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Mapping groundwater vulnerability at the pan-African scale

Issoufou Ouedraogo
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Jury members:

Supervisor : Prof. Marnik Vanclooster (UCL, Belgium)
President : Prof. Bruno Delvaux (UCL, Belgium)
Readers : Prof. Pierre Defourny (UCL, Belgium)
: Prof. Olivier Cogels (UCL, Belgium)
: Dr. Alice Aureli (UNESCO, France)

Credits

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« Là où s'abat le découragement s'élève la victoire des persévérants.»

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Table of Contents

List of Figures ... xv

List of Tables ... xxii

Acronyms and abbreviations ... xiv

Chapter 1 General introduction ... 1

1.1 Introduction ... 3

1.2 Problem statement and challenges ... 7

1.3 Research objectives ... 13

1.5 Contributions of the study ... 15

1.6 Outline of the thesis ... 16

Chapter 2 Groundwater Vulnerability: Literature Review ... 21

2.1 Introduction ... 23

2.2 Groundwater vulnerability ... 25

2.3 Definitions of groundwater vulnerability ... 25

2.4 Nitrogen sources and pollution ... 30

2.5 Nitrate: health and environmental impacts ... 38

2.6 Review of global and regional nitrogen and nitrate assessment maps ... 42

2.7 Nitrate vulnerability modelling at the continental and regional scale ... 50

2.7.1 Notions of scale and definition ... 50

2.7.2 Problems of scale ... 50

2.8 Conclusions ... 52

Chapter 3 Description of the study area ... 55

3.1 Regional layout ... 57

3.2 Climate and rainfall in Africa ... 59

3.3 Surface water 60
3.4 Geological and hydrogeological context 62
3.5 Transboundary aquifer distribution and current knowledge ... 65
3.6 Resource availability 68
3.6.1 Groundwater storage 68
3.6.2 Aquifer productivity 70
3.7 Pressures on water quality in Africa 71
Chapter 4 Mapping the groundwater vulnerability for pollution at the pan African scale 83
4.1 Abstract 85
4.2 Introduction 86
4.3 Materials and methods 90
4.3.1 The DRASTIC model 90
4.3.2 Data acquisition and data base compilation 91
4.3.3 Development of the DRASTIC variables 92
4.3.3.1 Depth of groundwater (D) 93
4.3.3.2 Net Recharge(R) 93
4.3.3.3 Aquifer media (A) 95
4.3.3.4 Impact of the vadose zone (I) 95
4.3.3.5 Topography (T) 96
4.3.3.6 Soil media (S) 96
4.3.3.7 Hydraulic conductivity (C) 96
4.3.4 Sensitivity analysis 98
4.3.5 Development of groundwater risk map 99
4.3.6 Validation using observed nitrate concentration data 103
4.4 Results and discussion 104

4.4.1 Ratings of DRASTIC parameters and aquifer vulnerability 104
4.4.2 Sensitivity of the DRASTIC model 115
4.4.2.1 Summary of the DRASTIC parameters.........................115
4.4.2.2 Map removal sensitivity analysis 116
4.4.2.3 Single-parameter sensitivity analysis...........................118
4.4.3 Mapping of groundwater pollution risk.............................119
4.4.4 Validation of the groundwater vulnerability map 123
4.4.4.1 Spatial concentrations of nitrate 123
4.4.4.2 Regression of aggregated nitrate concentration data with estimated groundwater risk 124
4.4.5 Limitations of vulnerability assessment 126
4.5 Conclusion 127
Chapter 5 A meta-analysis and statistical modelling of nitrates in groundwater at the African scale...131
5.1 Abstract 133
5.2 Introduction...134
5.3 Data and methods...138
5.3.1 Nitrate contamination data...138
5.3.2 Data quality evaluation 140
5.3.3 Determination of spatial explanatory variables.................142
5.3.4 Statistical model description...159
5.4 Results..160
5.4.1 Normality of the dependent variable 160
5.4.2 Correlation between nitrate in groundwater and explanatory variables...162
5.4.3 Development of the multi-variate statistical model...........168

5.5 Discussion 174

5.6 Conclusion 183

Chapter 6 Modelling groundwater nitrate concentrations at the African scale using Random Forest Regression Techniques 187

6.1 Abstract 189

6.2 Introduction 190

6.3 Materials and methods 193

6.3.1 The pan-African groundwater nitrate contamination dataset 193

6.3.2 The dataset of explaining factors 196

6.3.2.1 Climate 196

6.3.2.2 Topography 197

6.3.2.3 Soil type and land use 197

6.3.2.4 Geology and hydrogeology 197

6.3.2.5 Nitrogen fertilizer application 198

6.3.2.6 Population density 199

6.3.3 Description of the models 201

6.3.3.1 Multiple Linear Regression (MLR) 201

6.3.3.2 Random Forest Regression (RFR) 202

6.3.3.3 Variable importance in random forest 204

6.3.4 Model validation 204

6.4 Results 205

6.4.1 Modelling results 205

6.4.1.1 Multiple Linear Regression (MLR) 205

6.4.1.2 Estimating independent variables importance 209

6.4.1.3 Application of Random Forest Regression 210

6.4.2 Evaluation of model performance 213
6.5 Discussion 218
6.6 Conclusion 225
Chapter 7 Validating a continental-scale groundwater diffuse pollution model using regional datasets 229
7.1 Abstract 231
7.2 Introduction 232
7.3 Data and methods 235
7.3.1 Measurement of nitrate data in groundwater 235
7.3.2 Examining the distribution of nitrate data 239
7.3.3 Environmental variables 242
7.3.4 Model development and validation approach 245
7.4 Results 249
7.4.1 Validating the continental scale model with three countries datasets 249
7.4.2. Re-calibration of nonlinear RF regression at country level 251
7.4.3 Variable Importance Plots at country level 255
7.5. Discussion 256
7.6 Conclusion 260
Chapter 8 Time dynamic pollution risk modelling of groundwater at the African scale 263
8.1 Abstract 265
8.2 Introduction 266
8.3 Material and methods 268
8.3.1 Groundwater vulnerability modelling framework 268
8.3.2 Data sources 273

8.3.2.1 Dynamic Parameters Mapping 273
8.3.2.2 Data of Static Parameters 279
8.4 Results and discussion 281
8.4.1 Dynamic maps of the groundwater pollution risk.........281
8.4.2 Limitations of the study 289
8.5 Conclusion 290
Chapter 9 Conclusion and Perspectives 293
9.1 Main findings 295
9.2 Implications for science and policy: Addressing the challenges...301
9.3 Limitations of the study and perspectives for future research 309
Bibliography 319
Appendices 395
Appendix A 395
Appendix B 411
Appendix C..420
Publications and Conferences 421

List of Figures

Figure 1-1: Flowchart of the thesis....18
Figure 2-1: Simplified biological nitrogen cycle (Madison and Brunett, 1985)....32
Figure 2-2: Global map with the presence of zones with high nitrate in groundwater (from IGRAC 2012, cited in Zhou et al. 2015)....42
Figure 2-3: Vulnerability map of the main transboundary aquifers of the world using GOD method (Zhou et al.2015)....43
Figure 2-4: Groundwater nitrate concentration in the different regions of the world (Zhou et al.2015)....44
Figure 2-5: Groundwater nitrate concentration in the sampling wells around the world (Zhou et al.2015)....45
Figure 2-6: Spatial distribution of nitrate stored in the vadose zone. Global vadose zone N storage (in kg N ha−1) is shown for 1925 (a), 1950 (b), 1975 (c) and 2000 (d) (Ascott et al.2017)....45
Figure 2-7: Nitrate concentration (NO3- in mg/L) in groundwater at a country level (source: EEA, 2002)....46
Figure 2-8: Groundwater nitrate-N concentration in United States (Townsend et al. 2003)....47
Figure 2-9: Final modified DRASTIC index of groundwater vulnerability map in USA (Kumarasamy, 2007)....47
Figure 2-10: Asia nitrogen fertilizer application and nitrate level in groundwater (Zhou et al.2015)....48
Figure 2-11: Groundwater nitrate distribution in southern Africa (Tredoux et al. 2009)....49
Figure 2-12: Vulnerability map of South Africa (Musekiwa and Majola, 2013)....49
Figure 3-1: Human geographic conditions in Africa (Braune and Adams, 2013)....58
Figure 3-2: Aridity zones of climate classes for the African continent (Church, 2011)....60
Figure 3-3: Rivers and major surface water bodies in Africa (BGS, 2015)....62

Figure 3-4: The lithological context of the African continent (from Hartmann and Moosdorf, 2012)..64
Figure 3-5: Transboundary groundwater (cited in AGW-Net, 2014) .67
Figure 3-6: Groundwater storage map for Africa, expressed as water depth in millimetres, with modern annual recharge for comparison (MacDonald et al., 2012)..69
Figure 3-7: Groundwater productivity map (MacDonald et al. 2011) 71
Figure 3-8: Groundwater dependent cities in Africa (Morris et al., 2003) 75
Figure 3-9: Relationship between mean nitrate levels, population density, and DRASTIC aquifer vulnerability risk score among 31 studies that a predominantly sampled boreholes and b predominantly sampled wells and springs (Lapworth et al. 2017)...............................76
Figure 3-10: Slum population in urban Africa (from Pravettoni, 2011) 77
Figure 3-11: Eleven countries in the project (M'mayi/ UNEP/DEWA, 2014) 77
Figure 3-12: The source/pathway/receptor concept for groundwater pollution (MacDonald, n.d) 78
Figure 3-13: South African informal settlements (UNEP/DEWA, 2014) 79
Figure 3-14: Relating groundwater source vulnerability to land use: (A) a vulnerable, unlined, shallow well adjacent to the road in a lower cost housing area; (B) a shallow well and a borehole with protective headworks, located in gated properties within higher cost areas; (C) a fully-sealed public water supply borehole within a secure compound in the peri-urban Mukobeko wellfield in Zambia (Sorensen et al., 2015a). 79
Figure 3-15: Evolution in average levels of drilling water nitrate in Abidjan city (Ahoussi et al. 2013) 80
Figure 3-16: Groundwater nitrate distribution in Burkina Faso (Pavelic et al. 2012)...81
Figure 4-1: Flow chart of the methodology used to develop the groundwater vulnerability map using the DRASTIC model in GIS ..97

Figure 4-2: Land cover/ land use map for Africa (modified from Defourny et al. 2010)....101
Figure 4-3: Reclassify categories of land cover/land use map (modified from Defourny et al. 2010)....102
Figure 4-4: DRASTIC rating for the depth to groundwater (D).....109
Figure 4-5: DRASTIC ratings for the net recharge (R) for Africa....110
Figure 4-6: DRASTIC rating for the Aquifer type (A) for Africa....111
Figure 4-7: DRASTIC rating for Soil media (S) for Africa....112
Figure 4-8: DRASTIC rating for the Topography (T) for Africa.....113
Figure 4-9: DRASTIC rating for the Impact of vadose zone (I) for Africa 114
Figure 4-10: DRASTIC rating for the hydraulic conductivity (C) for Africa....115
Figure 4-11: Groundwater intrinsic vulnerability map of Africa.
Figure 4-12: Risk map of groundwater pollution for Africa....120
Figure 4-13: Risk map overlaying Transboundary aquifers (TBAs) defined by Altchenko and Villhoth (2013)....122
Figure 4-14: Spatial distribution of mean nitrate concentration in groundwater....123
Figure 4-15: Relation between nitrate maximum and DRASTIC with R^2=0.89....125
Figure 4-16: Relation between nitrate maximum and risk degree with R^2=0.65....125
Figure 5-1: Distribution of studies identified across Africa....140
Figure 5-2:The locations and the maximum values of nitrate in Africa superimposed on risk pollution map as generated in the previous generic vulnerability study of Ouedraogo et al. (2016)....142
Figure 5-3: Land Cover/Land Use map of Africa (modified from Defourny et al., 2014)....145
Figure 5-4: Histograms of observed mean nitrate concentration (mg/l) and logtransformed mean nitrate concentration (ln (mg/l))....162
Figure 5-5: Log transformed mean nitrate concentration for different land use classes....165
Figure 5-6: Log transformed mean nitrate concentration for different aquifer system classes....166

