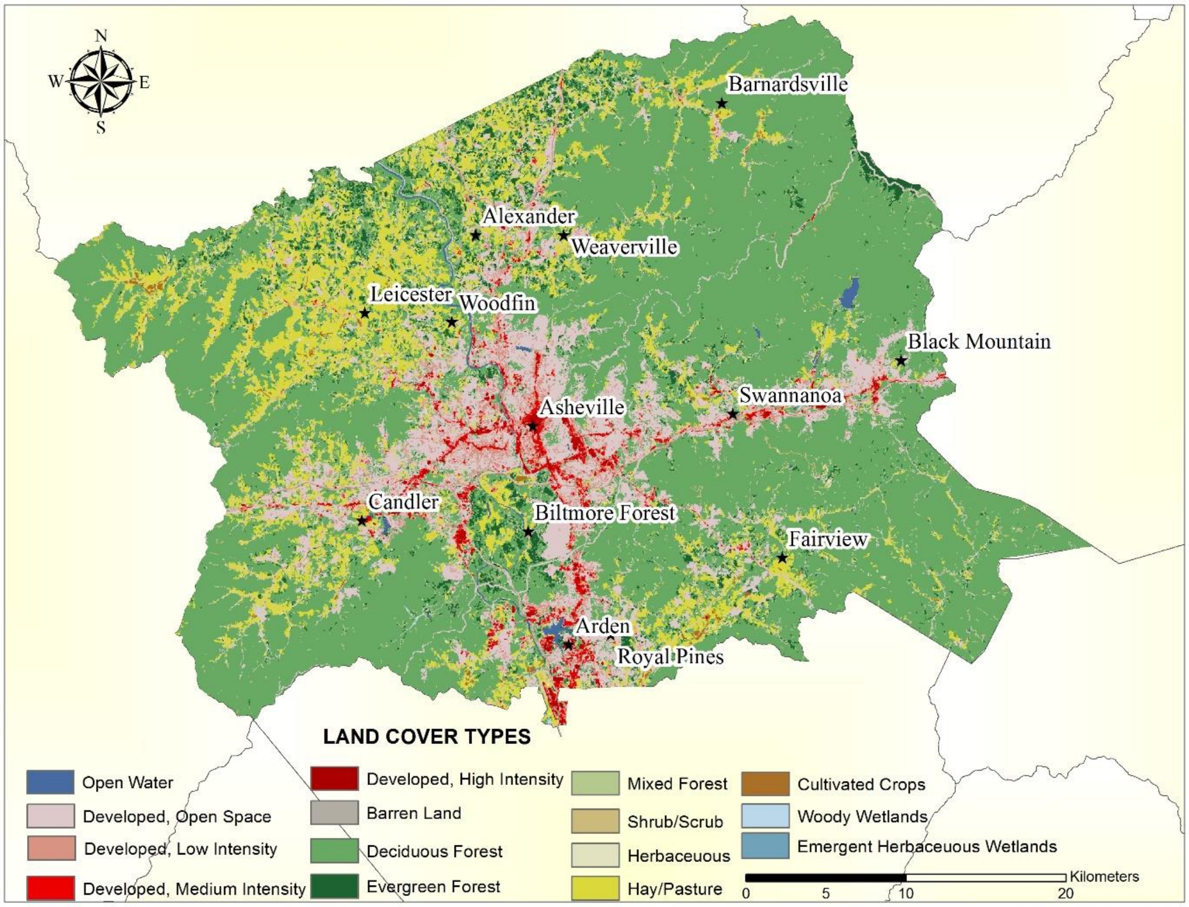

Fig 2.3 Land cover map of Buncombe County (Source: MRLC)

3.2 Exploratory Non-Spatial Statistics

Per USEPA statistical protocol, all NO_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_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 NO_3 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 NO_3 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 NO_3 concentration map from the NO_3 point data to examine the variation and spatial extent of NO_3 contamination in Buncombe County. Variogram was created for NO_3 using the NO_3 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 NO_3 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 NO_3 surface and the cokriged NO_3 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 NO_3 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

NO_3 contaminated wells in Buncombe County had concentration values ranging from 0.25 mg/L to 8.5 mg/L (Fig 2.4). The mean NO_3 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 NO_3 (2.0 mg/L and above). Descriptive statistics of NO_3 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.

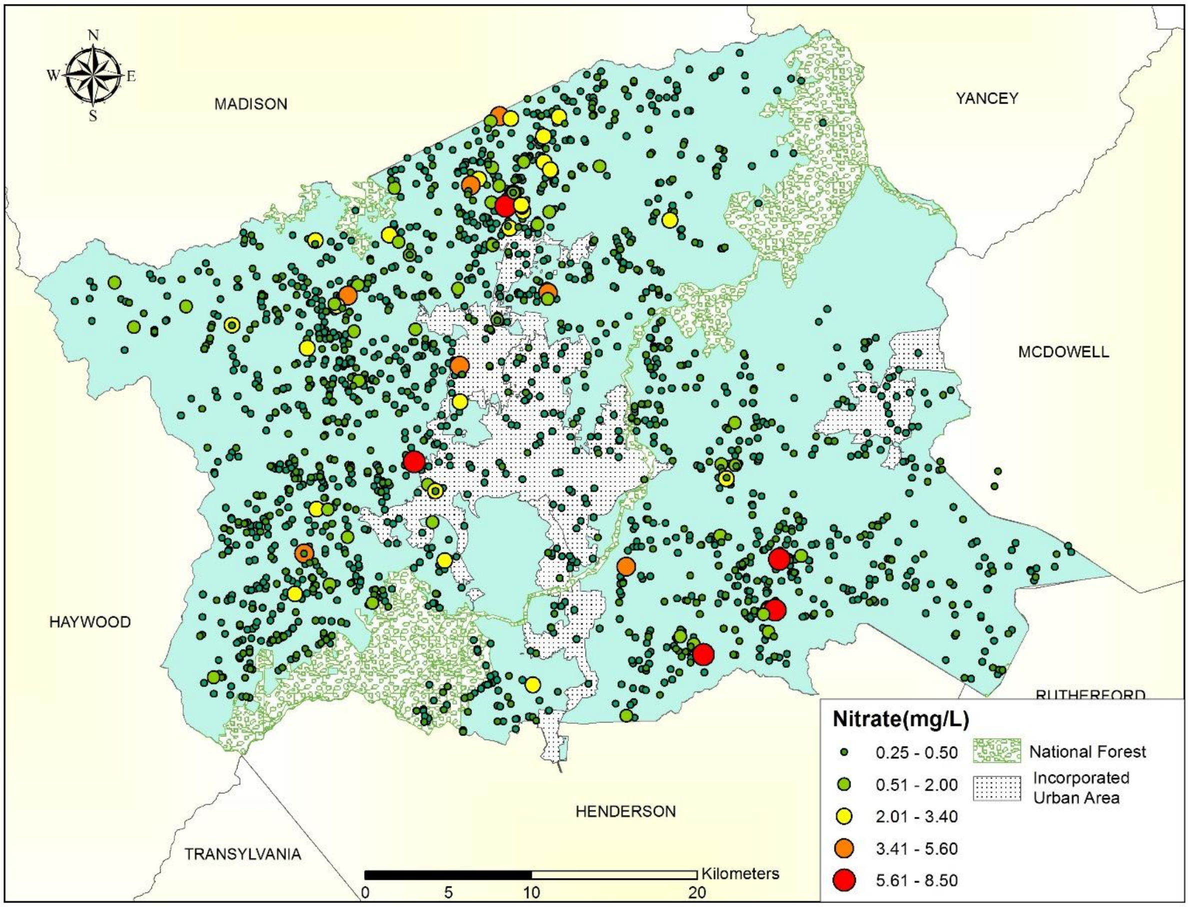

Fig 2.4 Nitrate contaminated wells in Buncombe County

Table 2.1 Descriptive statistics of NO_3 and depth to water table

	Nitrate (ppm)	**Depth to water table (m)**
Mean	0.673	347.172
Standard deviation	0.951	179.518
Minimum	0.25	0
Maximum	8.5	1300

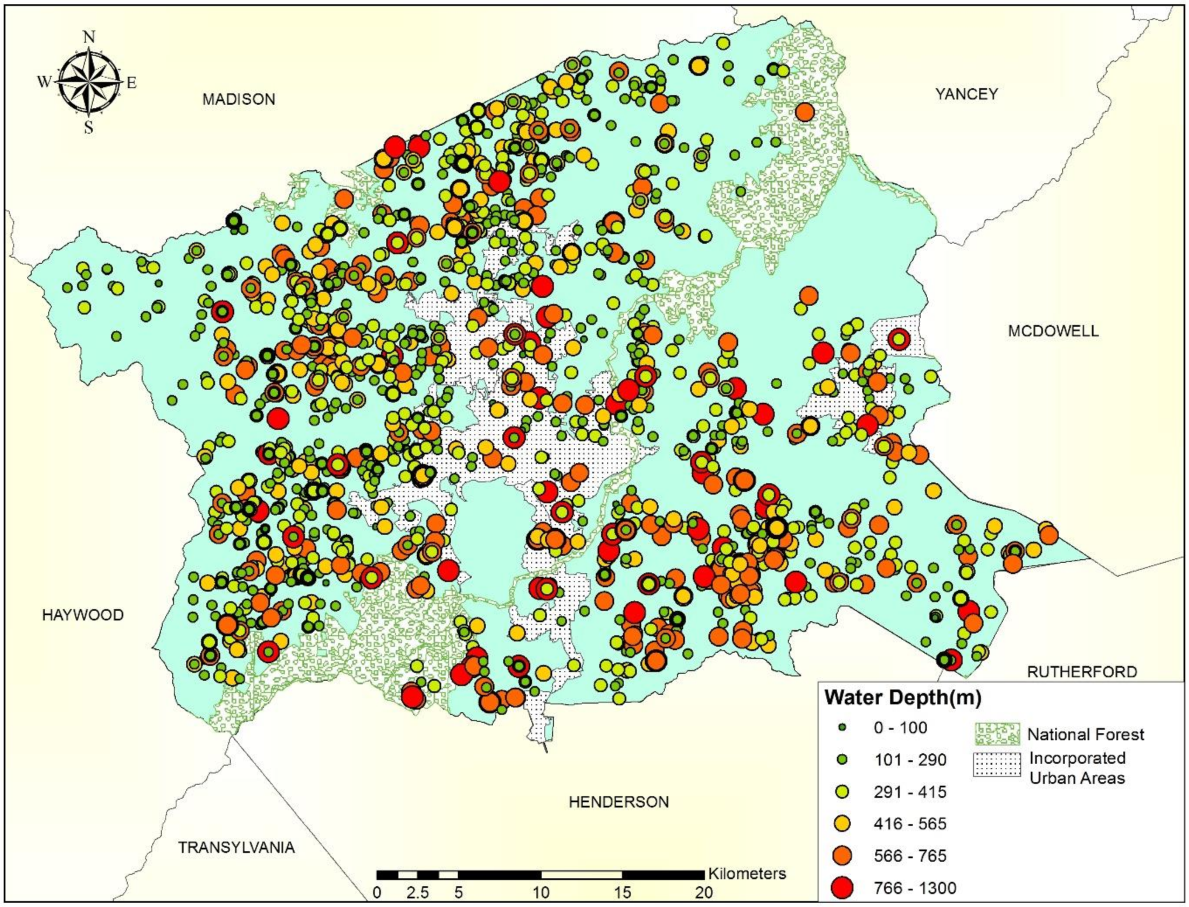

Fig 2.5 Depth to water table of wells in Buncombe County

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.

Landcover type	Pixel count	% landcover in county	% landcover in high NO_3 area
Open Water	7663	0.404	
Developed Urban Open Space	264258	13.921	34.286
Developed low intensity	59816	3.151	
Developed medium intensity	27313	1.439	
Developed high intensity	8474	0.446	
Barren land	1435	0.076	
Deciduous forest	1149712	60.567	28.571
Evergreen forest	69504	3.661	
Mixed forest	31100	1.638	
Shrub/Scrub	11015	0.58	
Herbaceous	22791	1.201	
Hay/Pasture	237599	12.517	37.143
Cultivated crops	6041	0.318	
Woody wetlands	1484	0.078	
Emergent herbaceous wetland	45	0.002	

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.