Figure 5-7:Log transformed mean nitrate concentration for different population density classes (a), nitrogen application rate classes (b), groundwater depth classes (c) and recharge classes (d). 167
Figure 5-8: Predicted versus observed mean log transformed nitrate concentration (R^2=0.65)...172
Figure 5-9: Normal probability distribution of model residuals for the predicted log transformed mean nitrate concentration.....................173
Figure 5-10: Relation between residuals and predicted log transformed mean nitrate concentration. 174
Figure 6-1: Spatial distribution of mean nitrate concentration in groundwater (Ouedraogo et al. 2016) 195
Figure 6-2: Comparison of observed and predicted log (ln) nitrate concentration on training dataset: (a) Linear regression and (b) RF regression 208
Figure 6-3: Variable importance according to the percent increase in mean squared error (%IncMSE)...210
Figure 6-4: comparison of validation results on tested dataset: (a) Linear model and (b) RF regression 212
Figure 6-5: Goodness-of-fit evaluation for training dataset in the MLR 214
Figure 6-6: Goodness-of-fit evaluation for training dataset in the RFR 215
Figure 6-7: Goodness-of-fit evaluation for validation dataset in the MLR 216
Figure 6-8: Goodness-of-fit evaluation for validation dataset in the RFR 217
Figure 7-1: Distribution of nitrate concentration in groundwater in South Africa 238
Figure 7-2: Distribution of nitrate concentration in groundwater in Burkina Faso 238
Figure 7-3: Distribution of nitrate concentration in groundwater in Senegal...239
Figure 7-4: Q-Q plots for the three country data sets: a) Burkina Faso; b) South Africa; c) Senegal)..241

Figure 7-5: RF regression for observed and predicted log (ln) nitrate concentration on training dataset (a) and tested dataset (b) using the continental-scale nitrate data set....248
Figure 7-6: Validation results of the continental scale RFR model on the observed groundwater nitrate of Burkina Faso....250
Figure 7-7: Validation results of the continental scale RFR model on the observed groundwater nitrate of Senegal....250
Figure 7-8: Validation results of the continental scale RFR model on the observed groundwater nitrate of South Africa....251
Figure 7-9: Log nitrate of observed versus predicted values for Burkina Faso....252
Figure 7-10: Log nitrate of observed versus predicted values for Senegal....253
Figure 7-11: Log nitrate of observed versus predicted values for South Africa....254
Figure 7-12: Variable importance plot for Burkina Faso....255
Figure 8-1: Impact of climate change, land use change, and environmental factors on groundwater (modified from Huang et al. 2017)....270
Figure 8-2: Rating of Recharge (R) map in Africa for 1990, 2000, and for 2010....275
Figure 8-3: Rating of Density of Population (P) map in Africa for 1990, 2000, and for 2010....278
Figure 8-4: Depth to groundwater (D) rates map for Africa....281
Figure 8-5: Groundwater pollution risk for 1990, 2000, and 2010....284
Figure 8-6: Relative comparison of groundwater pollution risk for 1990, 2000, and 2010....285
Figure 8-7: Absolute comparison of groundwater pollution risk for 1990, 2000, and 2010....286
Figure 8-8: Diagram in percentage of pollution risk for 1990, 2000, and 2010....288
Figure 9-1: Media Release: World Water Day 22 March. Relationship between urban centres in sub-Saharan Africa (SSA) and estimated aquifer pollution risk using an intrinsic aquifer modelling approach (Ouedraogo et al. 2016). The location of studies included in the paper

are shown. Major cities in SSA are shown and are from the ESRI cities dataset (2006) (Lapworth et al.2017)..308
Figure 9-2: Pathways that climate change can affect groundwater quality (in Fares, 2016) 317
Figure 9-3: Flowchart for modeling nitrate contamination in groundwater using physical models (from Almasri and Kaluarachchi 2007 in Fares, 2016) 318
Figure A-1: Histograms of maximum nitrate concentration and log transformed maximum nitrate concentration. 396

Figure A-2: Log transformed maximum nitrate concentration for different land use classes. 398
Figure A-3: Log transformed maximum nitrate concentration for different groundwater depth classes..399
Figure A-4: Log transformed maximum nitrate concentration for different rainfall classes. 400
Figure A-5: Log transformed maximum nitrate concentration for different climate classes. 401
Figure A-6: Log transformed maximum nitrate concentration for different regions classes 402
Figure A-7: Log transformed maximum nitrate concentration for different soil classes. 403
Figure A-8: Log transformed maximum nitrate concentration for different slope classes...404
Figure A-9: Observed versus predicted log transformed maximum nitrate concentration (**R^2=0.42**). 408
Figure A-10: Normal probability distribution of model residuals for log transformed maximum nitrate concentration. 409
Figure A-11: Relation between residuals and predicted log transformed maximum nitrate concentration. 410

Figure B-1: Histograms of the original and log transformed minimum nitrate concentration...412
Figure B-2: Log transformed minimum nitrate concentration for different land use classes 414

Figure B-3: Log transformed minimum nitrate concentration for different aquifer system classes 415
Figure B-4: Log transformed minimum nitrate concentration for different climate classes 416
Figure B-5: Log transformed minimum nitrate concentration for different slope classes 417
Figure B-6: Log transformed minimum nitrate concentration for different hydraulic conductivity classes 418
Figure B-7: Log transformed minimum nitrate concentration for different soil classes 419

List of Tables

Table 2-1: Examples of different approaches to vulnerability assessment (Barber et al., 1993) 24
Table 2-2: Sources of nitrate in soil and groundwater (modified from Aljazzar, 2010) 35
Table 2-3: Main sources of groundwater pollution with some of their main characteristics (Sililo et al.2001) 36
Table 3-1: Evolution of the number of TBAs in Africa inventoried and mapped by various efforts and subdivided into regions (Altchenko and Villholth, 2013) 68
Table 3-2: Typical problems of groundwater pollution (Wang et al. 2014) 82
Table 4-1: Weight settings for DRASTIC variables (Aller et al., 1987) 90
Table 4-2: Data used for the creation of the seven variable data layers of the pan African DRASTIC model 94
Table 4-3: Rating of Land use in this study: 103
Table 5-4: Rate and weight of the seven DRASTIC parameters (Aller et al., 1987) 107
Table 5-5: Rate and weights (A=3 and I=5) of aquifer media and impact of the vadose zone (Aller et al., 1987) 108
Table 5-6: Statistical summary of the DRASTIC parameters map 116
Table 5-7: Statistics of map removal analysis 117
Table 5-8: Statistics of map removal sensitivity 117
Table 5-9: Statistics of single parameter sensitivity analysis 119
Table 6-1: Criteria used to identify nitrate data studies within web data bases. 139
Table 6-2: Localisation of study sites considered in the meta-analysis 146
Table 6-3: Explanatory variables used in the MLR analysis. 158
Table 6-4: Summary statistics of original and log (ln) transformed nitrate data. 161

Table 6-5: Optimal linear regression model for explaining the log transformed mean nitrate concentration 170
Table 7-1: Summary statistics of original and ln-transformed nitrate data (from Ouedraogo and Vanclooster, 2016a)................................ 196
Table 7-2: Explanatory variables and nitrate concentrations used in the Random Forest model 200
Table 7-3: Optimal MLR model for explaining the ln-transformed mean nitrate concentration... 207
Table 7-4: Variables includes in the final RFR model, in descending order of importance based on percentage of mean decrease in accuracy (% IncMSE).. 211
Table 8-1: Summary statistics and sources of compiled nitrate measurements... 237
Table 8-2: Sources of the collected pan-African scale databases related to environmental parameters. 243
Table 9-1:Weight, Range and Rating and of the DRASTIC parameters and Land-Use parameter (based on Ouedraogo et al., 2016, and Girard, 2017) 272
Table 9-2: Percent of different pollution risk classes.......................... 287
Tableau A-1: Optimal linear regression using logarithm maximum nitrate as independent variable….. 407

Acronyms and abbreviations

Abbreviation	Meaning
ADB	African Development Bank
AGW-Net	African GroundWater Network
AMCOW	African Ministerial Council on Water
AU	African Union
BGR	Bundesanstalt für Geowissenschaften und Rohstoffe/Federal Institute for Geosciences and Natural Resources
BGS	British Geological Survey
CARET	Classification And REgression Training
CCB	California Coastal Basin aquifer system
CGIAR	Consultative Group for International Agricultural Research
CSI	Consortium for Spatial Information
DEIE	Direction des Etudes et de l'Information sur l'Eau
DEWA	Division of Early Warning and Assessment
DGPRE	Direction de la Gestion et de la Planification des Ressources en Eau
DRASTIC	Depth, Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone, Conductivity
DVI	Dynamic Vulnerability Index
EAC	East African Community
ECC	European Council Directive
ECCAS	Economic Community of Central African States
ECOWAS	Economic Community of West African States
ELI	Earth and Life Institute
EPIK	Epikarst, Protective Cover, Infiltration Conditions, Karst network
ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organization
FSR	Fonds Spécial de Recherche
GDP	Gross Domestic Product
GEMS/Water	Global Environment Monitoring System/Water
GIS	Geographic Information System
GLHYMPS	A glimpse beneath the Earth's surface: Global Hydrogeology MaPS

GliM	The new global lithological map database
GMI	Groundwater Management Institute
GOD	Groundwater occurrence, Overall aquifer class, Depth to groundwater
IDB	Islamic Development Bank ou Banque Islamique de Dévelopment
GWP	Global Water Partnership
IGAD	Intergovernmental Authority for Development
IGRAC	International Groundwater Resources Assessment Centre
INBO	International Network of Basin Organizations
ISARM	Internationally Shared Aquifer Resources Management
ISRIC	World Soil Information
LC	Land Cover
LU	Land Use
LUC	Land Use Change
MCDM	Multi-criteria decision-making
MLR	Multiple Linear Regression
MODFLOW	MOdular finite-Difference Flow model (U.S. Geological Survey
NARIS	Nubian Aquifer Regional Information Systems
NPS	Non-Point-Source
NRC	National Research Council
NWSAS	The North Western Sahara Aquifer System
OECD	Organization for Economic Cooperation and Development
P	density of Population
R^2	Coefficient of determination
RFR	Random Forest Regression
SADC	Southern African Development Community
SASS	Système Aquifère du Sahara Septentrional
SDG	Sustainable Development Goals
SEDAC	Socioeconomic Data and Applications Center
SEEPAGE	System for Early Evaluation of Pollution Potential of Agricultural Groundwater Environment
SINTACS	S : Soggiacenza; I : Infiltrazione; N : Azione del Non Saturo ; T : Tipologia della Copertura ; A : Carratteri

	Idrogeologici dell' Acquifero; C : Conducibilita Idraulica; S : Acclività della Superficie Topographica
SRTM90	90-meter Shuttle Radar Topography Mission
SSA	Sub-Saharan Africa
TBAs	Transboundary aquifers
UCAD	Université Cheikh Anta Diop de Dakar
UCL	Université Catholique de Louvain
UN	United Nations
UNECA	United Nations Economic Commission for Africa
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
US EPA	United States Environmental Protection Agency
WFD	Water Framework Directive
WHO	World Health Organization
WHYMAP	Worldwide Hydrogeological Mapping and Assessment Programme
WWAP	World Water Assessment Program

Chapter 1 General introduction

1.1 Introduction

Groundwater is a key renewable resource all over the world, valuable for human life and economic development. It constitutes a major portion of the Earth's hydrologic cycle and occurs in permeable geologic formations known as aquifers. These aquifers have a structure that can store and transmit water at rates fast enough to supply reasonable amounts of water to water wells. Groundwater's importance stems from its ability to act as a large reservoir of water, providing 'buffer storage' during periods of drought. It accounts for about 98 per cent of available freshwater (and about 0.76 per cent of all the water on Earth), the remaining 2 per cent being either surface water (i.e. streams and lakes) or distributed in the soil and atmosphere (Shiklomanov, 1998). According to WWAP (2009), groundwater supplies almost half of the world's drinking water and plays a key role in food production, accounting for over 40 per cent of global consumption of water for agricultural irrigation (Siebert et al., 2010).

According to UNEP et al. (2003), the last 50 years have seen unprecedented development of groundwater resources. Indeed, it is a major source of water in arid and semi-arid regions, in rural areas of developing countries, and for several mega-cities in industrialised territories. Groundwater is the world's most extracted natural resource, given that it is so intensively consumed in order to meet so many and variable needs, for the domestic, agricultural and industrial sector. Groundwater use has significantly increased in recent decades and groundwater is currently at a global withdrawal rate of about 700–800 km^3 per year (Zektser and Everet, 2004). Given all this, and as the WHO (2006) affirms, it is not surprising that in many regions of the world groundwater represents the main, if not the only, source of drinking water—particularly where surface water resources are limited and/or contaminated to some degree. However, some of these regions are rapidly depleting their aquifers, consuming groundwater faster than it is naturally replenished (e.g., Postel, 1993 cited in

Sorichetta, 2010). By studying global depletion of groundwater resources, Wada et al. (2010) confirms with higher certainty that groundwater depletion is indeed a significant factor. According to Foster and Loucks (2006), unplanned depletion of non-renewable groundwater reserves can undermine, and potentially erode, the economic and social vitality of the traditional groundwater-dependent community – and instances of the collapse of such rural communities are known. On the one hand, 1.7 billion people live in areas where groundwater resources are overexploited (Gleeson et al., 2012) and an unknown number are experiencing pollution problems and/or degradation of groundwater dependent ecosystems (Conti et al., 2016). In the near future, population growth is expected to stress water availability even more (Shiklomanov, 1998), especially in developing countries, which are home to the majority of those people who do not have access to safe drinking water (Bidlack et al., 2004, cited in Sorichetta, 2010). This matter tends to be complicated by the vulnerability of all aquifers to some degree or other (NRC, 1993). In addition, once groundwater is contaminated, remediation is very challenging, costly, time consuming, and sometimes even unfeasible (e.g., USEPA, 1990). Indeed, according to Aljazzar (2010), groundwater systems worldwide are experiencing an increasing risk of pollution from agricultural activities, urbanisation, and industrial development.

In short, the rapid growth of human population is exerting enormous stresses on the available groundwater resources, inducing a real water crisis that is represented both in terms of scarcity and deterioration of water quality. For example in a recent study published in 2017 on "Global aquifers dominated by fossil groundwater bit wells vulnerable to modern contamination" Jasechko says "Deep wells mostly pump fossil groundwater but many still contain some recent rain and snow melt, which is vulnerable to modern contamination". The authors of this study conclude that water quality risk should be considered along with sustainable use when managing fossil groundwater resources. It is in such a context that Sorichetta (2010) claims that it is more important than ever to develop and adopt an integrated water resources management approach at national and international levels (GWP, 2000). Groundwater quality protection must be one of the first aspects to be considered in any such approach, in order to tackle the problem of global freshwater scarcity (WHO, 2004 and previous editions). Arthur et al. (2007) argue that to effectively and properly protect groundwater it is crucial to be able to identify areas where groundwater may be most vulnerable to contamination—and to then translate this information into vulnerability maps, which can be used to prevent or minimise harmful impacts on groundwater quality by potential end-users, such as land and water resources managers.

The first attempt to produce groundwater vulnerability maps was made in France by Margat (1968), with the intention of showing where contamination was more likely to occur as a function of different hydrogeological settings. Many different methods to assess groundwater vulnerability maps exist in the literature, based on different approaches and with diverse input variables. Generally, these methods are restricted to assessing intrinsic groundwater vulnerability. Among numerous methods, the most popular is the DRASTIC index (Aller et al., 1987). As a basic requirement for effective management, this method to map vulnerability allows for the delineation of groundwater systems according to their sensitivity to pollution. According to Aljazzar (2010) efforts to undertake groundwater vulnerability assessment will provide a fundamental overview of the degree of protection of a certain groundwater system, after which the more vulnerable zones will receive more concern, and faster action plans and measures—and such a scenario will save time and costs and provide the possibility of safeguarding groundwater effectively. However, the outputs of such methods (i.e., groundwater vulnerability maps) must be scientifically sound, meaningful and reliable (Sorichetta, 2010) in order to be considered as effective tools in environmental planning and management. For Focazio et al. (2002), a groundwater vulnerability map must support scientifically-defensible decisions to protect groundwater resources, represent the study area through a limited number of vulnerability classes, and depict the actual spatial distribution of the contamination in the study area.

In the case of DRASTIC, since the method is subject to different forms of adjustment, it is subject to various critiques among hydrogeologists (Aljazzar, 2010). To this regard, according to Focazio et al. (2002), the use of statistical methods to assess groundwater vulnerability represents a reasonable compromise of model complexity and cost, in order to produce scientifically-defensible end products. Indeed, as cited by Sorichetta (2010), statistical methods provide the possibility to objectively identify the factors influencing vulnerability in the study area, over various spatial scales ranging from catchment (Worral and Kolpin, 2003) to subnational (Arthur et al., 2007) and national (Nolan, 2001). Nevertheless, it should be highlighted that the meaningfulness of these outputs is not always straightforward and that additional interpretation is often required to obtain functional (reclassified) vulnerability maps (Focazio et al., 2002), the reliability of which needs to be carefully addressed before they can be used in environmental planning and management. Therefore, at present, research efforts in this field should primarily be aimed not at implementing new statistical modelling techniques, but rather at evaluating the robustness of already available ones and the reliability of their end-products (i.e. reclassified groundwater vulnerability maps)—as also stated by Fabbri and Chung (2008).

Nitrate contamination is very often a proxy for other possible groundwater pollutants and can, therefore, be very informative when assessing overall groundwater quality. The results of this study of groundwater vulnerability assessment provide a fundamental overview of the degree of protection of a specific groundwater system at the pan-African scale. Following this, the more vulnerable zones of transboundary aquifers will receive greater attention, as well as faster action plans and measures; such a scenario will save time and costs and provide the potentiality to safeguard groundwater effectively.

1.2 Problem statement and challenges

Under natural conditions, groundwater is usually potable and needs almost no treatment before distribution and use. Because it is naturally protected by the soil and underlying unsaturated zones or confining strata, it is less vulnerable to anthropogenic impacts than surface water bodies. However, water quality is influenced by both direct point sources and non-point source pollution (NPS). According to Gogu, and Dassargues (2000), the single greatest, globally ubiquitous threat to groundwater quality is NPS contamination. Gurdak (2014) declares that all groundwater resources are vulnerable to NPS contamination. NPS contamination is often associated with land use or anthropogenic activities, including agriculture (pesticides from agricultural use, nitrogen from fertiliser and manure and livestock-borne pathogens, particle associated contaminants following erosion), built infrastructure (road salts, oil and grease,…), atmospheric deposits of anthropogenic and natural chemicals, etc. (Gurdak, 2008). Furthermore, Clarke et al. (1996) affirms that contamination is persistent and difficult to reverse, as a result of large storage and long residence times when aquifers become polluted. Other scholars, such as Boy-Roura (2013), add to this that aquifers are often overexploited, exploited at an unsustainable rate, or affected by pollution.

In most countries throughout the world, urban and industrial development, and agriculture and mining activities have caused groundwater contamination (Boy-Roura, 2013). Furthermore, Sililo et al. (2001) affirms that the pollution of groundwater resources is often a consequence of poor land-use planning—in particular, locating high risk activities in areas where they will have a negative impact on groundwater resources. According to Groundwater Governance

(2013, cited in Zhou et al., 2015), the last few decades have witnessed an increased pressure on groundwater resources globally, which has in many cases induced abstraction beyond sustainable levels and increased levels of pollution. Diffuse NPS pollution from farming activities and point source pollution from sewage treatment and industrial discharge are the principal contaminant sources (Boy-Roura, 2013). One of the most common and persistent problems of groundwater pollution is associated with diffuse pollution generated through the intensification of agricultural activities over the last decades, with increased use of chemical fertilisers and higher concentrations of animal excrement in smaller areas (Boy-Roura, 2013). Agricultural land use leads to elevated concentrations of nutrients. According to Haller et al. (2013), on a global scale agricultural land use represents the largest diffuse pollution threat to groundwater quality. Elevated concentrations of nutrients (especially nitrogen and phosphorus) can cause a variety of problems, including degradation of ecosystems (for example, eutrophication of water bodies), and human health issues.

The nitrate parameter is one of the indicators that reflects groundwater quality and its appropriateness to be safely used. Nitrate contamination due to emissions from agricultural and non-agricultural sources continues to exert considerable pressure on subsurface groundwater bodies all over the world (Mattern et al., 2009); it is probably the most widespread groundwater pollutant, especially in agricultural areas, and of great concern due to its existence in high concentrations, which threatens both human health and the environment (Aljazzar, 2010).

The presence of nitrates in groundwater is generally revealed by analysing samples taken from wells or springs of a groundwater body. The data needed to monitor groundwater quality may be part of routine measurements (usually performed by water-supply companies) or be undertaken in a specific field campaign. However, in many cases, the origins of groundwater contamination can remain unclear (Loague and Soutter, 2006), especially when this consists of compounds used in both agricultural and non-agricultural practices. High concentrations of nitrate in drinking water can cause blue baby syndrome, and its relation to cancer risk is still a point of discussion. In addition, nitrate ingestion has been linked to methemoglobinemia, adverse reproductive outcomes, and specific cancers, according to Ward et al. (2005).

Protection of groundwater resources, both quantitatively and qualitatively, is becoming an increasingly global concern, as mentioned by several new directives in the past decade. As noted for example by Mattern (2009), Europe adopted Directives for reducing pressures of N on water resources: the European Council Directive concerning urban waste-water treatment for domestic and industrial sectors (91/271/EEC) and the Directive concerning the protection of waters against pollution caused by nitrates from agricultural sources (91/676/EEC). To achieve good qualitative and quantitative status of all water bodies by 2015, European Union Member States committed also to the European Water Framework Directive (2000/60/EEC).

The continuous depletion of groundwater and the deterioration of its quality have forced hydrogeologists as well as decision makers to focus on implementing management and protection plans in order to sustainably safeguard water resources for current and future generations. According to Vrba and Zaporozec (1994), the compilation of aquifer vulnerability maps can provide land use managers with a valuable tool for establishing preventive and protective measures. And assessing the protection capacity of groundwater aquifers and their vulnerability to pollutants (nitrate, for example) is very important for an effective protection plan.

At the continental scale framework for Africa, groundwater is an important source of water for meeting various demands. It is particularly important for arid and semi-arid countries in the Northern and Southern parts of Africa since it is often the only source of water (UNEP, 2010). For example, in some arid and semi-arid countries and in the case of Libya groundwater dependence is as high as 95 % (Margat, 2010). According to Adelana and MacDonald (2008), it is estimated that more than 100 million people, including rural people throughout Sub-Saharan Africa utilize groundwater for domestic supplies and livestock rearing. Seventy five per cent (75 %) of the continent's population use groundwater as the source of drinking water (UNECA et al., 2000). However, the distribution of renewable groundwater in Africa is highly skewed. Indeed, according to Giordano (2005), more than half of Africa's renewable groundwater is contained in just four countries: the Democratic Republic of Congo, The Republic of Congo, Cameroon and Nigeria. At the continent-scale, in terms of quantity, groundwater is mainly used for irrigation (75 %) while domestic water use represents around 20 %, although a high heterogeneity exists, with groundwater use in rural areas being very important for domestic use (UNECA et al. 2000).

Although in Africa, water use is substantially less than in other continents, pressures on water resources are rapidly increasing. According to Sharaky (2016), water use in Africa is dominated by agriculture, as it is in other developing regions. Indeed, compared to any other major region, Africa has the highest percentage of water use for agriculture but the lowest percentage for domestic or industrial activities: it is estimated that 88 per cent of water in Africa is used for agriculture. Water quality can therefore be linked to agricultural pressures.

Several studies in groundwater mapping at large scale have already been undertaken by organisations, associations and researchers. The most important ones, which support and contribute significantly to the management and protection of groundwater, include cartographic products developed by WHYMAP (the Worldwide Hydrogeological Mapping and Assessment Programme) and IGRAC (International

Groundwater Resources Assessment Centre). However, the majority of the activities developed in these programs are focusing on the quantitative aspects, while qualitative aspects (crucial for drinking water) are often ignored.

Increasingly, methods that protect groundwater resources are being incorporated into land-use planning, or at least considered in the approval of new developments. Indeed, the review by Xu and Usher (2006) entitled '*Groundwater pollution in Africa*' was one of the more important qualitative works providing insights into common issues with regards to groundwater pollution in Africa. Compilation of this book was made possible thanks to local scale information from a UNEP/UNESCO project, 'Assessment of pollution status and vulnerability of water supply aquifers of African cities'. Xu and Usher confirm that groundwater in African cities is subject to different pollution pressures exerted by several sources, such as leaking sewage systems, solid waste dumpsites, household waste pits, surface water infiltration spots, peri-urban agriculture sites, petrol service stations (underground storage tanks), and wellfields. Xu and Usher affirm that: 'groundwater vulnerability in the urban areas of Africa is a pressing problem that urgently needs to be addressed'. MacDonald et al. (2012), affirms that the vast majority of urban centres, and in particular urban growth hotspots in the Lake Victoria Basin and much of West Africa are underlain by high vulnerability aquifers, and are often of moderate-low productivity. Indeed, the high population densities found in urban areas has led to the proliferation of unimproved sanitation provision largely through the use of pit latrines, which are often little more than a hole in the ground, and are in very close proximity to wells and springs that are important for domestic use (Stenström, 1996 cited in Lapworth et al. 2017). According to World Bank (2012),urban sanitation provision and waste management systems across SSA are inadequate, with an estimated average of 40 % coverage for improved sanitation facilities.