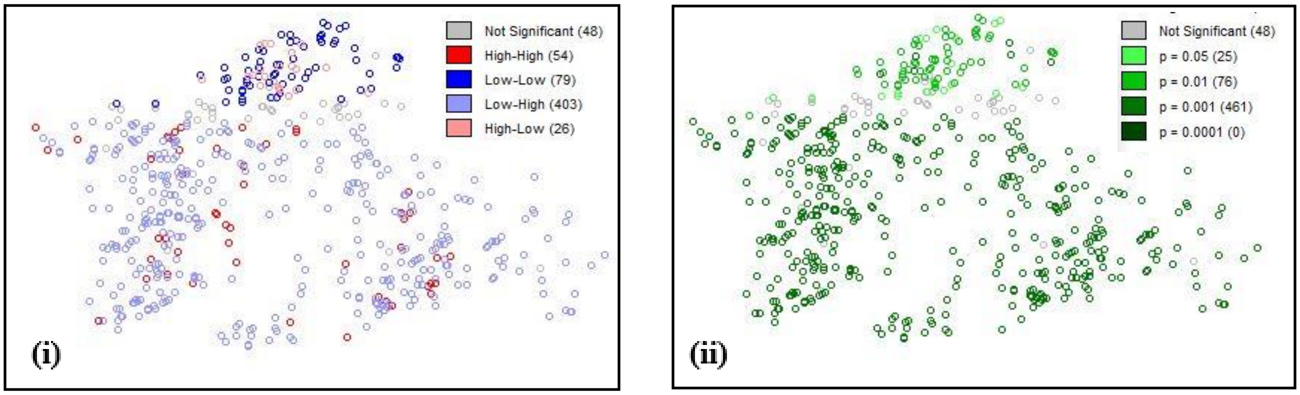

Fig 2.6A   Cluster (i) and significance (ii) map of nitrate

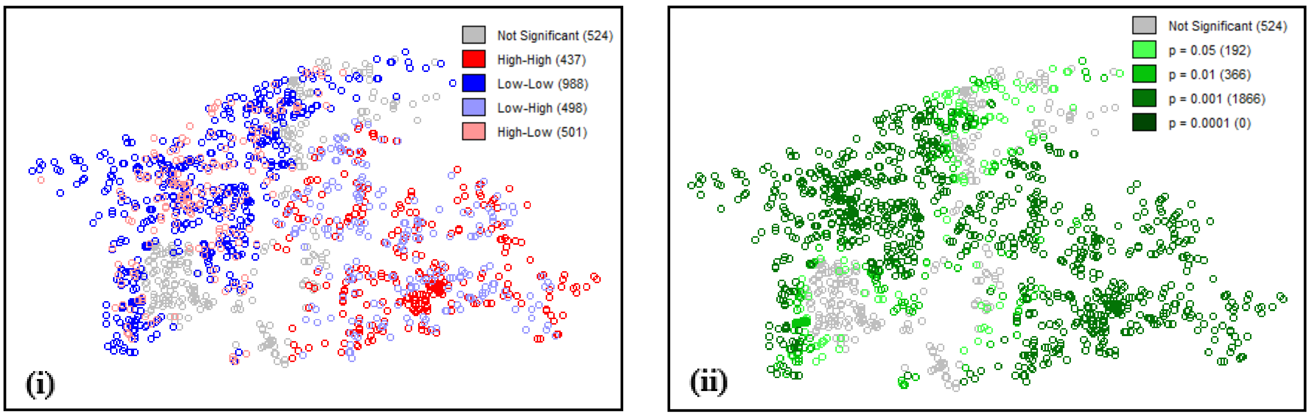

Fig 2.6B   Cluster (i) and significance (ii) map of depth to water table

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 NO_3 kriging and NO_3/ 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 NO_3 concentrations. The kriged NO_3 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

Prediction errors	NO_3	NO_3 + Landcover	NO_3 + Depth to Water	NO_3 + Landcover + Depth to Water
ME	-0.0044	-0.0047	-0.0048	-0.0052
RMS	0.986	0.979	0.980	0.979
RMSSE	0.9469	0.8956	0.8989	0.8975
ASE	1.0390	1.0941	1.0908	1.0919