Overexploitation and contamination are the two main threats to groundwater in Africa (MacDonald et al. 2013). According to Xu and Usher (2006), the major issues of water quality in Africa can be listed in order of importance as follows: (1) nitrate pollution, (2) pathogenic agents, (3) organic pollution, (4) salinization, and (5) acid mine drainage. In light of these local studies, Xu and Usher conclude that groundwater supplies in Africa are increasingly threatened by human activities, resulting in pollution of groundwater resources, incorrect exploitation and utilisation of aquifers, and abstraction facilities (boreholes or wells) being vandalised. They add that 'degradation of groundwater is one of the most serious water resources problems in Africa'. The occurrence of emerging organic contaminants within aquatic environments in Africa is currently unknown (Sorensen et al., 2015a). As population increases and economic development occurs in Africa, it is likely that a wider range of emerging contaminants will be released into the environment. Shallow groundwater sources on the continent are particularly important as local sources of drinking water but are at the same time potentially very vulnerable to anthropogenic contamination (Howard et al., 2003; Cronin et al., 2006; Nkhuwa et al., 2006; Kulabako et al., 2007). Nitrate contamination of groundwater tends to increases in many African aquifers (Spalding and Exner, 1993; Puckett et al., 2011).

While groundwater plays a large role in supporting social and economic development in Africa, the resource base is far from being adequately understood in such a context, which faces several threats. There is therefore a need to understand all the potential risks to groundwater resources, in particular the occurrence and sources of nitrate at the pan-African scale. To this regard, we address this significant knowledge gap by developing tools to map groundwater quality and degradation risk at the African scale. Protecting groundwater sources is becoming a widespread global concern, particularly in the African context, and it is more important than ever to develop more sustainable practices for the management and efficient use of groundwater resources, as well as to protect the environmental ecosystems where such resources are located. A holistic approach is required for the management and protection of groundwater resources.

1.3 Research objectives

The overall aim of this thesis is to improve our understanding of groundwater quality at the continental scale for Africa, supporting the monitoring of the implementation of the UN Sustainable Development Goals agenda. This research has mainly been based on spatially best available database comes from many parts of the world. The first contribution of this thesis is the scope of the region covered: it is the first time this kind of study has been undertaken at the pan-African scale. However, the study has to cope with limits imposed by relative data scarcity, even though nitrate is often the best monitored NPS. Many authors have highlighted the data availability problem in Africa. Indeed, Adelana and MacDonald (2008) have found that there is a lack of systematic data and information on groundwater monitoring across Sub-Saharan Africa, with studies occurring on an ad-hoc basis and without strategic oversight or coordination (cited in Pavelic et al.,2012). In the study entitled '*Monitoring groundwater use in Sub-Saharan Africa: issues and challenges*', Adelana (2009), mentions that: 'modelling groundwater management scenarios suffers from a paucity of reliable data with which to calibrate and validate numerical models'. Other authors, such as Allaire, (2009) and Foster et al. (2006), find that groundwater monitoring is limited or absent, and that groundwater monitoring systems for gathering, collating and analysing information have failed in several countries, despite numerous amounts of wells drilled each year, which present a significant opportunity. The availability and reliability of water resources data has been a problem for many decades across sub-Saharan Africa (Robins et al., 2006; Carter and Bevan, 2008). According to Pavelic et al. (2012), data still remains scarce and the information that is gathered is being done in an unsystematic manner. Recently, Comte et al. (2016) affirms that groundwater information services (i.e. databases) and systematic long-term monitoring are non-existent or fragmented and of inadequate quality. Adelana and MacDonald (2008) argue that the reasons behind this are numerous and complex, including lack of clear institutional arrangements and responsibilities, inadequate resourcing, lack of technical expertise, and the absence of (or disconnection from) database management and retrieval systems.

In spite of this context of data scarcity, this Ph.D. thesis seeks to achieve the following key objectives.

The first main objective is to map the vulnerability of groundwater to water quality degradation at the continental scale. This first main objective will be reached by addressing these specific steps:

- To build a best available pan-African hydrogeological geodatabase;
- To estimate the intrinsic vulnerability of groundwater at the pan-African scale using the standard DRASTIC method;
- To map groundwater's vulnerability to pollution at the pan-African scale using actual, high-resolution land cover/land use data, and;
- To validate groundwater vulnerability map using a nitrate meta-database compiled through meta-analysis of the available literature.

The second main objective of the thesis is to identify the environmental factors contributing to the nitrate degradation of groundwater. This second main objective will be reached by addressing the following specific steps:

- To use the power of meta-analysis, to build a pan-African database groundwater pollution by nitrates;

- To use this meta-database to develop an exploratory linear statistical model of nitrate degradation of groundwater in terms of driving attributes available in the best available database;
- To use the same database to develop a machine-learning method and compare it with a statistical linear model; and

The third main objective is to validate both approaches using detailed datasets collected at the level of some African countries.

The fourth and last main objective in this thesis is to integrate time dimension in the modelling approach to better understand the relationships between groundwater pollution risk and time dynamic variables of this pollution risk such as land use. To achieve this main objective of the assessment of dynamic behaviour of groundwater pollution risk at the continental scale, we used the DRASTIC model defined in the first objective of the thesis.

It is essential to test and improve our ability to scientifically assess potential groundwater contamination by nitrates. By developing an objective vulnerability model that includes the most important factors affecting the vulnerability of groundwater to nitrate pollution, this study will support efforts to protect public water supplies in areas of high or rising groundwater nitrate levels. The developed methodology (the tool) will be used to evaluate groundwater vulnerability to nitrate pollution at the pan-African scale.

1.5 Contributions of the study

The study makes the following contributions to the existing literature on groundwater quality and vulnerability:

1) The study attempts reaching the above mentioned objectives by compiling, at the pan-African scale, the most recent environmental data, relating to groundwater degradation and

its driving factors, in particular, climate, topography, land cover/land use, (hydro-)geology, and population density;

2) The study provides insights at the African scale into the spatial variation of groundwater vulnerability to pollution, together with an examination of the environmental factors that influence this vulnerability;
3) The study offers two statistical models (linear and nonlinear algorithms) that can be used to explain observed nitrate concentration in groundwater at the African scale, and;
4) The study attempt to validate the continental scale model for groundwater diffusion pollution using regional datasets.
5) In addition, we developed a new approach to assess the dynamic aspect of groundwater vulnerability to pollution risk at the continental scale of Africa.

1.6 Outline of the thesis

With the exception of general introduction, Chapter 1, Chapter 2 and general conclusion, this thesis is based on articles published or submitted to international peer-reviewed journals. This may in some cases lead to repetitions in the text; however, in this way the different chapters of the thesis may be read independently.

The general introduction outlines the research problem and presents our objectives have been summarized in Chapter 1.

Chapter 2, entitled "Literature Review", gives an overview of some main concepts associated with groundwater vulnerability and pollution risk; nitrate sources and issues; review of nitrate assessment at continental and regional scale, and scale problem in environmental sciences.

Chapter 3 describes the main features of the study area, i.e. topography, climate and rainfall, drainage, land use, vegetation, geology and hydrogeology, and groundwater resources.

In Chapter 4, the main components of DRASTIC approach are presented. This chapter delineates the different steps undertaken to map the vulnerability of groundwater to pollution using the DRASTIC index—a mapping which is based on environmental high-resolution data collected in many parts of the world.

Chapter 5 is concerned with a statistical modelling of nitrate concentration. In this chapter, a meta-database based on the available literature was constructed by using the power of meta-analysis. We investigate, using simple models, the potential effects of environmental attributes on the assessment of groundwater vulnerability.

Chapter 6 explores the same concepts and uses the same meta-database as Chapter 4, in order to compare *nonlinear random forest regression* and *multiple linear regression* techniques. This is done in order to explain and predict groundwater nitrate concentration in African groundwater.

In Chapter 7, we apply the same nonlinear random forest methodology with a higher number of nitrate datasets from three countries. We then examine and discuss the validity at the country level of the continental scale model of groundwater quality.

In Chapter 8, the dynamic aspects of vulnerability to pollution for the African continent is elaborated through three risk maps realized, for three different years.

The last part of this thesis concludes with a synthetic view of the main findings of the thesis into Chapter 9. The principal contributions of the thesis are presented, as well as their implications for scientific research and decision-making, as well as the limitations and perspectives for future research.

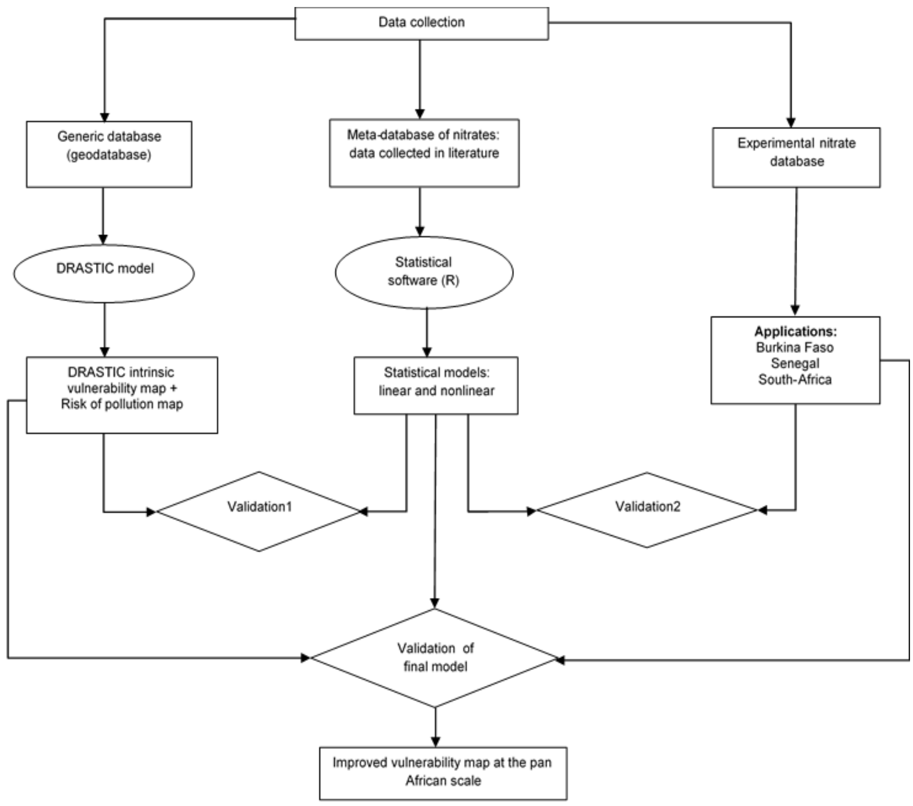


Figure 1-1: Flowchart of the thesis

Chapter 2 Groundwater Vulnerability: Literature Review

2.1 Introduction

Groundwater pollution has negatively impacted the safe use of water resources around the world (Aljazzar, 2010). There are different sources and types of pollutants that could occur on the land surface due to a wide range of human activities according to Aljazzar (2010). These pollutants can potentially migrate towards and pollute groundwater. Thus, groundwater pollution (or groundwater contamination) is defined as an undesirable change in groundwater quality resulting from human activities (Harter, 2003). The same definition was given by Aljazzar (2010) "groundwater pollution or contamination is defined as any adverse change in groundwater quality". According to this author, these changes impair water quality to the extent it does not meet health and environmental standards. Such undesirable change in groundwater quality results from natural environmental agents or human (anthropogenic) activities. Therefore, groundwater vulnerability studies are crucial to understand the cause-effect relation between groundwater quality and both natural and anthropogenic factors to develop effective groundwater protection plans (Stevenazzi et al.2015). A number of methods for predicting groundwater vulnerability have been developed (NRC, 1993; Barber et al., 1993; Vrba and Zaporozec, 1994). Barber et al. (1993) subdivided the different approaches into empirical, deterministic, probabilistic and stochastic methods (Table 2.1).