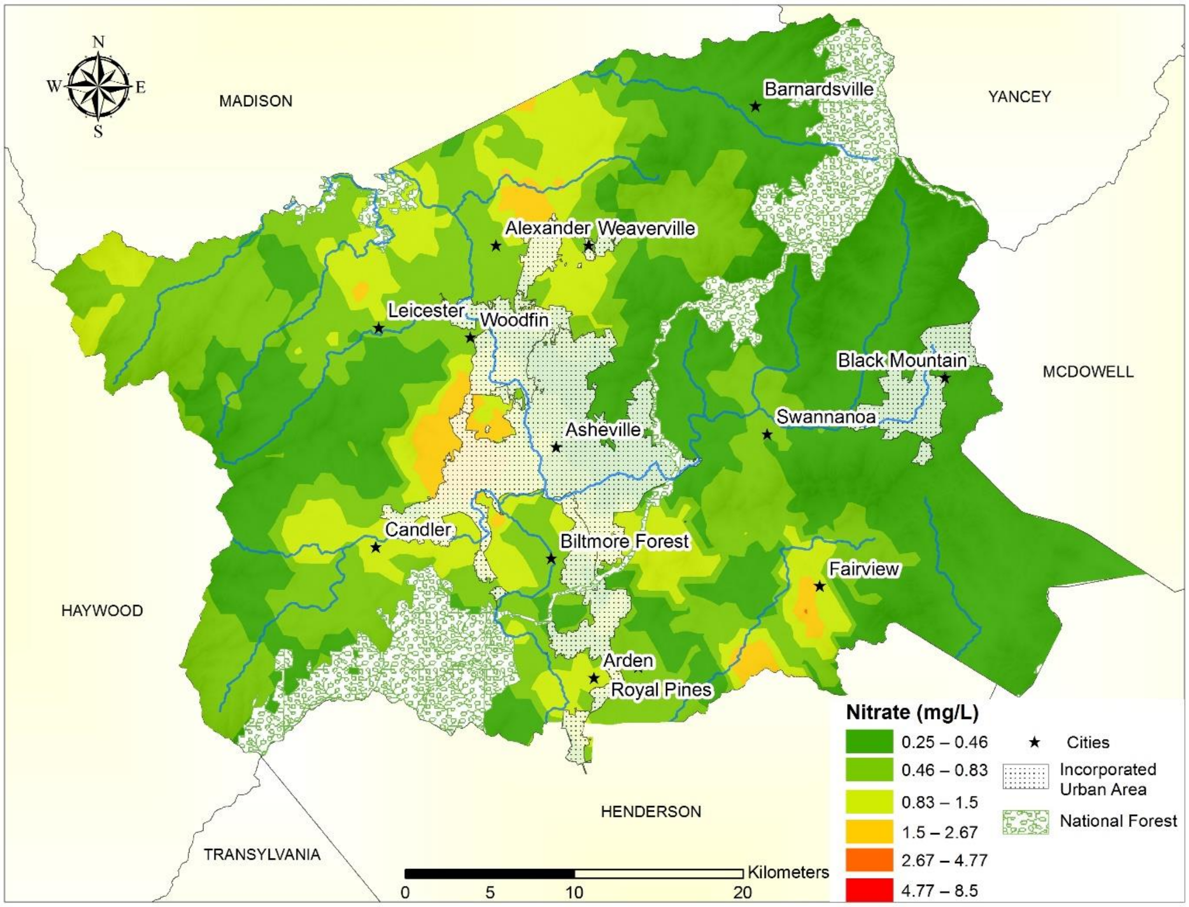

Fig 2.7 Kriging interpolation map of NO_3 concentrations, Buncombe County

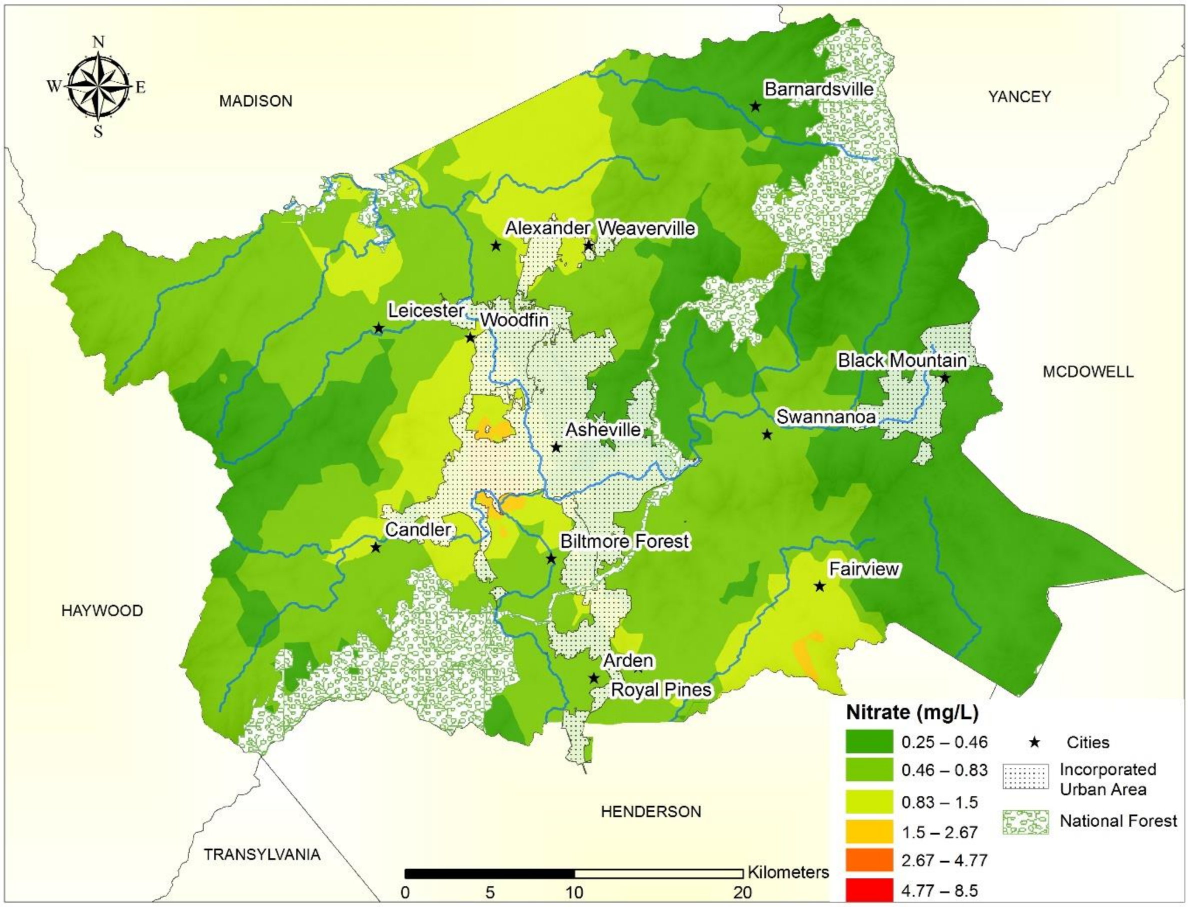

Fig 2.8 Prediction map of NO_3 concentrations cokriged with land cover

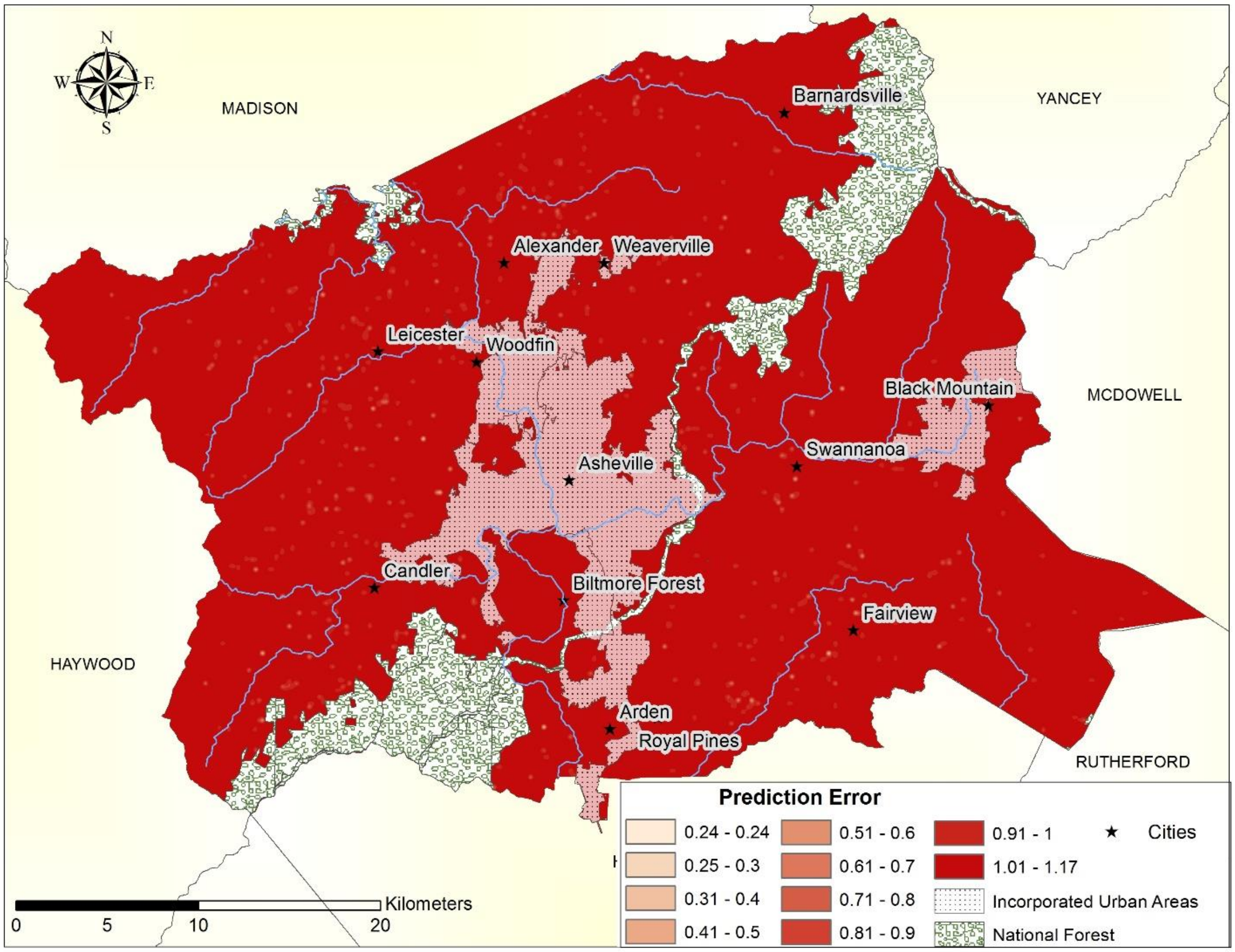

Fig 2.9 Prediction error map of NO_3 kriging interpolated surface

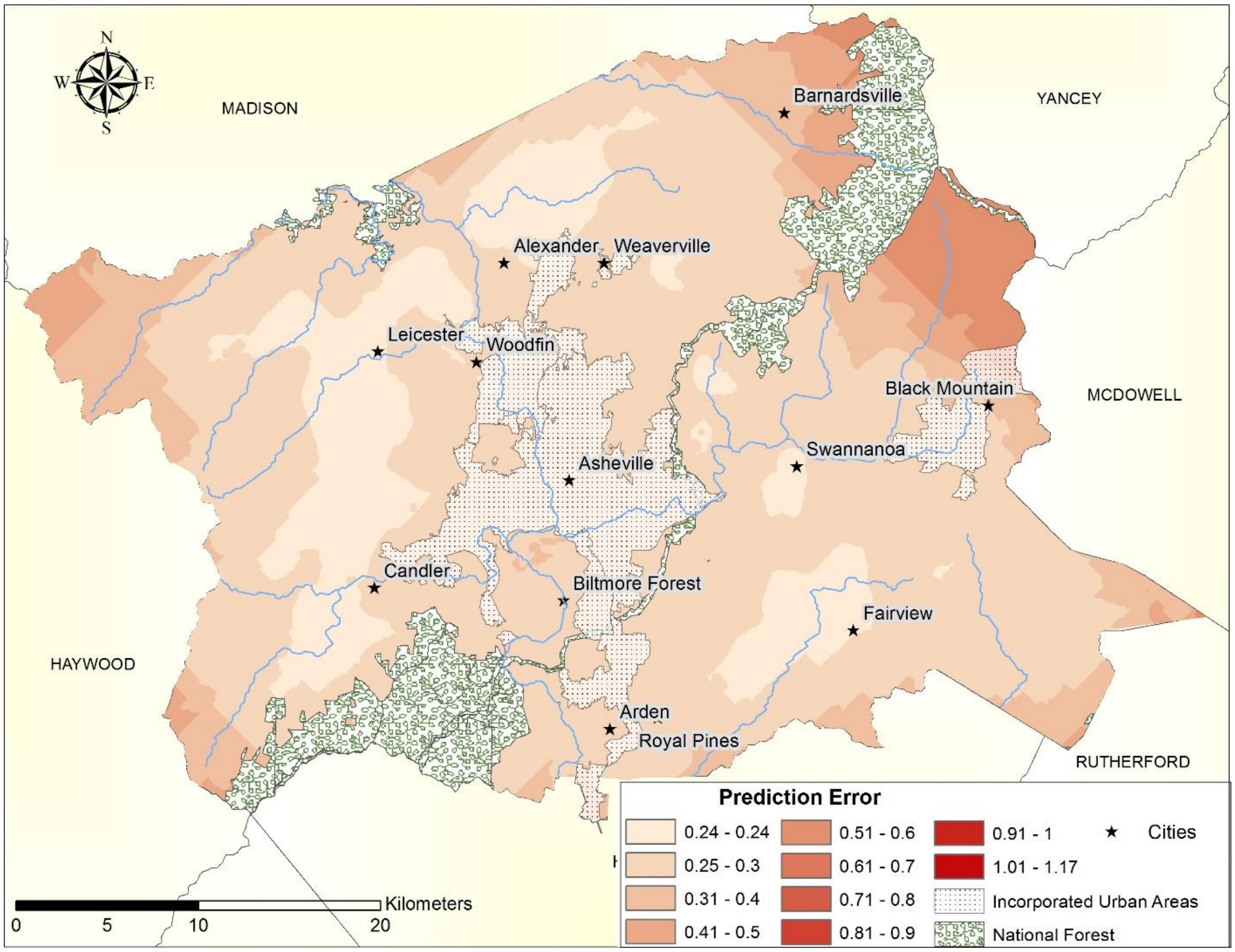

Fig 2.10 Prediction error map of NO cokriged with land cover

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 NO_3 content (0.24 at $p = 0.04$), and high NO_3 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 NO_3 concentration between these landcover types, indicating they all contribute to high NO_3 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 NO_3 point map influenced the level of NO_3 concentrations in parts of the county. NO_3 cokriged with land cover produced the model which best represented the NO_3 concentrations in the county. The evergreen forested areas, developed intensity (low, medium, high), barren land, and wetlands had very low NO_3 concentrations, whereas hay/pasture, developed open urban space, and deciduous forest areas had high NO_3 concentration.

The eastern part of Buncombe County (mountainous areas) recorded very low concentrations of NO_3 in groundwater compared to the central, northern, and southern parts. Nearly half of the county had NO_3 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 NO_3 concentrations were found in some regions, none of the regions' NO_3 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

Addiscott, T. M., & Benjamin, N. (2004). Nitrate and human health. Soil use and management, 20(2), 98-104.

Aller, L., Bennet, T., Lehr, J. H., & Petty, R. J. (1987). DRASTIC: A standardized system for evaluating groundwater pollution potential using hydrogeologic settings. USEPA document no. EPA /600/ 2-035.

Anselin, L., Syabri, I., & Kho, Y. (2006). GeoDa: an introduction to spatial data analysis. *Geographical analysis*, *38*(1), 5-22.

Avery, A. A. (1999). Infantile methemoglobinemia: reexamining the role of drinking water nitrates. *Environmental health perspectives*, *107*(7), 583.

Babiker, I. S., Mohamed, M. A., Terao, H., Kato, K., & Ohta, K. (2004). Assessment of groundwater contamination by nitrate leaching from intensive vegetable cultivation using geographical information system. *Environment International*, *29*(8), 1009-1017.

Barringer, T., Dunn, D., Battaglin, W., & Vowinkel, E. (1990). Problems and methods involved in relating land use to groundwater quality. *Jawra Journal of the American Water Resources Association*, *26*(1), 1-9.

Luettich, R. A., McNinch, J.E., Paerl, H., Peterson, C.H., Wells, J.T., Alperin, M., Martens, C.S., and Pinckney, J.L., (2000), Neuse River estuary modeling and monitoring project stage 1: hydrography and circulation, water column nutrients and productivity, sedimentary processes and benthicpelagic coupling, and benthic ecology: The University of North Carolina Water Resources Research Institute, Report 325-B.

Burkholder, J. M., Dickey, D. A., Kinder, C. A., Reed, R. E., Mallin, M. A., McIver, M. R., ... & Deamer, N. (2006). Comprehensive trend analysis of nutrients and related variables in a large eutrophic estuary: a decadal study of anthropogenic and climatic influences. Limnology and Oceanography, 51(1part2), 463-487.

Burow, K. R., Nolan, B. T., Rupert, M. G., & Dubrovsky, N. M. (2010). Nitrate in groundwater of the United States, 1991− 2003. *Environmental Science & Technology*, *44*(13), 4988-4997.

Burow, K. R., Shelton, J. L., & Dubrovsky, N. M. (2008). Regional nitrate and pesticide trends in ground water in the eastern San Joaquin Valley, California. *Journal of environmental quality*, *37*(5_Supplement), S-249.

Cressie, N. (1990). The origins of kriging. *Mathematical geology*, *22*(3), 239-252.

Dicken, C. L., Nicholson, S. W., Horton, J. D., Foose, M. P., & Mueller, J. A. (2005). *Preliminary Integrated Geologic Map Databases for the United States: Alabama, Florida, Georgia, Mississippi, North Carolina, and South Carolina* (No. 2005-1323).

Drever, J. I. (1997). The Geochemistry of Natural Waters: Surface and Groundwater Environments, 436 pp.

Eckhardt, D. A., & Stackelberg, P. E. (1995). Relation of Ground-Water Quality to Land Use on Long Island, New York. *Ground Water, 33*(6), 1019-1033.

Edward, H., Isaaks, E. H., & Srivastava, R. M. (1989). An introduction to applied geostatistics. *New York*.

Gaus, I., Kinniburgh, D. G., Talbot, J. C., & Webster, R. (2003). Geostatistical analysis of arsenic concentration in groundwater in Bangladesh using disjunctive kriging. *Environmental geology*, *44*(8), 939-948.

George, D., & Mallery, P. (2016). *IBM SPSS Statistics 23 step by step: A simple guide and reference*. Routledge.

Goldberg, D. W. (2011). Advances in geocoding research and practice. Transactions in GIS, 15(6), 727-733.

Goldberg, D. W. (2011). Improving Geocoding Match Rates with Spatially-Varying Block Metrics. *Transactions in GIS, 15*(6), 829-850.

Hallberg, G. R., & Keeney, D. R. (1993). Nitrate, Regional groundwater quality, WJ Alley, Ed.

Hardin, S. L., & Spruill, T. B. (2004). Ionic Composition and Nitrate in Drainage Water from Fields Fertilized with Different Nitrogen Sources, Middle Swamp Watershed, North Carolina, August 2000-August 2001. *Scientific Investigations Report. United States Geological Survey*, 24.

Keith, A. (1904). Description of the Asheville Quadrangle. *North Carolina and Tennessee: US Geological Survey Geologic Atlas, Folio, 116*.

Kross, B. C., Hallberg, G. R., Bruner, D. R., Cherryholmes, K., & Johnson, J. K. (1993). The nitrate contamination of private well water in Iowa. *American Journal of Public Health*, *83*(2), 270-272.

Kupfersberger, H., Deutsch, C. V., & Journel, A. G. (1998). Deriving constraints on small-scale variograms due to variograms of large-scale data. *Mathematical Geology, 30*(7), 837-852.

Lenat, D. R. (1984). Agriculture and stream water quality: a biological evaluation of erosion control practices. Environmental management, *8*(4), 333-343.

Lowrance, R. (1992). Groundwater nitrate and denitrification in a coastal plain riparian forest. *Journal of environmental Quality*, *21*(3), 401-405.

Majumdar, D., & Gupta, N. (2000). Nitrate pollution of groundwater and associated human health disorders. *Indian Journal of Environmental Health, 42*(1), 28-39.

McLay, C. D.A, Dragten, R., Sparling, G., Selvarajah, N. (2001). Predicting groundwater nitrate concentrations in a region of mixed agricultural land use. Environmental Pollution 115, 191–204

Meisinger, J. J., Randall, G. W. (1991). Estimating N budgets for soil-crop systems. In: Follet, R. F., Keeney, D. R., Cruse, R. M. (Eds.), Managing N for Groundwater Quality and Farm Profitability. Soil Science of America, Madison Wisconsin, pp. 85-124

Messier, K. P., Kane, E., Bolich, R., Serre, M. L. (2014), Nitrate Variability in Groundwater of North Carolina using Monitoring and Private Well Data Models, Environmental Science &Technology, 48(18), 10804-10812.

Miller, J., Franklin, J., & Aspinall, R. (2007). Incorporating spatial dependence in predictive vegetation models. *ecological modelling*, *202*(3), 225-242.

Nas, B., & Berktay, A. (2006). Groundwater contamination by nitrates in the city of Konya, (Turkey): A GIS perspective. *Journal of Environmental Management*, *79*(1), 30-37.

Nas, B., & Berktay, A. (2010). Groundwater quality mapping in urban groundwater using GIS. *Environmental monitoring and assessment*, *160*(1), 215-227.

NCDHHS, (2014). Well Water and Health; Contaminants by County. Retrieved from: http://epi.publichealth.nc.gov/oee/wellwater/by_county.html.

Nolan, B. T., Ruddy, B. C., Hitt, K. J., & Helsel, D. R. (1997). Risk of Nitrate in groundwaters of the United States a national perspective. *Environmental science & technology*, *31*(8), 2229-2236.

Oliver, M. A., & Webster, R. (1990). Kriging: a method of interpolation for geographical information systems. *International Journal of Geographical Information System*, *4*(3), 313-332.

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

Robinson, T. P., & Metternicht, G. (2006). Testing the performance of spatial interpolation techniques for mapping soil properties. *Computers and electronics in agriculture*, *50*(2), 97-108.

Shamrukh, M., Corapcioglu, M., Hassona, F. (2001). Modeling the effect of chemical fertilizers on ground water quality in the Nile Valley Aquifer, Egypt. Groundwater 39(1), 59-76

Stein, M. L. (2012). *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media.

Thorburn, P. J., Biggs, J. S., Weier, K. L., & Keating, B. A. (2003). Nitrate in groundwaters of intensive agricultural areas in coastal Northeastern Australia. *Agriculture, ecosystems & environment*, *94*(1), 49-58.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. Economic geography, 46(sup1), 234-240.

Townsend, M. A., & Young, D. P. (1995). Factors affecting nitrate concentrations in ground water in Stafford County, Kansas. *Bull*, *238*.

Trapp Jr, H. (1970). Geology and ground-water resources of the Asheville area. *North Carolina: North Carolina Department of Water and Air Resources Ground-Water Bulletin*, *16*, 127.

Trapp Jr, H., & Horn, M. A. (1997). Ground Water Atlas of the United States, Delaware, Maryland, New Jersey, North Carolina, Pennsylvania, Virginia, West Virginia. *US Geol Surv Hydrol Atlas HA.*

Zandbergen, P. A. (2008). A comparison of address point, parcel and street geocoding techniques. *Computers, Environment and Urban Systems*, *32*(3), 214-232.

Zhang, W. L., Tian, Z. X., Zhang, N., & Li, X. Q. (1996). Nitrate pollution of groundwater in northern China. *Agriculture, Ecosystems & Environment*, *59*(3), 223-231.

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 NO_3 contaminant level of 10 milligrams per Liter (10 mg/L) for drinking water, beyond which NO_3 in groundwater could be harmful (EPA, 1995).

Several methods have been developed to assess the potential for groundwater to be contaminated by NO_3 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

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

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 mi^2, of which 657 mi^2 is land and 3.5 mi^2 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).

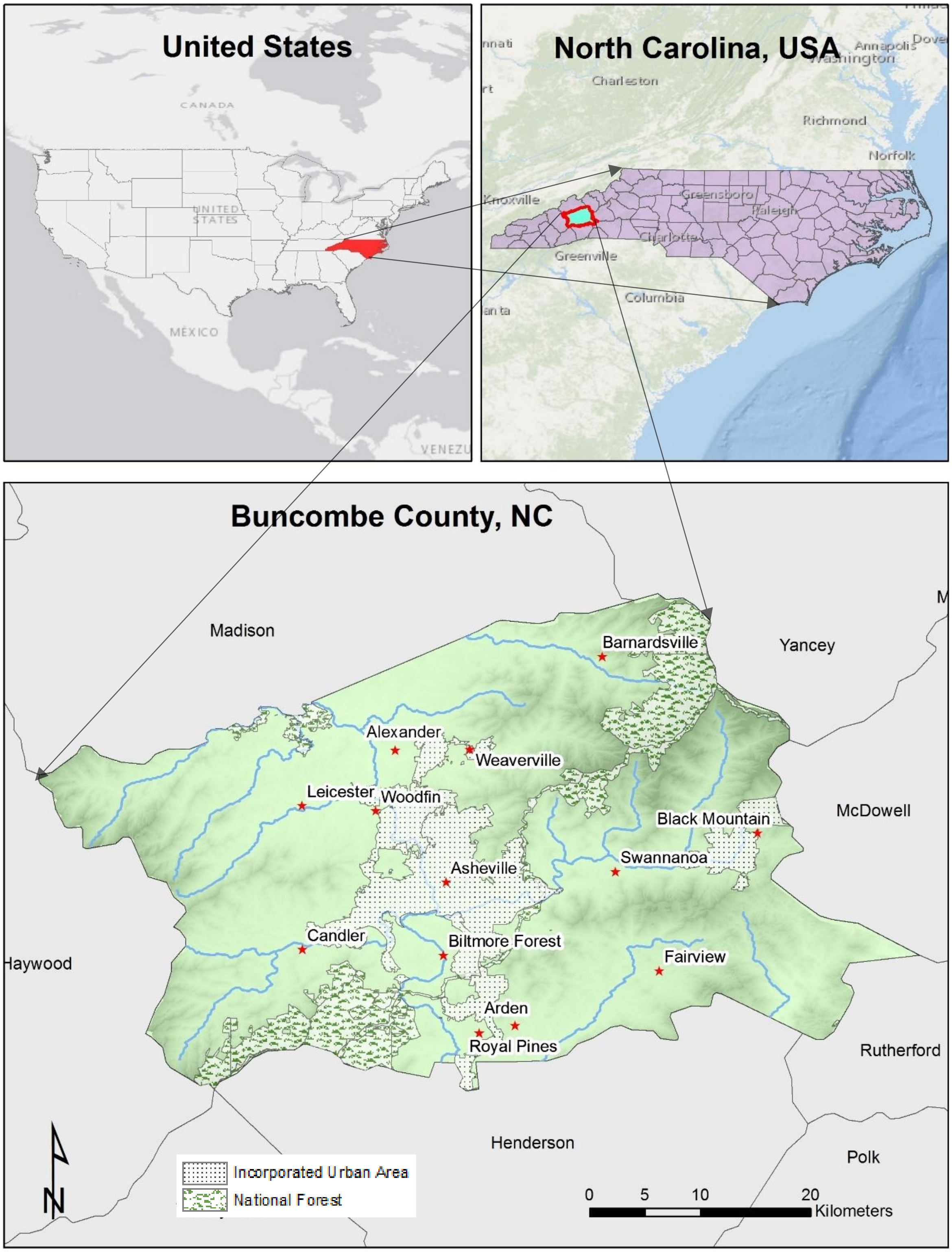

Fig 3.1 Map of Buncombe County, North Carolina, USA (Study Area)

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).

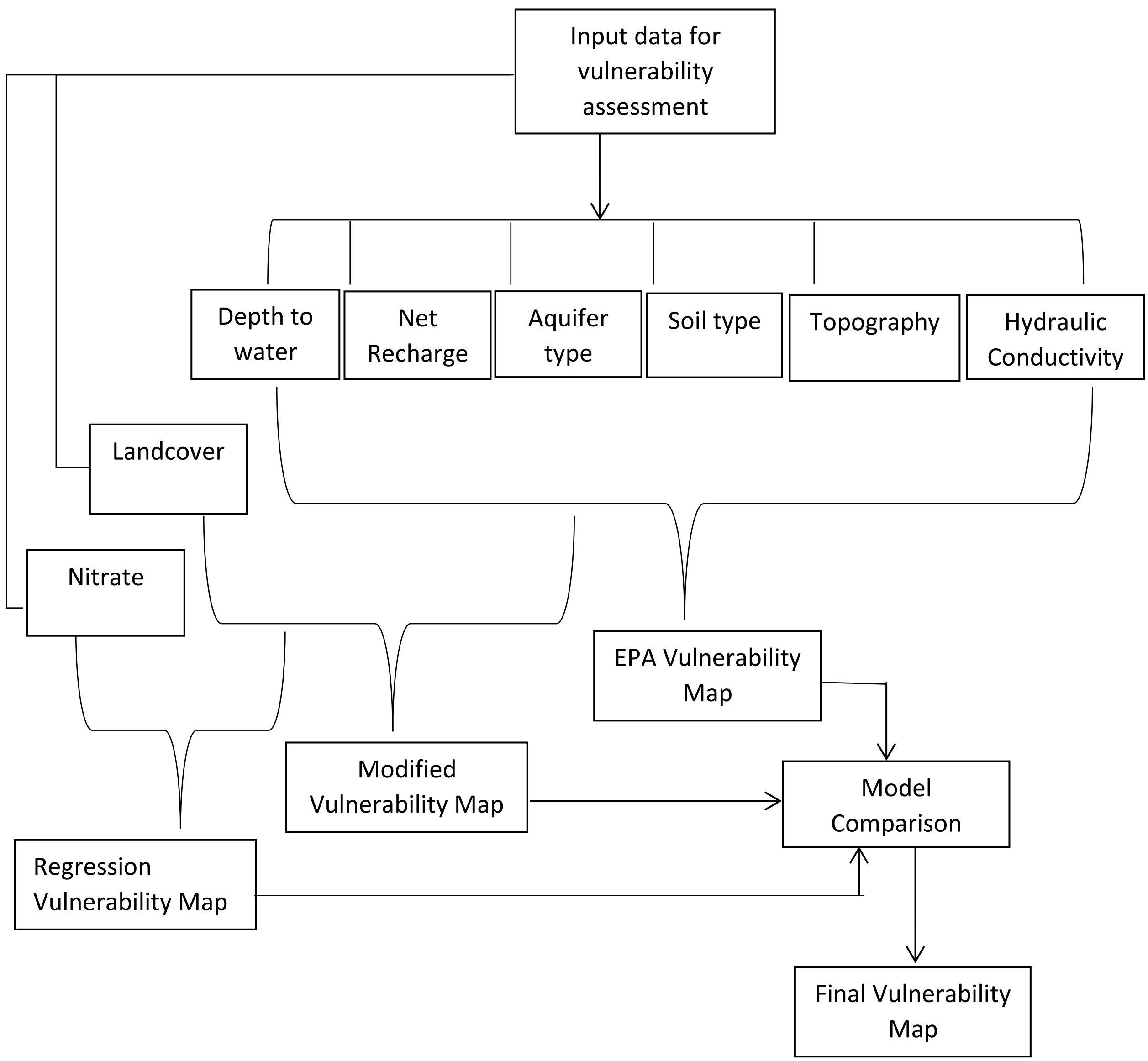

Fig. 3.2 Methodology for groundwater vulnerability assessment using DRASTIC Model in GIS

3.1 Input Data Collection

DRASTIC parameters used in the study include **D**epth to water, net **R**echarge, **A**quifer media, **S**oil media, **T**opography (percent slope), **I**mpact of vadose zone, and hydraulic **C**onductivity. 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, Metaultramafic 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 goup 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 ounty 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 infiltation 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 m^2 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 x10^{-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.