Table 2-1: Examples of different approaches to vulnerability assessment (Barber et al., 1993)

Type of assessment	**Scale of Application**	**Pollution Hazard**	**Example Identifier**	**Reference**
Empirical	Local Local Regional & Local Regional Regional/National	UST -petroleum Landfill leachate Universal Universal Universal Aldicarb	MATRIX LeGrand DRASTIC GOD	Oregon DEQ, 1991 LeGrand, 1983 Aller et al., 1985 Foster, 1987 NRA, 1991 Lorber et al. 1989
Deterministic	Local/regional Regional	Specific pollutants Pesticides	LPI	Bachmat & Collin, 1987 Meeks and Dean, 1990
Combined Empirical Deterministic	Regional Regional	Pesticides Pesticides	DRASTIC-CLMS DRASTIC-PRZM	Ehteshami et al. 1991 ; Banton & Villeneuve, 1989
Probabilistic	Regional	Pesticides	VULPEST	Villeneuve et al., 1990
Stochastic	Regional Regional possible National	Pesticides Universal/ Pesticides	Discriminant Analysis weight of evidence models	Teso, 1989 New LWRRC project

2.2 Groundwater vulnerability

The term "vulnerability" is generally used to describe how a certain system is sensitive to any kind of perturbation or stress (Sorichetta, 2010). As stated by Sorichetta (2010), vulnerability can be conceptualized in different ways in different fields, or even within the same field (Füssel, 2007). Furthermore, it can be identified for a given system exposed to a specific hazard or to a group of hazards (Brooks, 2003). According to WHO (2006), when considering an aquifer system exposed to a potential source of contamination, the concept of vulnerability has to be derived from the assumption that soil and aquifer characteristics may provide some degree of protection, especially against sources located on the land surface.

2.3 Definitions of groundwater vulnerability

One of the first definitions of groundwater/aquifer vulnerability found in the literature has been proposed by Albinet and Margat (1970). It is described as "the penetrating and spreading abilities of the pollutants in aquifers according to the nature of the surface layers and the hydrogeological conditions". Since then, the concept of groundwater vulnerability has considerably evolved (Popescu et al., 2008). Nowadays, different definitions of groundwater vulnerability are now available in the literature. The concept is commonly used and widely applied to assess protection potential of aquifer systems all over the world (Aljazzar, 2010). It is important to be aware that a clear distinction between intrinsic and specific vulnerability is not always possible (NRC, 1993). Some examples to illustrate the diversity in terminology may create a better idea of what can be meant by the vulnerability (After Gogu, 2000, and NRC, 1993).

Civita (1987)

Intrinsic (i.e., natural) aquifer vulnerability to contamination is the specific susceptibility of aquifer systems, in their parts, geometric and hydrodynamic settings, to receive and diffuse fluid and/or hydro-vectored contaminants, the impact of which, of the groundwater quality, is a function of space and time".

Foster (1987)

Aquifer pollution vulnerability is the intrinsic characteristic which determine the sensitivity of various parts of an aquifer to being adversely affected by an imposed contaminant load.
Ground water pollution risk is the interaction between the natural vulnerability of the aquifer, and pollution loading that is, or will be applied to the subsurface environment as a result of human activity.

Pettyjohn et al. (1991)

Aquifer vulnerability is the geology of the physical system that determines vulnerability.
Aquifer sensitivity is related to the potential for contamination. That is an aquifer that have a high degree of vulnerability are in areas of high population density, are considered to be most sensitive…

U.S. Environmental Protection Agency (1993)

Aquifer sensitivity is the relative ease with which a contaminant (in this case a pesticide) applied on or near the land surface can migrate to the aquifer of interest. Aquifer sensitivity is a function of the intrinsic characteristics of the geologic materials of interest, any overlying saturated materials, and the overlying unsaturated zone. Sensitivity is not dependent on agronomic practices or pesticide characteristics.
Ground water vulnerability is the relative ease with which a contaminant (in this case a pesticide) applied on or near the land surface can migrate to the aquifer of interest under a given set of

agronomic management practices, pesticide characteristics, and hydrogeologic sensitivity conditions.

United States National Research Centre for Assessing Ground Water Vulnerability (NRC, 1993)

Ground water vulnerability to contamination is the tendency or likelihood for contaminants to reach a specified position in the groundwater system after introduction at some location above the upper most aquifer.
Specific vulnerability is used when a vulnerability is referenced to a specific contaminant class or human activity.
Intrinsic vulnerability refers to vulnerability determined without consideration of the attributes and behavior of particular contaminants.

Robins et al. (1994)

Aquifer vulnerability would thus be a function of the intrinsic properties of the overlaying soil and rock column or unsaturated zone of the aquifer, with the risk of groundwater pollution dependent on the interaction of the natural aquifer vulnerability and the subsurface contaminant load imposed by human activity.

International Association of Hydrogeologists (Vrba and Zaporozec, 1994)

Vulnerability is an intrinsic property of a groundwater system, depending on the sensitivity of that system to human and/or natural impacts.
Intrinsic vulnerability (natural), is the vulnerability defined solely as a function of hydrogeological factors, the characteristics of an aquifer and the overlaying soil and geological materials.

Most recently, the working group of the European COST Action 620 (EU, 2003), Vulnerability and risk mapping for the protection of carbonates (karst) aquifers

Intrinsic vulnerability is the term used to define the vulnerability of groundwater to contaminants generated by human activities. It takes into account the inherent geological, hydrological and hydrogeological characteristics of an area, but is independent of the nature of the contaminants and the contamination.
Specific vulnerability is the term used to define the vulnerability of groundwater to a particular or group of contaminants. It takes into account the properties of a particular contaminant or group of contaminants and its (their) relationship(s) to the various aspects of the intrinsic vulnerability.

Thus, according to Sorichetta (2010) from a practical point of view, in absence of a standard and unanimously accepted definition, when performing a groundwater vulnerability assessment it is extremely important to:

- carefully establish the objectives that must be achieved;
- explicitly refer to the definition of groundwater vulnerability to be used;
- select the proper assessment method according to the established objectives and the adopted definition.

This is done in order to avoid mis- interpretation of the results and a consequently improper use of them.
In this thesis, groundwater pollution risk is limited to the Foster (1987) definition presented above by considering the human aspects (e.g. human activity) that could be affected intrinsic groundwater vulnerability. Furthermore, the definitions given by NRC (1993), and EU (2003) can be found in the thesis. In addition, the term “pressure”

is used in this research to describe human activities which contribute to groundwater quality deterioration.

Finally, the definition of groundwater quality is presented in Box 1 (Harter, 2003) and the difference between groundwater contamination and pollution is illustrated in Box 2 (Zhou et al. 2015).

Box 1. Groundwater quality (Harter, 2003)
Groundwater quality comprises the physical, chemical, and biological qualities of ground water. Temperature, turbidity, color, taste, and odor make up the list of physical water quality parameters. Since most ground water is colorless, odorless, and without specific taste, we are typically most concerned with its chemical and biological qualities. Although spring water or groundwater products are often sold as "pure," their water quality is different from that of pure water.

Box 2. The difference between groundwater contamination and pollution (Zhou et al.2015)
Although the terms contamination and pollution are often used interchangeably in colloquial speech, they are distinct environmental concepts. Contamination is simply the presence of a substance that is normally not present or at a concentration above natural background level. When contamination reaches a level that results in or can causing negative biological effects to resident communities it becomes pollution (Chapman, 2007). All pollutants are contaminants, however, not all contaminants are pollutants. Pollution can produce highly damage or disturb ecosystem while contaminant should be supported by the system without stopping general life cycle. There are many different reasons causing groundwater pollution, which is important to clarify two broad categories, "point source" - occurs when harmful substances are emitted directly into a body of water and "non-point source"- delivers pollutants indirectly through transport or environmental change.

2.4 Nitrogen sources and pollution

Nitrogen is a major constituent of the earth's atmosphere and is one of the most important vital elements without which organisms cannot survive (Delgado, 2002). It is naturally part of the environment. The major nitrogen source is the atmosphere, as it represents more than two thirds of the extent of the atmosphere (Aljazzar, 2010). Zhou et al. (2015) argue that nitrate contamination in groundwater systems is caused by various processes and sources. The author adds that identifying the various sources of nitrate contamination and understanding system dynamics is fundamental to address groundwater quality problems. Nitrate is the most highly oxidized form of nitrogen in the nitrogen cycle, which includes activities in the atmosphere, hydrosphere, and biosphere (Evans and Maidment, 1995). Thus, understanding the nitrogen cycle is also an important approach to study nitrate behavior in subsurface system. Figure 2-1 shows the major transformations from the nitrogen cycle (Madison and Brunett, 1985 cited by Evans and Maidment, 1995): (i) Assimilation of inorganic forms of nitrogen (ammonia and nitrate) by plants and microorganisms; (ii) Heterotrophic conversion of organic nitrogen from one organism to another; (iii) Ammonification of organic nitrogen to produce ammonia during the decomposition of organic matter; (iv) Nitrification of ammonia to nitrate and nitrite by the chemical process of oxidation; (v) Denitrification (bacterial reduction) of nitrate to nitrous oxide (N_2O) and molecular nitrogen (N_2) under anoxic conditions, and (vi) Fixation of nitrogen (reduction of nitrogen gas to ammonia and organic nitrogen) by microorganisms.

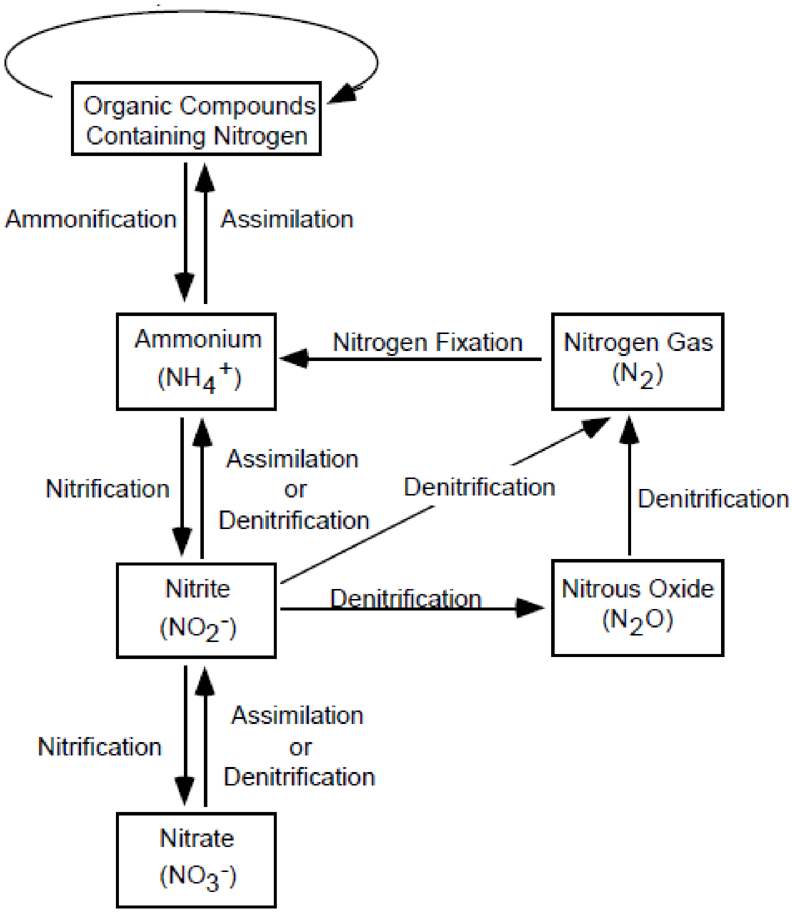


Figure 2-1: Simplified biological nitrogen cycle (Madison and Brunett, 1985)

Nitrate occurs naturally from mineral sources and animal wastes, and anthropogenically as a by product of agriculture and from human wastes (Evans and Maidment, 1995). The potential sources of nitrate can be divided into two main groups, naturally occurring and human-induced sources (Boy-Roura, 2013). These two groups also can be divided into two main categories, nonpoint (diffuse) and point-source pollution (Boy-Roura, 2013).

__Natural sources of nitrogen:__ Natural nitrate or nitrogen levels in groundwater are generally very low (typically less than 10 mg/l as NO_3; EAA, 1999). These concentrations of natural levels can be expected high and to be entirely caused by human activities, such as agriculture, industry, domestic effluents and emissions from combustion engines.

Anthropogenic nitrogen sources: Human activities related sources of nutrients can be groups into:

- Point sources (Non-Diffuse): the position of the release point can be identified. These sources are normally regulated by laws that place limits on the types and amounts of contaminants that can be released to water.
- Non-point (or Diffuse) sources: the local effect cannot be well tracked back to the source, or for which the source is characterize by a large geographical spread. Limiting nutrients from non-point sources is challenging because these sources are widespread and thus more difficult to identify and quantify than point sources.