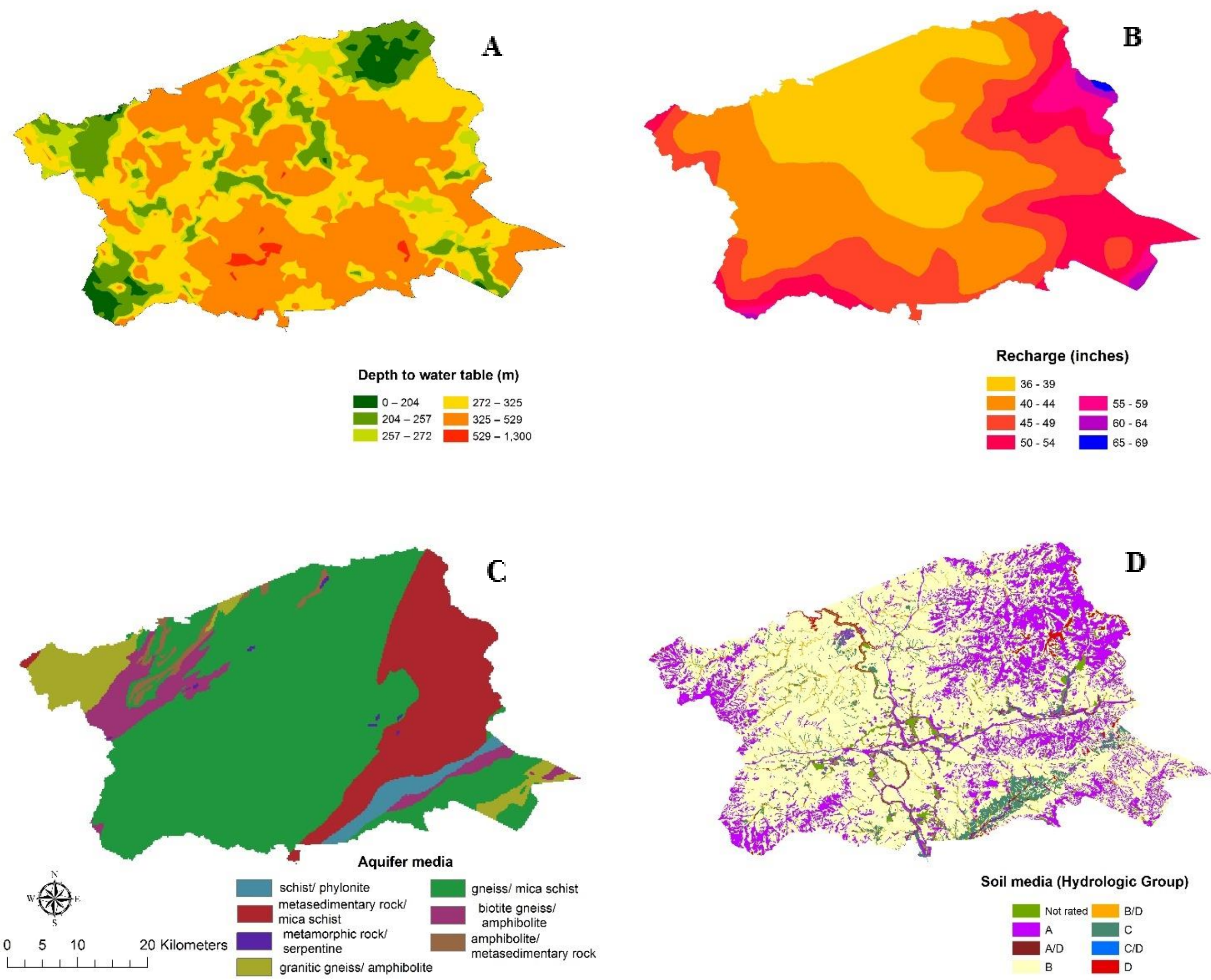

Fig 3.3: Parameters used in EPA vulnerability analysis: Depth to water (A), Net recharge (B), Aquifer media (C), and Soil media (D)

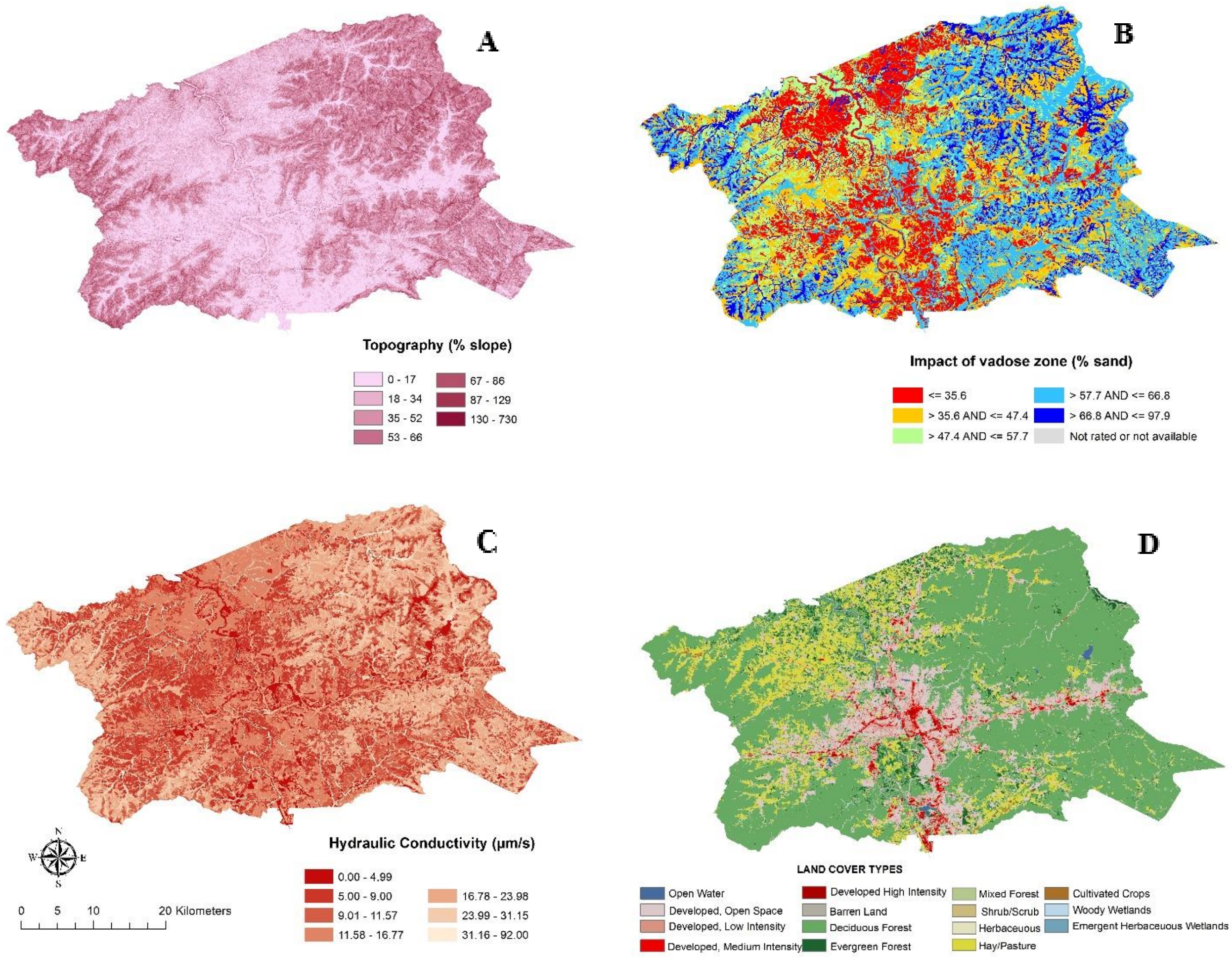

Fig 3.4: Parameters used in EPA vulnerability analysis: Topography (A), Impact of vadose zone (B), Hydraulic conductivity (C) and Land cover types (D)

Table 3.2 DRASTIC parameters and ratings used in the study

Parameters	Range	Rating	EPA based weight (DRASTIC)	weight (Modified DRASTIC)
Depth to water table (D) in (meters)	99-1300	1	5	-
Net recharge (R) in (inches)	36-69	10	4	1
Aquifer media (A)	metamorphic rock/ serpentine	8		
	schist/ phylonite	7		
	metasedimentary rock/ mica schist	6		
	amphibolite/ metasedimentary rock	5	3	-
	biotite gneiss/ amphibolite	4		
	gneiss/ mica schist	3		
	granitic gneiss/ amphibolite	2		
Soil media (S)	A	10		
	B	8		
	C	6	2	4
	A/D	4		
	B/D	3		
	C/D	1		
Topography (T) in (Percent Slope)	0-2	10		
	2-6	9		
	6-12	5	1	3
	12-18	3		
	>18	1		
Impact of vadose zone (I)	1-36	2	5	-
	37-45	3		
	46-51	4		
	52-58	5		
	59-61	6		
	62-63	7		
	64-68	8		
	66-76	9		
	77-98	10		
Hydraulic Conductivity (C) in (micrometer/sec)	1-5	2	3	2
	6-9	3		
	10-12	4		
	13-14	5		
	15-17	6		
	18-20	7		
	21-24	8		
	25-31	9		
	32-92	10		
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	-	5
	Shrub/Scrub	4		
	Deciduous Forest/Evergreen Forest	3		
	/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:

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:

Drastic index = $R_r R_w + S_r S_w + T_r T_w + C_r C_w + LC_r LC_w$

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:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots\dots\dots + \beta_n X_n + \varepsilon_i$$

Where 1, 2,….., n are number of variables, Y is nitrate, $X_1, X_2, \dots X_p$ are the DRASTIC and land cover parameters, and $\beta_1, \beta_2, \dots, \beta_p$ 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

	D (m)	R (In)	I (%)	C (µm/s)
Mean	347.172	52.5	50.38168	17.25516
Standard deviation	179.5178	9.9582	15.41168	10.74713
Minimum	0	36	0	0
Maximum	1300	69	97.9	92
Range	1300	33	97.9	92

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 km^2 (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 km^2 (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 km^2 and 312.2 km^2, 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 371.8km ^{2} (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 3.4 DRASTIC index values and their respective vulnerability zones and areas covered within the zones.

DRASTIC index value	Vulnerability Zone	Area (km^2)	% Area
62 – 93	Very low	418.41	24.57
94 – 102	Low	276.20	16.22
103 – 110	Moderate	324.32	19.04
111 – 122	High	312.20	18.33
123 – 170	Very high	371.80	21.83

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.

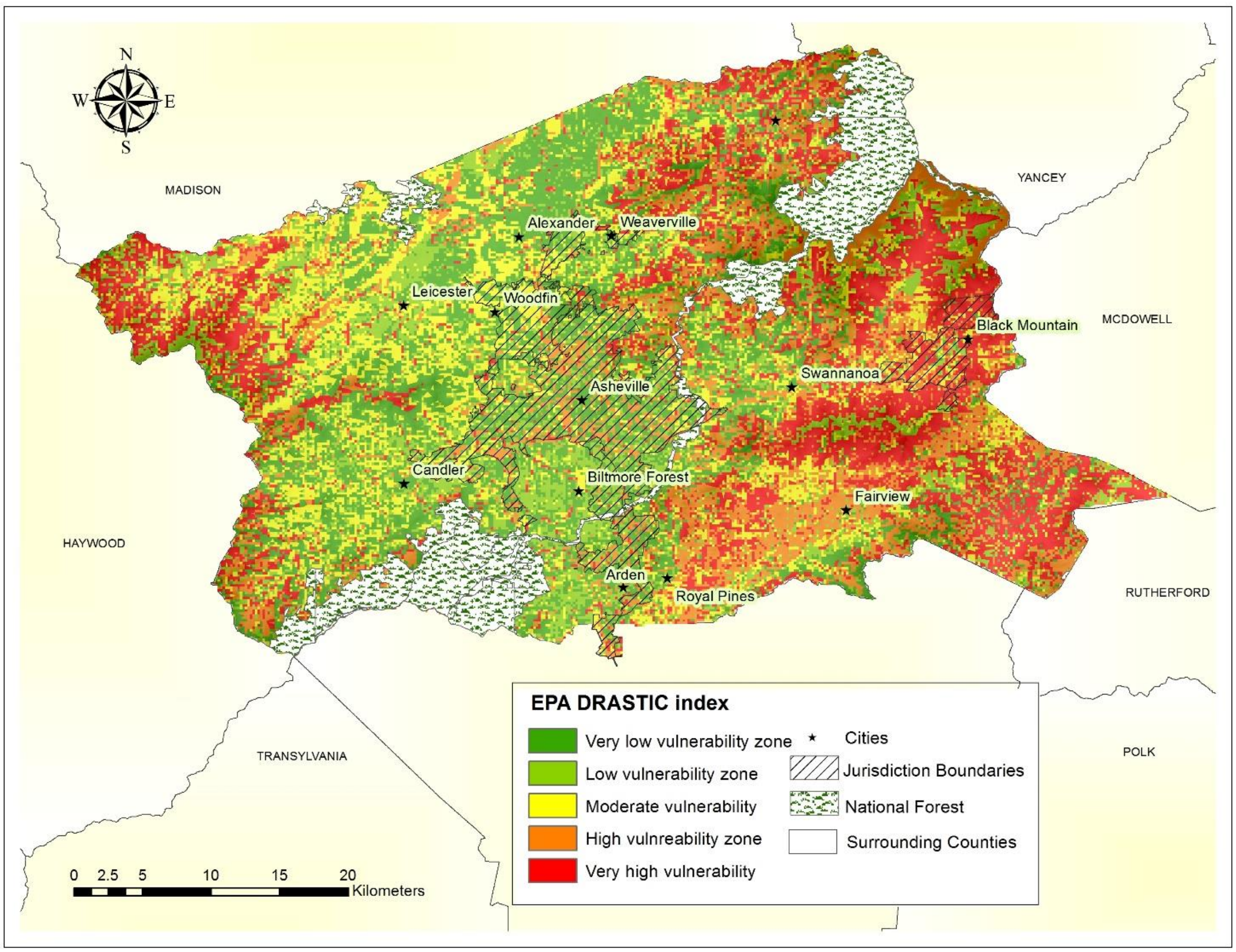

Fig 3.5 EPA DRASTIC index vulnerability map of Buncombe County, NC

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 km^2 (22.31%) lies in the no risk vulnerability zone with DRASTIC index ranging from 24 to 59. An area of 599.46 km^2 (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 32129 km^2 and 224 km^2 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.

DRASTIC index value	Vulnerability Zone	Area (km^2)	% Area
24 - 65	Very low	379.85	22.31
66 - 80	Low	599.46	35.20
81 - 96	Moderate	321.29	18.87
97 - 111	High	224	13.15
112 - 150	Very high	178.21	10.47

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 km^2 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.

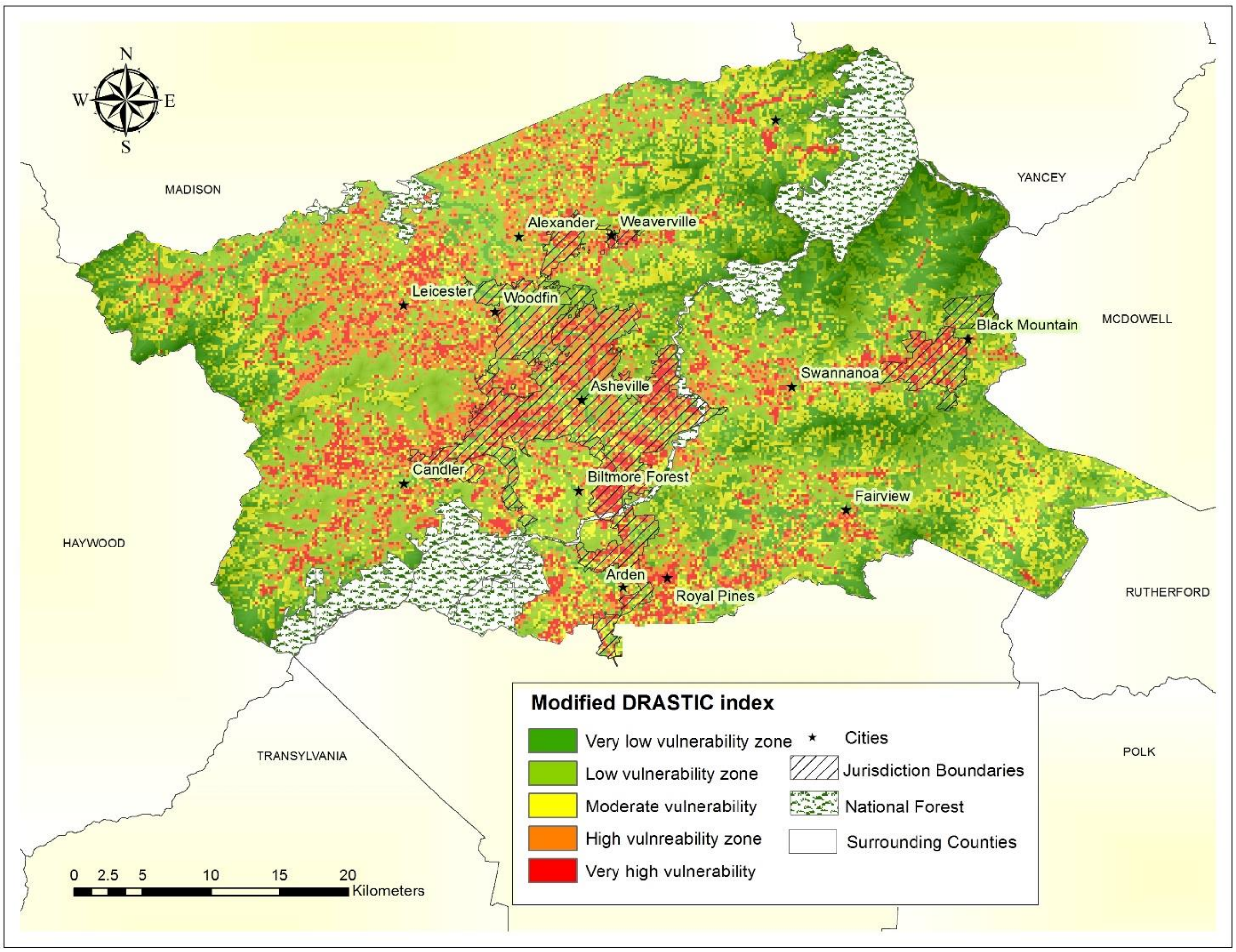

Fig 3.6 Modified DRASTIC index vulnerability map of Buncombe County, NC

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:

$$Y(N0_3) = 0.69 + 0.23T + 0.45C + 0.22LC$$

Where Y is the dependent variable (nitrate), and the independent variables are topography (T), hydraulic conductivity (C), and land cover (LC) respectively.

Table: 3.6 Regression model result using all variables and only significant variables

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

Normal Q-Q Plot of residuals

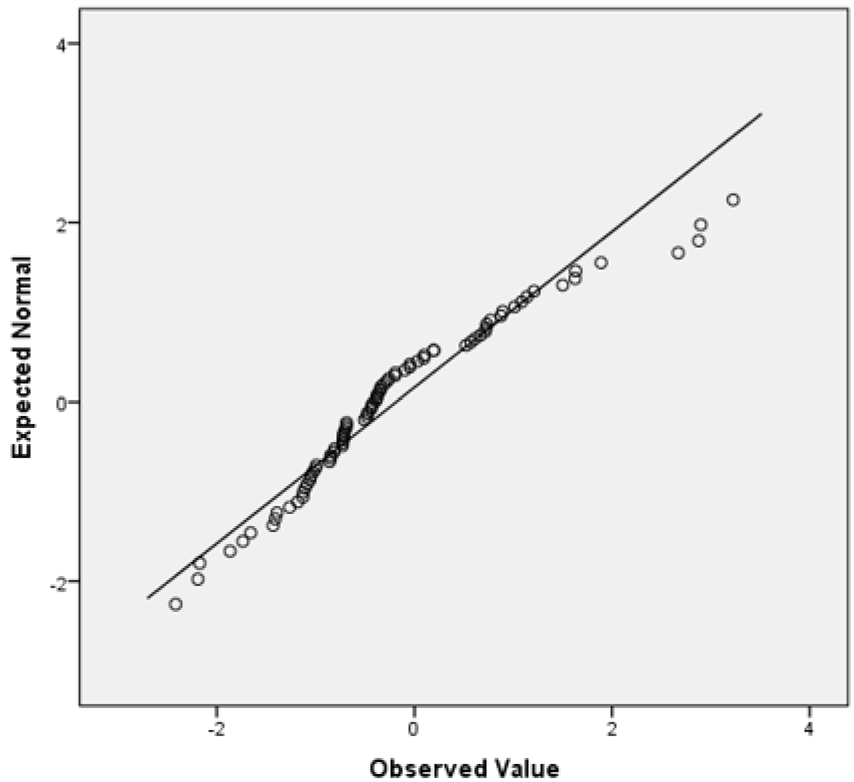

Fig 3.7 Relationship between observed and expected normal values of nitrate concentrations

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.

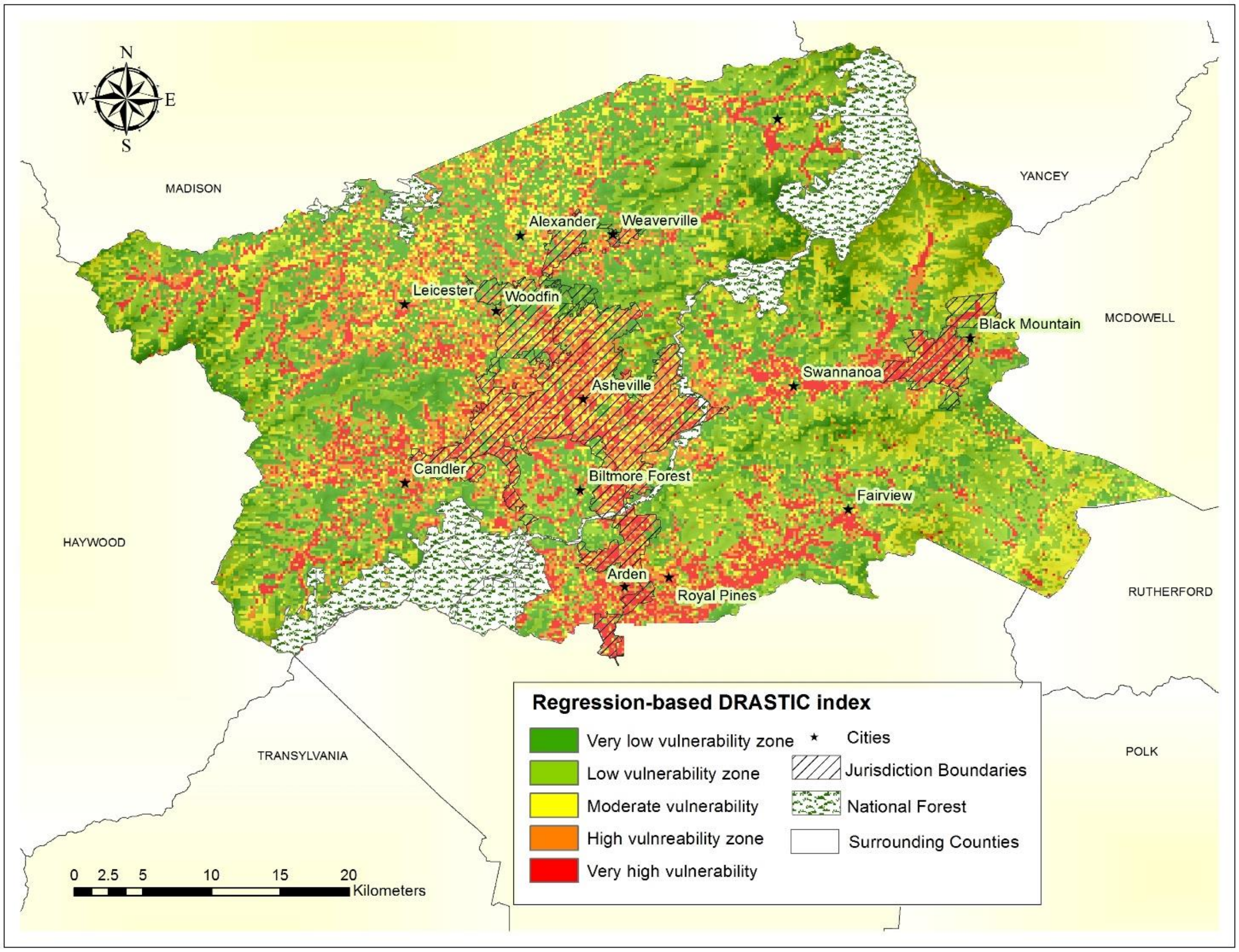

Fig 3.8 Regression DRASTIC index vulnerability map of Buncombe County, NC

Table 3.7 Modified DRASTIC index values and their respective vulnerability zones and areas covered within the zones.

DRASTIC index value	Vulnerability Zone	Area (km^2)	% Area
2.974 – 4.313	Very low	463.62	27.18
4.314 – 5.095	Low	483.23	28.33
5.096 – 5.865	Moderate	328.38	19.25
5.866 – 6.774	High	225.40	13.22
6.775 – 10.705	Very high	204.91	12.01

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.