Agricultural fertilizers application is the largest nonpoint source pollution affecting groundwater quality (Zhou et al. 2015). According to Aljazzar (2010), nitrate is an effective fertilizer and is used in agricultural activities due to the use of fertilizers and manure application. Many studies have shown that agricultural activities are a significant source of surface and ground water pollution due to long-term and excessive fertilizer use (Zhang et al.1995; Hudak, 2000). For example, as stated by Line et al. (1998), agricultural activities contributed to approximately 75 % of non-point pollution, which accounted for approximately two-thirds of the total pollution, in the United States (cited in Wang et al. 2015). Agriculture is the major source of nitrate, but it is not the only one (Aljazzar, 2010). There are several studies which showed a strong association between nitrate concentrations in groundwater and the above soil layers and land use categories including different agricultural activities, urban areas, and landfills (Aljazzar, 2010). Some studies in the few last years, have found that nitrate concentrations in groundwater in some urban aquifers are similar or even higher to those in their agricultural areas (Ford and Tellam, 1994; Lerner et al., 1999, cited in Aljazzar, 2010). This author Aljazzar (2010) affirm that there are several sources including sewage and remains leakage, septic tanks, industrial spillages, contaminated land, landfills, river or channel infiltration, fertilizers used in gardens, house building, storm water and direct recharge. Furthermore, the authors Madison and Brunett (1985) list the following as major anthropogenic sources of nitrate: "fertilizers, septic tank drainage, feedlots, dairy and poultry farming, land disposal of municipal and industrial wastes, dry cultivation of mineralized soils, and the leaching of soil as the result of the application of irrigation water." Natural sources include: "soil nitrogen, nitrogen-rich geologic deposits, and atmospheric deposition."

Also, many studies through the world were focused vulnerability of soil and groundwater to pollutants, on impact of agricultural activities on groundwater, impact of agriculture activities on groundwater, risk of groundwater pollution in developping countries (The Duijvenbooden and Waegeningh, 1987; Vrbaand Romijn, 1986; IHP, 1998; IAH, 1982; Foster, 1986; Lewis et al.1980; Egboka et al.1989). Independently to these few major studies on groundwater vulnerability and pollution cited. There are several studies which showed a strong association between nitrate concentrations in groundwater and the above soil layers and land use categories including different agricultural activities, urban areas, and landfills. Examples of previous studies related to nitrate sources from different reference through the World and available in the literature are: Andersen and Kristiansen, 1984; Baker, 1992; Singh et al., 1995; Postma et al., 1991; Ling and Al-Kadi, 1998; Joosten et al., 1998.

Table 2 provides a summary of the different sources of nitrate independently of authors (modified from Aljazzar, 2010); while Table 3 provides a summary of the major sources of groundwater pollution with a description of some of their health risks (Sililo et al. 2001).

Table 2-2: Sources of nitrate in soil and groundwater (modified from Aljazzar, 2010)

Sources	Diffuse (Non-Point sources)	Non-Diffuse (Point sources)
Natural	• Dissolution of minerals from soil or geologic formations • N atmospheric deposition • N-rich effluent discharge from groundwater baseflow to rivers	• N-rich effluent discharge from springs to rivers
Agriculture	• Use of industrial fertilizers • Use of organic fertilizers (manure and slurries) • House animals and animals used in agriculture field	• Accidental spills of nitrogen-rich compounds • Absence or leakage of slurry and manure storage facilities
Domestic	• Combustion engines in vehicles • Improper disposal of municipal effluents of wastewater, sludge and solid wastes	• Old and badly designed landfills • Septic tanks and leakage from sewage systems
Industry	• Atmospheric emissions from energy production • Combustion engines in vehicles • Disposal of effluents by sludge on fields	• Disposal of nitrogen-rich wastes using well-injection techniques • Old and badly designed industrial-waste landfills

Table 2-3: Main sources of groundwater pollution with some of their main characteristics (Sililo et al.2001)

Pollution category	**Pollution source**	**Main Pollutant**	**Potential impact**
Municipal	Sewer leakage	Nitrate Viruses and Bacteria	Health risk to users, eutrophication of water bodies, odour and taste
	Septic tanks, cesspools, privies		
	Sewage effluent and sludge	Nitrate, Minerals, Organic compounds, Viruses and Bacteria	
	Storm water runoff	Bacteria and Viruses	Health risk to water users
	Landfills	Inorganic minerals, Organic compounds, Heavy metals, Bacteria and Viruses	Health risk to water users, eutrophication of water bodies, odour and taste
	Cemeteries	Nitrate, Viruses and Bacteria	Health risk to water users
Agriculture	Feedlot wastes	Nitrate-nitrogen-ammonia, Viruses and Bacteria	Health risk to water users (e.g. Methemoglobinemia)
	Pesticides and herbicides	Organic compounds	Toxic/Carcinogenic
	Fertilisers	Nitrogen, Phosphorous	Eutrophication of water bodies.
	Leached salts	Dissolved salts	Increased TDS in groundwater

Pollution category	Pollution source	Main Pollutant	Potential impact
Industrial	Process water and plant effluent	Organic Compounds Heavy metals	Carcinogens and toxic elements (As, Cn)
	Industrial landfills	Inorganic minerals, Organic compounds, Heavy metals, Bacteria and Viruses	Health risk to water users, eutrophication of water bodies, odour and taste
	Leaking storage tanks (e.g. petrol stations)	Hydrocarbons, Heavy Metals	Odour and taste
	Chemical transport	Hydrocarbons, chemicals	Carcinogens and toxic compounds
	Pipeline leaks		
Atmospheric Deposition	Coal fired power stations	Acidic precipitation	Acidification of groundwater and toxic leached heavy metals
	Vehicle emissions		
Mining	Mine tailing &stockpiles	Acid Drainage	
	Dewatering of Mine shafts	Salinity, Inorganic compounds, Metals	May increase concentrations of some compounds to toxic levels.
Groundwater Development	Salt Water Intrusion	Inorganic minerals Dissolved salts	Steady water quality deterioration

2.5 Nitrate: health and environmental impacts

We present in this section a brief review of NO_3^- in groundwater, relevant to the present study, rather than a comprehensive review of the extensive literature available on NO_3^- in groundwater. NO_3^- is the most widespread contaminant among all inorganic constituents of health significance (Kumarasamy, 2007). In many parts of the world, groundwater is the single most important supply for the production of drinking water, particularly in areas with limited or polluted surface water sources (Schmoll et al. 2006). According to Boy-Roura (2013), nitrate in groundwater has two major problems and risks. On one hand, nitrate pollution poses a recognized risk for its use as drinking water; while on the other hand, excessive nutrient loads can lead to the deterioration of ecosystems. Nitrate is a common surface water and groundwater contaminant that cause health problems in infants and animals, as well as eutrophication in surface waters (cited in Fennessy and Cronk, 1997).

Health concern

Nitrate, itself, has a low toxicity at massive doses and is generally of no concern with respect to human health (Aljazzar, 2010). High levels of nitrate in drinking water are associated with adverse health effects (Boy-Roura, 2013). In others words, excessive levels of nitrate in drinking water can produce negative health impacts on human well-being. Thus, the immediate health concern is the reduction (conversion) of nitrate to nitrite in the digestive tract by nitrate reducing bacteria (Aljazzar, 2010). This author adds that nitrite is readily absorbed into the blood where it combines with the hemoglobin that carries oxygen. It forms methaemoglobin, which cannot carry oxygen. The reduced oxygen supply to the body tissues produces physical stress. When severe enough, nitrate poisoning is life threatening because of suffocation. This condition is called methemoglobinemia, or blue baby syndrome, in infants (Knobeloch et al. 2000), because of blue color or blue-grey around eyes and mouth. The authors such as Curry (1982); White and Weiss (1991) affirms that nitrate is therefore directly linked to the blue-baby syndrome, the case in which human blood is not able to carry oxygen. Infants, human and animals (such as cattle, horses, sheep, baby pigs, and baby chickens), are the most susceptible to nitrate poisoning because bacteria that convert nitrate to nitrite are abundant in their digestive systems (Aljazzar, 2010). Boy-Roura (2013) affirms that animals may also be affected by high nitrate concentrations in drinking water. For example, nitrate poisoning of cattle has resulted in devastating losses across southern Africa as stated in Limpopo River Awareness Kit in Website. In year 2000, 356 heads of cattle died on Ghanzi River in the Ghanzi-Karakubis area in Botswana. Nitrate levels have been detected above 500 mg/L in the southern Kalahari. (See two photos in below). http://www.limpopo.riverawarenesskit.org (Accessed online October 29th 2017).

However, according to Aljazzar (2010) the syndromes of blue baby are rarely observed in adults where the low gastric acidity and the high-active enzymes inhibit nitrate-reducing bacteria. But, the author Aljazzar (2000) affirms that The Britain Royal Commission on Environmental Pollution has documented the last ten cases of blue-baby syndrome occurred in the United Kingdom (UK) in 1979, one of them was fatal. According to Croll and Hayes (1988), no cases occurred after that where nitrate concentration in drinking water were less than 100 mg/L. Ferrant (1946) observed two case of methemoglobinemia in newborn infants were recorded in Belgium and appeared to be caused by high nitrate level in the well water used for the dilution of powdered milk. Still, according to Aljazzar (2010), nitrate in groundwater is a serious problem in Gaza Strip. Indeed, after the study of Al-Absi (2008) to investigate blue baby cases in this region of Gaza, the experimental results indicated that the prevalence of methemoglobinemia is very high and more than 70 % of the tested infants were suffering from a blue-baby syndrome.

Photo 1: A heifer in Botswana killed by nitrate poisoning from contaminated groundwater (From Prozesky 2000)

Photo 2: Tock losses from nitrate poisoning have been significant across the western (Botswana) and southern (South Africa) portions of the basin. (From Prozesky 2000).

The relationship between nitrate levels in drinking water and cancer has been inconclusive (Aljazzar, 2010). However, this author declares that nitrogen-nitrosamine compounds are some of the strongest known carcinogens. Jalali (2005) argues that they have been found to induce cancer in variety of organs in various animal species including higher primates. Almasri and Kaluarachchi (2004) affirm that therefore, nitrates may also have a possible role as procarcinogenics. Yang et al. (2007) showed that there was no significant association between nitrate concentration in drinking water and the risk of death from colon cancer. Despite many uncertainties regarding the association of nitrate intake and cancer (Zeegers et al., 2006), nitrate in drinking water is still considered as a risk factor says Aljazzar (2010). Because, certain authors such as Clough (1983); Weyer (2001) found that intensive experimental data suggests a role for nitrate in the formation of carcinogenic N-nitrosamines and stated that high concentration of nitrate in drinking water can not be excluded as a factor in analysing gastric cancer. Moreover, Gulis et al. (2002) found a positive correlation between nitrate concentration in drinking water and colorectal cancer has been found Trnava District in Slovakia. To conclude, as stated in Zhou et al.(2015), long term exposure to high nitrate levels in drinking water has been found in some studies to be a risk factor for several types of cancer including gastric, colorectal, bladder, urothelial and brain tumor (CDPH, 2013).

Environmental and social concerns

Water quality is a major concern throughout the world. High levels of nitrate in water are also of environmental. Many aquifers discharge or are in hydraulic continuity with rives reaching coastal areas or surface water bodies as wetlands, where important nutrients loads can lead to eutrophication (Boy-Roura, 2013). Elevated nitrate concentrations may lead to excessive algal growth, which can cause oxygen deficiencies causing fish kills, toxic algal blooms and a general decrease in biodiversity (EEA, 1999).

All problems mentioned in above related to nitrate pollution have implied an organized concern about this potential health hazard among local citizens. According to Boy-Roura (2013), since the mid-80's, agricultural pollution has become on the most prominent environmental issues at the European Union and public opinion regards agriculture as one of the most environmental disruptive social activities. As a result, the pressures on farmers to decrease pollution and achieve higher environmental standard were reinforced (Izcara et al., 2002). The implementation of different European directives regarding water quality, setting legal standards for a range of water quality parameters was the result of these social pressures. Furthermore, financial costs are also social concern associated with poor water quality. Indeed, nitrate pollution in groundwater implies additional drinking water treatment, construction for new wells, monitoring, and other safe drinking water actions.

Certain authors such as Auréli and Brelet (2004); and Asmal (2004) investigated some aspects of water resources in relation to social and environmental problems not with nitrate impact but focus on water and ethics. They concerned with the ethical issues arising from the special role of women in social and environmental issues, and water in civil society.

2.6 Review of global and regional nitrogen and nitrate assessment maps

In this section, we present several maps developed at global and regional scale related to nitrate contamination in groundwater. Most of the review of nitrate and nitrogen assessment maps can be find in Zhou et al. (2015). Figure 2-2 showed the global map with high nitrate in groundwater produced by IGRAC in 2012. According to Zhou et al. (2015), this map was based on a literature study and demonstrated the percentage of regions with high nitrate contamination in the world. However, one drawback of this map is that the legend is of qualitative range, without specifying quantitative definition for "high nitrate", "many" and "few" (Zhou et al.2015).

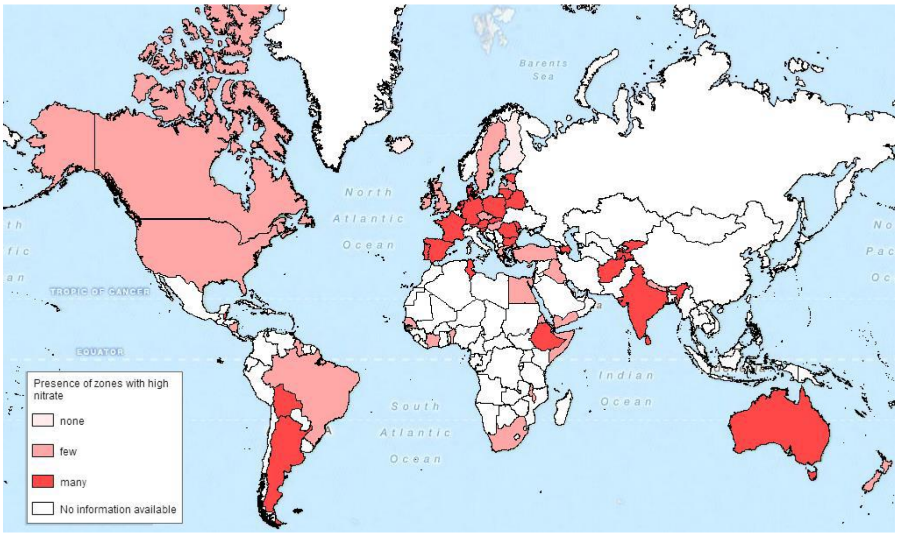


Figure 2-2: Global map with the presence of zones with high nitrate in groundwater (from IGRAC 2012, cited in Zhou et al. 2015)

Figure 2-3 present the global aquifer vulnerability map developed by Zhou et al. (2015) using GOD method. Index based methodologies such as GOD utilize Multi-criteria decision making (MCDM) approaches to define aquifer vulnerability. The method was developed by Foster in 1987, and used three variables, where: G is Groundwater occurrence; O is Overall aquifer class; and D is Depth to the groundwater table. By collecting the data points that represents the nitrate concentration in certain region of several countries, Zhou et al. (2015) show on Figure 2-4 the spatial distribution of nitrate level in groundwater through the world. According to the authors, the data collected represent only the nitrate level in the local regional groundwater system.

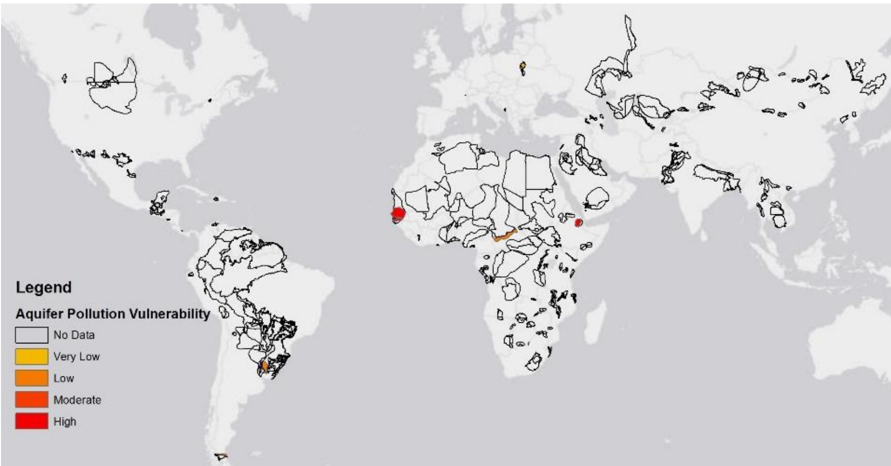


Figure 2-3: Vulnerability map of the main transboundary aquifers of the world using GOD method (Zhou et al.2015)

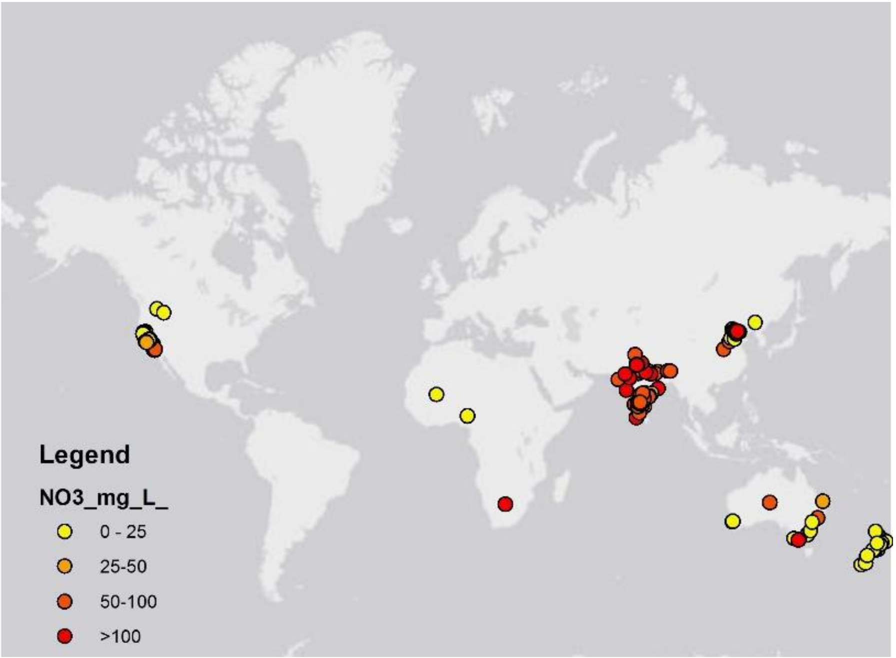


Figure 2-4: Groundwater nitrate concentration in the different regions of the world (Zhou et al.2015)

Using nitrate data provides by Federal Institute of Germany coming from GEMstat, Zhou et al. (2015) showed the spatial distribution of nitrate sampling in the world on Figure 2-5. In recent study published by Ascott et al. (2017) on the modelled spatiotemporal distribution of nitrate stored in the vadose zone shows substantial increases between 1950 and 2000 associated with increased global use of N fertilizers and subsequent leaching (see Figure 2-6). The authors affirms that in some developed countries, the amount of nitrate stored in the rocks is increasing, despite improvements in farming practice and the introduction of rules to control the pollutant. Basins in North America, China and Central and Eastern Europe have developed large amounts of nitrate stored in the vadose zone due to thick vadose zones, slow travel times and high nitrate loadings. However, they affirm in developing countries, the problem is currently not so severe. But there is an urgent need for early intervention to avoid the environmental damage experienced by rich countries.

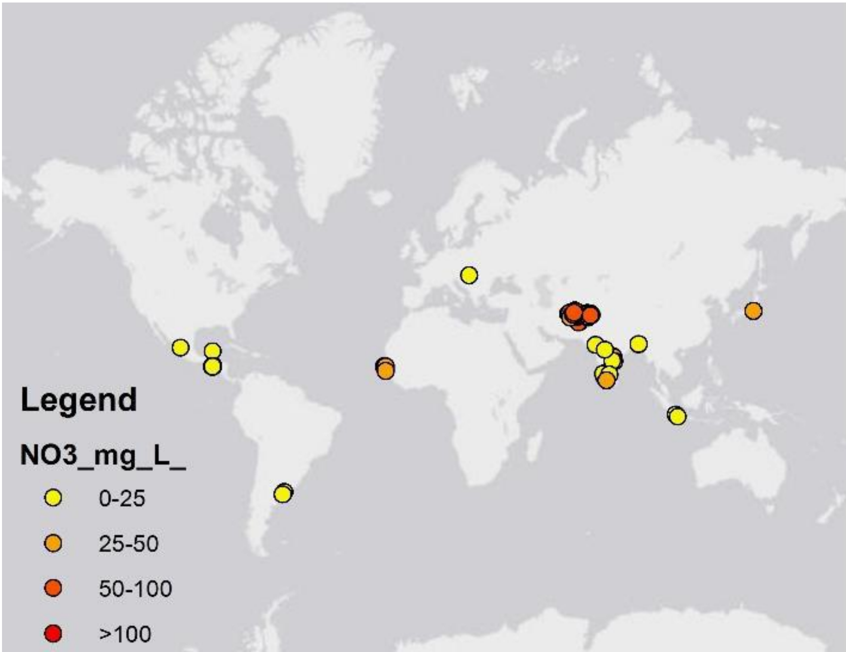


Figure 2-5: Groundwater nitrate concentration in the sampling wells around the world (Zhou et al.2015)

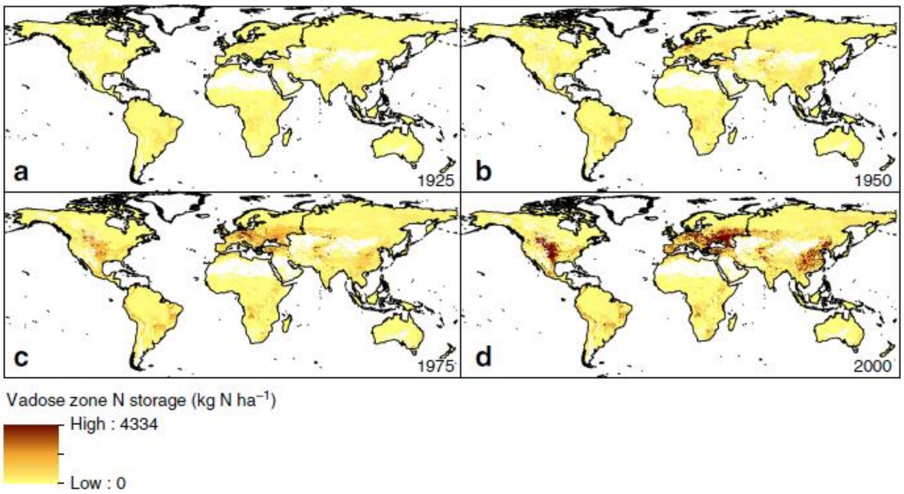


Figure 2-6: Spatial distribution of nitrate stored in the vadose zone. Global vadose zone N storage (in kg N ha−1) is shown for 1925 (a), 1950 (b), 1975 (c) and 2000 (d) (Ascott et al.2017)

Figure 2-7 presents nitrate concentration in groundwater in European countries. We observe that the majority of countries show nitrate levels higher than 50 mg/L. Zhou et al. (2015) affirms that the data value was measured by a number of sampling sites in different countries.

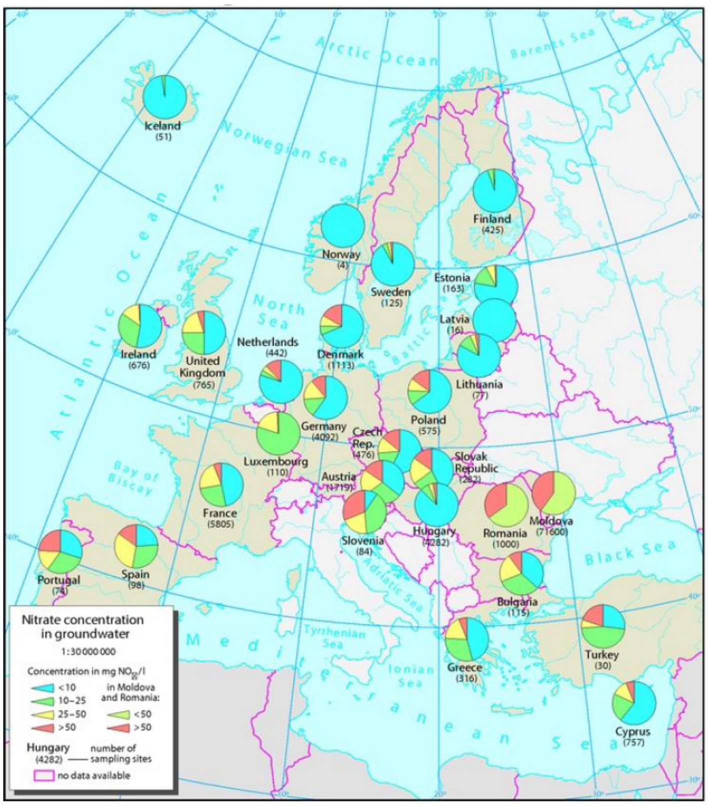


Figure 2-7: Nitrate concentration (NO3- in mg/L) in groundwater at a country level (source: EEA, 2002)

We observed on the Figure 2-8 nitrate-N concentration in groundwater for the United States with three classes of values with the legend presenting a range greater than 30 ppm who does not give the maximum limited nitrate-N value. Figure 2-9 showed the final DRASTIC index map of the entire of USA developed by Kumarasamy in 2007. This map was developed by addition nitrogen loading as land use proxy with the seven environmental variables. We observe five classes of vulnerability index.