Nitrate Conc (ppm/L)	Vulnerability Category	EPA DRASTIC (% of Nitrate)	Modified DRASTIC (% of Nitrate)	Regression DRASTIC (% of Nitrate)
2.0 – 3.4	Medium	9.5	7.1	21.4
3.4-5.6	High	0	4.8	4.8
5.6-8.5	Very High	2.4	2.4	7.1
Total		11.9	14.3	34.4

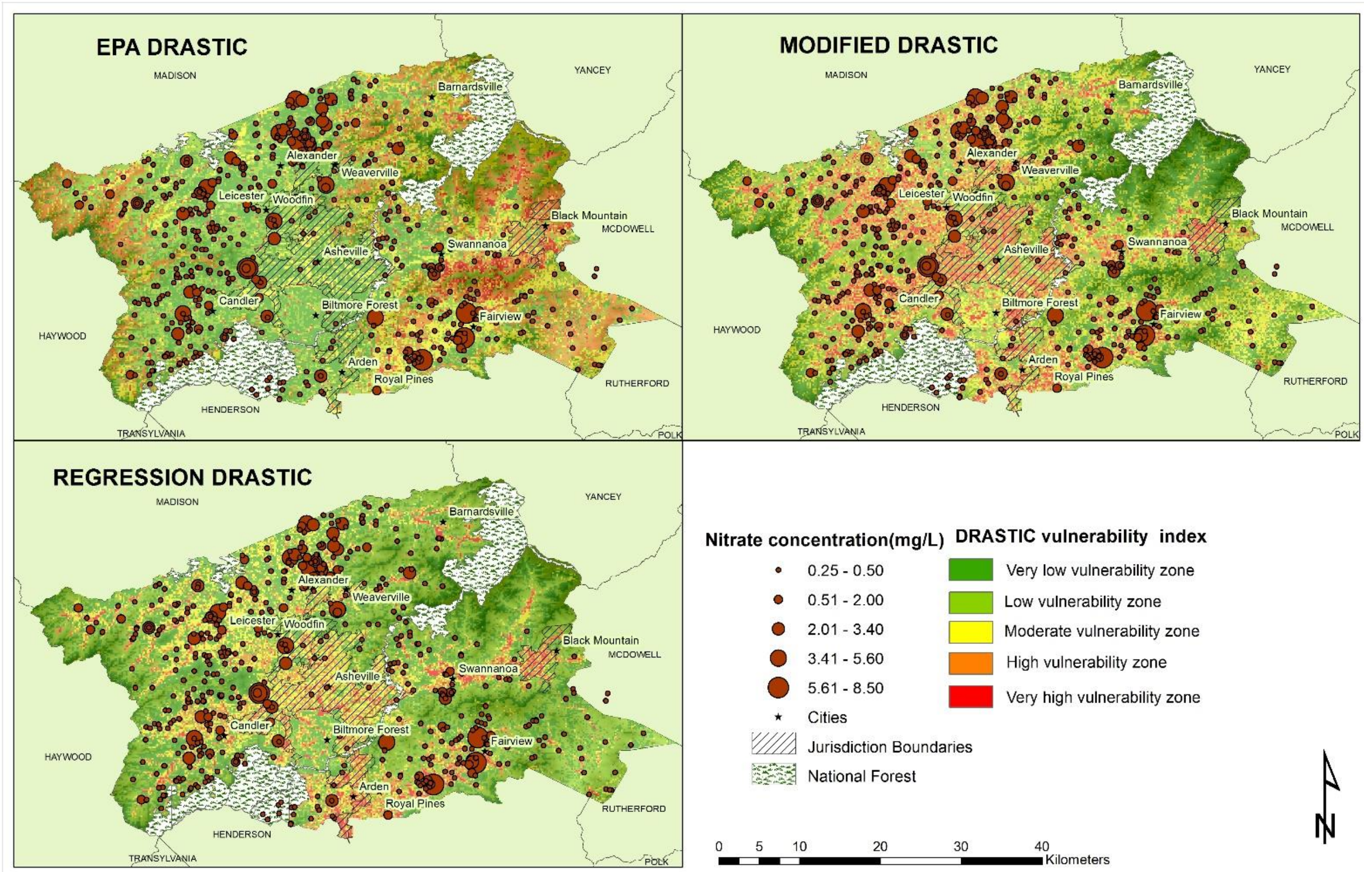

Fig 3.9 Comparison of EPA DRASTIC, Modified DRASTIC and Regression DRASTIC index vulnerability map

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 ground water movement in the soil and fractured crystalline aquifer is controlled by hydraulic conductivity, and the average hydraulic conductivity was $1.7 \text{ X}10^{-5}$ 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

Aller, L., Bennet, T., Lehr, J. H., & Petty, R. J. (1987). DRASTIC: A standardized system for evaluating groundwater pollution potential using hydrogeologic settings. USEPA document no. EPA /600/ 2-035.

Al-Adamat, R. A., Foster, I. D., &Baban, S. M. (2003). Groundwater vulnerability and risk mapping for the Basaltic aquifer of the Azraq basin of Jordan using GIS, Remote sensing and DRASTIC. Applied Geography, *23*(4), 303-324.

Al-Rawabdeh, A. M., Al-Ansari, N. A., Al-Taani, A. A., & Knutsson, S. (2013). A GIS-based drastic model for assessing aquifer vulnerability in Amman-Zerqa groundwater basin, Jordan.

Anornu, G. K., Kabo-bah, A. T., & Anim-Gyampo, M. (2012). Evaluation of groundwater vulnerability in the Densu River basin of Ghana. *American Journal of Human Ecology*, *1*(3), 79-86.

Antonakos, A. K., &Lambrakis, N. J. (2007). Development and testing of three hybrid methods for the assessment of aquifer vulnerability to nitrates, based on the drastic model, an example from NE Korinthia, Greece. Journal of Hydrology, *333*(2), 288-304.

Babiker, I. S., Mohamed, M. A., Hiyama, T., & Kato, K. (2005). A GIS-based DRASTIC model for assessing aquifer vulnerability in Kakamigahara Heights, Gifu Prefecture, central Japan. *Science of the Total Environment*, *345*(1), 127-140.

Bartzas, G., Tinivella, F., Medini, L., Zaharaki, D., & Komnitsas, K. (2015). Assessment of groundwater contamination risk in an agricultural area in north Italy. *Information Processing in Agriculture*, *2*(2), 109-129.

Brown, L.J., 1998. Ground water contamination vulnerability map of Heretaunga plains, Hawkes Bay. Institute of Geological and Nuclear Sciences Client Report— 92769D. CGWB 1998.

Chenini, I., & Khemiri, S. (2009). Evaluation of ground water quality using multiple linear regression and structural equation modeling. *International Journal of Environmental Science & Technology*, *6*(3), 509-519.

Colins, J., Sashikkumar, M. C., Anas, P. A., & Kirubakaran, M. (2016). GIS-based assessment of aquifer vulnerability using DRASTIC Model: A case study on Kodaganar basin. *Earth Sciences Research Journal*, *20*(1), 1-8.

Drever, J. I. (1997). The Geochemistry of Natural Waters: Surface and Groundwater Environments, 436 pp.

Eckhardt, D.A.V., Stackelberg, P.E., (1995). Relation for ground-water quality to land use on Long Island, New York. Groundwater 33, 1019–1033.

Fritch, T. G., McKnight, C. L., Yelderman Jr, J. C., Arnold, J. G., (2000), An aquifer vulnerability assessment of the Paluxy Aquifer, Central Texas, USA, using GIS and a modified DRASTIC approach

Gupta, N. (2014). groundwater vulnerability assessment using DRASTIC method in Jabalpur District of Madhya Pradesh. *International Journal of recent technology and Engineering*, *3*(3), 36-43.

Huan, H., Wang, J., & Teng, Y. (2012). Assessment and validation of groundwater vulnerability to nitrate based on a modified DRASTIC model: a case study in Jilin City of northeast China. *Science of the total environment*, *440*, 14-23.

Jamrah, A., Al-Futaisi, A., Rajmohan, N, Al-yaroubi, S., (2008), Assessment of groundwater vulnerability in the coastal region of Oman using DRASTIC index method in GIS environment, Environ Monit Assess 147, 125-138

Javadi, S., Kavehkar, N., Mousavizadeh, M. H., & Mohammadi, K. (2010). Modification of DRASTIC model to map groundwater vulnerability to pollution using nitrate measurements in agricultural areas. Journal of Agricultural Science and Technology, 13, 239-249.

Keeney, D., (1986). Sources of nitrate to groundwater. CRC Critical Reviews in Environmental Control 16, 257–304.

Kemper, K. E. (2004). Groundwater—from development to management. *Hydrogeology Journal*, *12*(1), 3-5.

Li, R., & Zhao, L. (2011, May). Vadose zone mapping using geographic information systems and geostatistics a case study in the Elkhorn River Basin, Nebraska, USA. In *Water Resource and Environmental Protection (ISWREP), 2011 International Symposium on* (Vol. 4, pp. 3177-3179). IEEE.

Lindsey, B. D., & Bickford, T. M. (1999). *Hydrogeologic framework and sampling design for an assessment of agricultural pesticides in ground water in Pennsylvania*. US Department of the Interior, US Geological Survey.

McLay,C.D.A, Dragten,R., Sparling,G., Selvarajah,N., (2001). Predicting groundwater nitrate concentrations in a region of mixed agricultural land use. Environmental Pollution 115, 191–204

Meisinger, J. J., Randall, G. W., (1991). Estimating N budgets for soil-crop systems. In :Follet, R. F., Keeney, D. R., Cruse, R. M. (Eds.), Managing N for Groundwater Quality and Farm Profitability. Soil Science of America, Madison Wisconsin, pp. 85-124

MENG, X. M., SHU, L. C., & LU, Y. R. (2007). Modified DRASTIC model for groundwater vulnerability assessment based on entropy weight [J]. *Journal of Hydraulic Engineering*, *1*, 013.

Muhammad, A. M., Zhonghua, T., Dawood, A. S., & Earl, B. (2015). Evaluation of local groundwater vulnerability based on DRASTIC index method in Lahore, Pakistan. *Geofísica internacional*, *54*(1), 67-81.

Muthulakshmi, L., Ramu, A., Kannan, N., & Murugan, A. (2013). Application of correlation and regression analysis in assessing ground water quality, Virudhunagar, India. *International Journal of ChemTech Research*, *5*, 353-361.

Neshat, A., Pradhan, B., Pirasteh, S., &Shafri, H. Z. M. (2014). Estimating groundwater vulnerability to pollution using a modified DRASTIC model in the Kerman agricultural area, Iran. Environmental earth sciences, *71*(7), 3119-3131.

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

Remesan, R., & Panda, R. K. (2008). Groundwater vulnerability assessment, risk mapping, and nitrate evaluation in a small agricultural watershed: using the DRASTIC model and GIS. *Environmental Quality Management*, *17*(4), 53-75.

Rupert, M. G. (2001). Calibration of the DRASTIC ground water vulnerability mapping method. *Groundwater*, *39*(4), 625-630.

Saha, D., & Alam, F. (2014). Groundwater vulnerability assessment using DRASTIC and Pesticide DRASTIC models in intense agriculture area of the Gangetic plains, India. *Environmental monitoring and assessment*, *186*(12), 8741-8763.

Sener, E., & Davraz, A. (2013). Assessment of groundwater vulnerability based on a modified DRASTIC model, GIS and an analytic hierarchy process (AHP) method: the case of Egirdir Lake basin (Isparta, Turkey). *Hydrogeology Journal*, *21*(3), 701-714.

Shamrukh, M., Corapcioglu, M., Hassona, F., (2001). Modeling the effect of chemical fertilizers on ground water quality in the Nile Valley Aquifer, Egypt. Groundwater 39(1), 59-76

Spalding, R.F., Exner, M.E., (1993). Occurrence of nitrate in groundwater — a review. Journal of Environmental Quality 22, 392–402.

Shirazi, S. M., Imran, H. M., & Akib, S. (2012). GIS-based DRASTIC method for groundwater vulnerability assessment: a review. *Journal of Risk Research*, *15*(8), 991-1011.

Tesoriero, A. J., Inkpen, E. L., & Voss, F. D. (1998, April). Assessing ground-water vulnerability using logistic regression. In *Proceedings for the source water assessment and protection 98 conference, Dallas, TX* (Vol. 157165).

Thirumalaivasan, D., Karmegam, M., Venugopal, K., (2003). AHP-DRASTIC: software for specific aquifer vulnerability assessment using DRASTIC model and GIS, Environmental Modelling & Software 18, 645–656

Tirkey, P., Gorai, A. K., & Iqbal, J. (2013). AHP-GIS based DRASTIC model for groundwater vulnerability to pollution assessment: a case study of Hazaribag district, Jharkhand, India. *International Journal of Environmental Protection*, *3*(9), 20.

Todd, D. K. (1980). Groundwater hydrology (2nd ed.). New York, NY: Wiley.

Trapp Jr, H., & Horn, M. A. (1997). Ground Water Atlas of the United States, Delaware, Maryland, New Jersey, North Carolina, Pennsylvania, Virginia, West Virginia. *US Geol Surv Hydrol Atlas HA.*

Wang, J., He, J., & Chen, H. (2012). Assessment of groundwater contamination risk using hazard quantification, a modified DRASTIC model and groundwater value, Beijing Plain, China. *Science of the Total Environment*, *432*, 216-226.

USEPA, 1993. A review of methods for assessing aquifer sensitivity and ground water vulnerability to pesticide contamination. Report No. EPA 813-R-93-002, United States Environmental Protection Agency, Washington, DC.

USEPA (Environmental Protection Agency), (1985). DRASTIC: a standard system for evaluating groundwater pollution potential using hydrogeological settings, Ada, Oklahoma WA/EPA Series; 163.

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 NO_3 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 NO_3 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 NO_3 concentrations across the county. The cross-validation matrix of the interpolated surfaces (kriging and cokriging) indicated that NO_3 cokriged with landcover provided the best model in terms of accuracy metrics.
7. The spatial distribution map of NO_3 concentrations in Buncombe County indicated that areas like Barnardsville, Biltmore Forest, Woodfin, and Black Mountain had very low NO_3 concentrations (below 0.5 mg/L). Swannanoa had low NO_3 concentration level above 0.5 mg/L but not exceeding 0.8 mg/L. High NO_3 content were present in Candler, Weaverville, Leicester Fairview, Arden, and some areas in Asheville.

The second study assessed groundwater vulnerability to NO_3 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 NO_3 (dependent variable) in groundwater and the results indicated that the DRASTIC and landcover accounted for 27% variability (adjusted R^2=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 NO_3 concentrations in Buncombe County. High NO_3 concentrations were mostly seen in high vulnerability areas with few appearing in medium to low vulnerability zones. Modified DRASTIC provided a better representation of NO_3 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.

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 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 implemented 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**.**

REFERENCES

Addiscott TM, Benjamin N. 2004. Nitrate and human health. Soil use and management, 20(2), 98-104.

Ahmadi SH, Sedghamiz A. 2007. Geostatistical analysis of spatial and temporal variations of groundwater level. *Environmental monitoring and assessment*, *129*(1-3), 277-294.

Ahmadi SH, Sedghamiz A. 2008. Application and evaluation of kriging and cokriging methods on groundwater depth mapping. *Environmental Monitoring and Assessment*, *138*(1), 357-368.

Ahn HI, Chon HT. 1999. Assessment of groundwater contamination using geographic information systems. *Environmental Geochemistry and Health*, *21*(3), 273-289.

Aller L, Bennet T, Lehr JH, Petty RJ. 1987. DRASTIC: A standardized system for evaluating groundwater pollution potential using hydrogeologic settings. USEPA document no. EPA /600/ 2-035.

Al-Rawabdeh AM., Al-Ansari NA, Al-Taani AA, Knutsson S. 2013. A GIS-based drastic model for assessing aquifer vulnerability in Amman-Zerqa groundwater basin, Jordan.

Anornu GK, Kabo-bah AT, Anim-Gyampo M. 2012. Evaluation of groundwater vulnerability in the Densu River basin of Ghana. *American Journal of Human Ecology*, *1*(3), 79-86.

Assaf H, Saadeh M. 2009. Geostatistical assessment of groundwater nitrate contamination with reflection on DRASTIC vulnerability assessment: the case of the Upper Litani Basin, Lebanon. *Water resources management*, *23*(4), 775-796.

Avery AA. 1999. Infantile methemoglobinemia: reexamining the role of drinking water nitrates. *Environmental health perspectives*, *107*(7), 583.

Babiker IS, Mohamed MA, Hiyama T, Kato K. 2005. A GIS-based DRASTIC model for assessing aquifer vulnerability in Kakamigahara Heights, Gifu Prefecture, central Japan. *Science of the Total Environment*, *345*(1), 127-140.

Bohling G. 2005. Introduction to geostatistics and variogram analysis. *Kansas geological survey*, 1-20.

Brown LJ. 1998. Ground water contamination vulnerability map of Heretaunga plains, Hawkes Bay. Institute of Geological and Nuclear Sciences Client Report— 92769D. CGWB 1998

.
Burow KR, Nolan BT, Rupert MG, Dubrovsky NM. 2010. Nitrate in groundwater of the United States, 1991− 2003. *Environmental Science & Technology*, *44*(13), 4988-4997.

Chiles JP, Delfiner P. 2009. *Geostatistics: modeling spatial uncertainty* (Vol. 497). John Wiley & Sons.

Cressie N. 1990. The origins of kriging. *Mathematical geology*, *22*(3), 239-252.

Deutsch CV. 2002. Geostatistical reservoir modeling: Oxford University Press, New York, 376 p. *Google Scholar*.

Erxleben J, Elder K, Davis R. 2002. Comparison of spatial interpolation methods for estimating snow distribution in the Colorado Rocky Mountains. *Hydrological Processes*, *16*(18), 3627-3649.

Jeffrey SJ, Carter JO, Moodie KB, Beswick AR. 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling & Software*, *16*(4), 309-330.

Fritch TG, McKnight CL, Yelderman Jr, JC, Arnold JG. 2000. An aquifer vulnerability assessment of the Paluxy Aquifer, Central Texas, USA, using GIS and a modified DRASTIC approach

Goovaerts P. 1997. *Geostatistics for natural resources evaluation*. Oxford University Press on Demand.

Hong Y, Nix HA, Hutchinson MF, Booth TH. 2005. Spatial interpolation of monthly mean climate data for China. *International journal of climatology*, *25*(10), 1369-1379.

Huan H, Wang J, Teng Y. 2012. Assessment and validation of groundwater vulnerability to nitrate based on a modified DRASTIC model: a case study in Jilin City of northeast China. *Science of the total environment*, *440*, 14-23.

Jamrah A, Al-Futaisi A, Rajmohan N, Al-yaroubi S. 2008. Assessment of groundwatervulnerability in the coastal region of Oman using DRASTIC index method in GIS environment, Environ Monit Assess 147, 125-138

Javadi S, Kavehkar N, Mousavizadeh MH, Mohammadi K. 2010. Modification of DRASTIC model to map groundwater vulnerability to pollution using nitrate measurements in agricultural areas. Journal of Agricultural Science and Technology, 13, 239-249.

Ju XT, Kou CL, Zhang FS, Christie P. 2006. Nitrogen balance and groundwater nitrate contamination: comparison among three intensive cropping systems on the North China Plain. *Environmental Pollution*, *143*(1), 117-125.

Kim YJ, Hamm SY. 1999. Assessment of the potential for groundwater contamination using the DRASTIC/EGIS technique, Cheongju area, South Korea. *Hydrogeology Journal*, *7*(2), 227-235.

Kitanidis PK. 1997. *Introduction to geostatistics: applications in hydrogeology*. Cambridge University Press.

Kross BC, Hallberg GR, Bruner DR, Cherryholmes K, Johnson JK. 1993. The nitrate contamination of private well water in Iowa. *American Journal of Public Health*, *83*(2), 270-272.

Lynch SD, Reynders AG, Schulze RE. 1997. A DRASTIC approach to groundwater vulnerability in South Africa. *South African Journal of Science (South Africa)*.

Majumdar D, Gupta N. 2000. Nitrate pollution of groundwater and associated human health disorders. *Indian Journal of Environmental Health*, *42*(1), 28-39.

Mehrjardi RT, Jahromi MZ, Mahmodi S, Heidari A. 2008. Spatial distribution of groundwater quality with geostatistics (case study: Yazd-Ardakan plain). *World Applied Sciences Journal*, *4*(1), 9-17.

Meisinger JJ, Randall GW, 1991. Estimating N budgets for soil-crop systems. In: Follet, R. F., Keeney, D. R., Cruse, R. M. (Eds.), Managing N for Groundwater Quality and Farm Profitability. Soil Science of America, Madison Wisconsin, pp. 85-124

Meng XM, Shu LC, Lu YR. 2007. Modified DRASTIC model for groundwater vulnerability assessment based on entropy weight [J]. *Journal of Hydraulic Engineering*, *1*, 013.

Morio M, Finkel M, Martac E. 2010. Flow guided interpolation–a GIS-based method to represent contaminant concentration distributions in groundwater. *Environmental Modelling & Software*, *25*(12), 1769-1780.

Nas B, Berktay A. 2006. Groundwater contamination by nitrates in the city of Konya,(Turkey): A GIS perspective. *Journal of Environmental Management*, *79*(1), 30-37.

Nas B, Berktay A. 2010. Groundwater quality mapping in urban groundwater using GIS. *Environmental monitoring and assessment*, *160*(1), 215-227.

Neshat A, Pradhan B, Pirasteh S, Shafri HZM. 2014. Estimating groundwater vulnerability to pollution using a modified DRASTIC model in the Kerman agricultural area, Iran. Environmental earth sciences, *71*(7), 3119-3131.

Nikroo L, Kompani-Zare M, Sepaskhah AR., Fallah Shamsi SR. 2010. Groundwater depth and elevation interpolation by kriging methods in Mohr Basin of Fars province in Iran. *Environmental monitoring and assessment*, *166*(1), 387-407.

Oliver MA, Webster R. 1990. Kriging: a method of interpolation for geographical information systems. *International Journal of Geographical Information System*, *4*(3), 313-332.

Power J, Schepers JS. 1989. Nitrate contamination of groundwater in North America. Agriculture, ecosystems & environment, 26(3-4), 165-187.

Queiroz JC, Sturaro JR, Saraiva AC, Landim PMB. 2008. Geochemical characterization of heavy metal contaminated area using multivariate factorial kriging. *Environmental geology*, *55*(1), 95-105.

Ramakrishnaiah CR, Sadashivaiah C, Ranganna G. 2009. Assessment of water quality index for the groundwater in Tumkur Taluk, Karnataka State, India. *Journal of Chemistry*, *6*(2), 523-530.

Rupert MG. 2001. Calibration of the DRASTIC ground water vulnerability mapping method. *Groundwater*, *39*(4), 625-630.

Rundquist DC, Peters AJ, Di L, Rodekohr DA, Ehrman RL, Murray G. 1991. Statewide groundwater-vulnerability assessment in nebraska using the drastic/GIS model. *Geocarto international*, *6*(2), 51-58.

Saidi S, Bouri S, Dhia HB. 2010. Groundwater vulnerability and risk mapping of the Hajeb-jelma aquifer (Central Tunisia) using a GIS-based DRASTIC model. *Environmental Earth Sciences*, *59*(7), 1579-1588.

Salih I, Pettersson H, Sivertun Å, Lund E. 2002. Spatial correlation between radon (222Rn) in groundwater and bedrock uranium (238U): GIS and geostatistical analyses. *Journal of Spatial Hydrology*, *2*(2).

Sener E, Davraz A. 2013. Assessment of groundwater vulnerability based on a modified DRASTIC model, GIS and an analytic hierarchy process (AHP) method: the case of Egirdir Lake basin (Isparta, Turkey). *Hydrogeology Journal*, *21*(3), 701-714.

Shamrukh M, Corapcioglu M, Hassona F. 2001. Modeling the effect of chemical fertilizers on ground water quality in the Nile Valley Aquifer, Egypt. Groundwater 39(1), 59-76

Stein ML. 2012. *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media.

Tang C, Chen J, Shindo S, Sakura Y, Zhang W, Shen Y. 2004. Assessment of groundwater contamination by nitrates associated with wastewater irrigation: a case study in Shijiazhuang region, China. *Hydrological processes*, *18*(12), 2303-2312.

Tesoriero AJ, Inkpen EL, Voss FD. 1998. Assessing ground-water vulnerability using logistic regression. In *Proceedings for the source water assessment and protection 98 conference, Dallas, TX* (Vol. 157165).

Thirumalaivasan D, Karmegam M, Venugopal K. 2003. AHP-DRASTIC: software for specific aquifer vulnerability assessment using DRASTIC model and GIS, Environmental Modelling & Software 18, 645–656

Tirkey P, Gorai AK, Iqbal J. 2013. AHP-GIS based DRASTIC model for groundwater vulnerability to pollution assessment: a case study of Hazaribag district, Jharkhand, India. *International Journal of Environmental Protection*, *3*(9), 20.

Wang J, He J, Chen H. 2012. Assessment of groundwater contamination risk using hazard quantification, a modified DRASTIC model and groundwater value, Beijing Plain, China. *Science of the Total Environment*, *432*, 216-226.

Yao L, Huo Z, Feng S, Mao X, Kang S, Chen J, Steenhuis TS. 2014. Evaluation of spatial interpolation methods for groundwater level in an arid inland oasis, northwest China. *Environmental earth sciences*, *71*(4), 1911-1924.

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