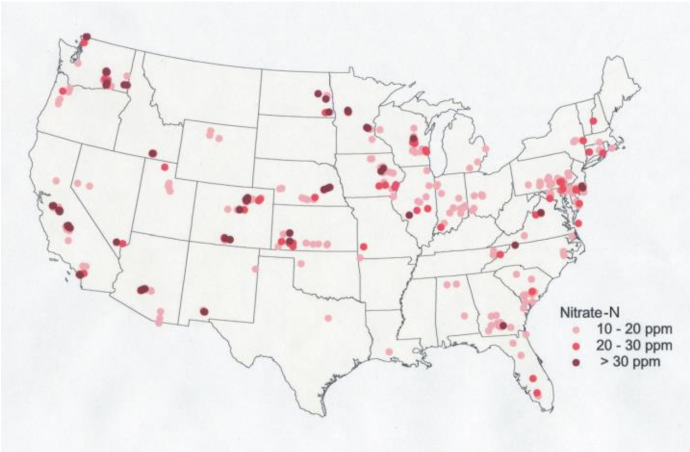


Figure 2-8: Groundwater nitrate-N concentration in United States (Townsend et al. 2003)

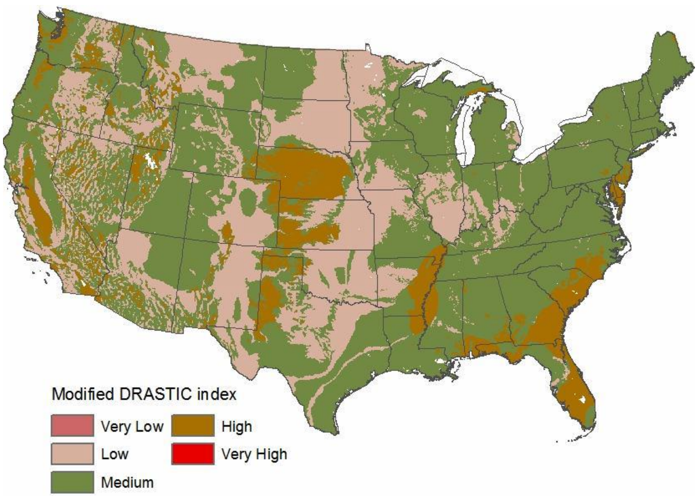


Figure 2-9: Final modified DRASTIC index of groundwater vulnerability map in USA (Kumarasamy, 2007)

Figure 2-10 show an overlapped map with nitrogen fertilizer application and nitrate levels of sampling wells (Zhou et al. 2015). According to the author, each sampling point was computed by average level, and high levels of nitrate occurs in India, Afghanistan and north part of China. Furthermore, we observe that the majority of points on the map corresponding to the area with high nitrogen fertilizer input as stated by Zhou et al. (2015).

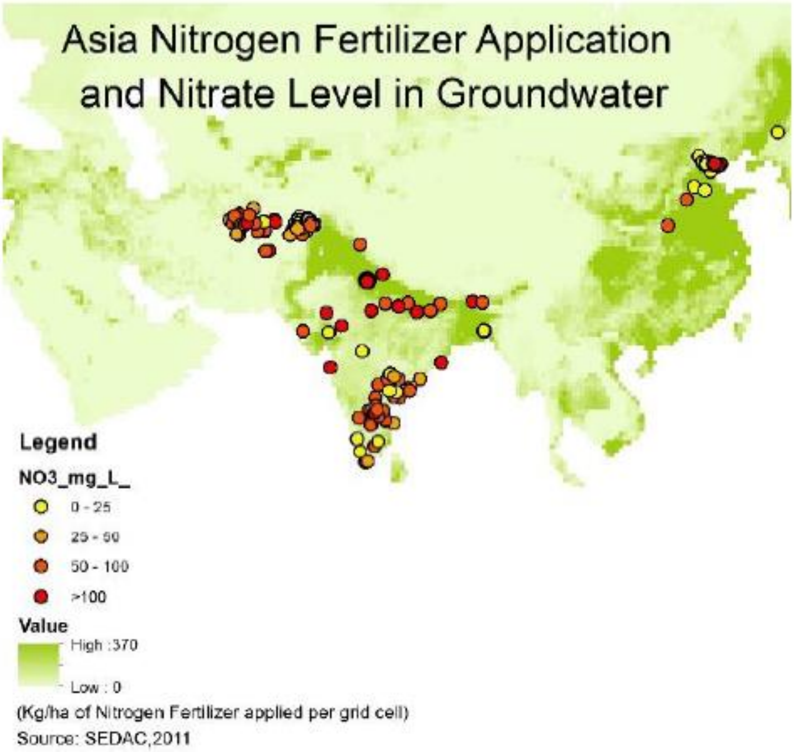


Figure 2-10: Asia nitrogen fertilizer application and nitrate level in groundwater (Zhou et al.2015)

An example of spatial distribution of nitrate concentration in Southern Africa region is presented in Figure 2-11. This regional map represents the distribution of nitrate concentration in the groundwater of Namibia, Botswana and South Africa. We observe that the highest nitrate concentration is found in the central part of these three countries, and all spatial distributions of boreholes and wells have a nitrate concentration above the WHO standard. To the end, the Figure 2-12 is a the groundwater vulnerability map of south Africa developed by Musekiwa and Majola (2013) using DRASTIC method.

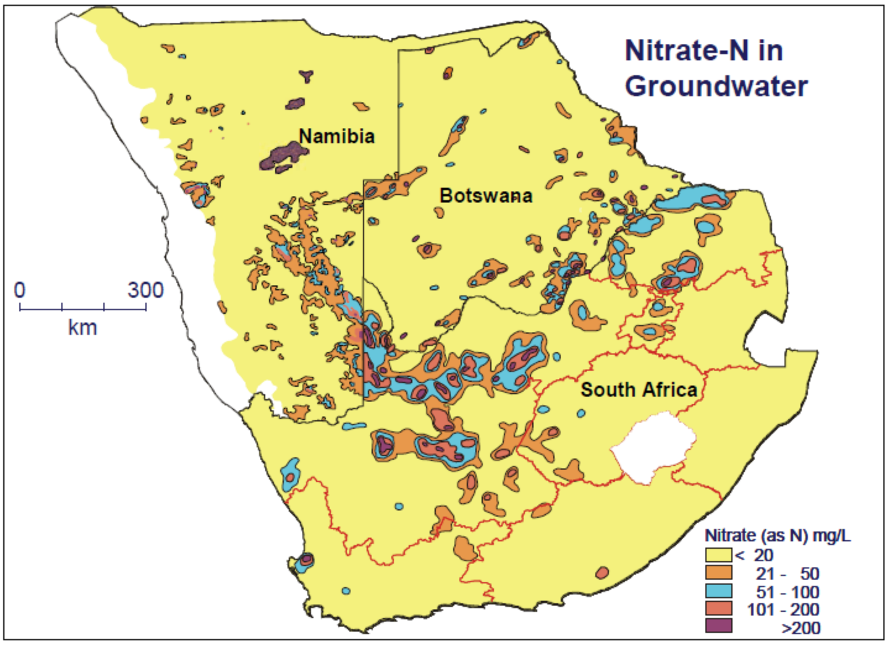


Figure 2-11: Groundwater nitrate distribution in southern Africa (Tredoux et al. 2009)

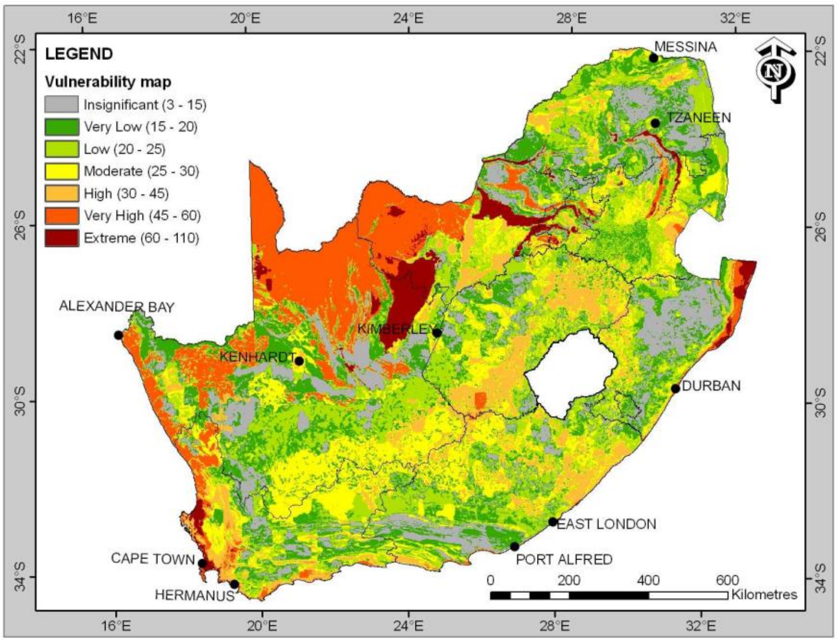


Figure 2-12: Vulnerability map of South Africa (Musekiwa and Majola, 2013)

2.7 Nitrate vulnerability modelling at the continental and regional scale

Vulnerability maps are typically made at a sub-basin, basin, or regional scale and they are not normally used for site-specific assessments involving areas smaller than a few tens of square miles (Harter and Walker, 2001). According to these two authors, vulnerability maps are therefore best used to demonstrate large-scale, regional differences in groundwater vulnerability. In spite this usefulness of groundwater vulnerability, NRC (1993) affirm that uncertainty is inherent in all vulnerability assessments.

2.7.1 Notions of scale and definition

In the field of environmental research, the scale issue is often a major point of concern. Many different adjectives are used when speaking about scale, e.g. cartographic scale, geographic scale, operational scale, relative scale or level of resolution (Jenerette and Wu, 2000; Marston, 2000) or measurement scales, e.g. nominal, ordinal, interval and ratio (Abella and Van Westen, 2007). However, in a general sense, scale refers to the spatial dimensions at which entities, patterns, and processes can be observed and characterized (Marceau, 1999).

2.7.2 Problems of scale

As stated by Leterme (2006), Beven et al. (1999) identified two problems of scale in hydrological modelling: the scale problem and the scaling problem. These are defined as follows (Beven et al. 1999):

The scale problem denotes the expectation that different processes may dominate hydrological processes at different scales so that different theories and models may be appropriate at different scales. The scaling problem denotes the development of a consistent theory that would allow a process description at one scale to be formally transformed to represent the hydrological response at a different scale (cited in Leterme, 2006).

Scale effects refer to the contrast of information or the different characteristics at different scales (Wu and Li, 2009). Model predictions at the regional scale are likely to be contaminated by several different modelling errors (Donigan and Rao, 1986; NRC, 1993). According to Mulla and Addiscott (1999), these errors include modelling structure error, experimental data measurement error, model parametrization errors and, as mentioned above, scale transitions errors. *Errors in model structure* occur when the process and the assumptions represented by the model fail to represent reality. The example could be a model which simulates solute transport using the convective dispersive equation for a region in which two-region or macropore transport is significant. *Errors in model parametrization* can result from a variety of causes. A major source of uncertainty is due to spatial and temporal variability. Mulla and Addiscot (1999) affirms that uncertainties *in model predictions* can result from errors in spatial scale transitions. The author argues that the first type of scale-transition error occurs when the source and sink terms or transport and fate processes operating at the scale of the calibration study (at the field scale for example) are different from those operating at the prediction scale (e.g., the watershed or aquifer scale). An example of problems can occur in groundwater modelling, including changes in dispersive or transformation processes, geologic influences on transmissivity and flow direction, and recharge patterns. The second type of scale-transition error is due to errors in extrapolation caused by spatial and temporal averaging of model parameters (Destouni, 1993), or due to bias caused when the calibration site is not representative of the region (Beven, 1993).

For example, in their study entitled "*Validation Approaches of Field-, Basin-, and Regional-Scale Water Quality Models*", Mulla and Addiscott (1999), argues that the main limitation of down-scaling approach is that the processes which dominate broad patterns and trends at the regional scale may be obscured by other processes that dominate at the local scale. According to these authors, an example to illustrate the limitations of down-scaling is a description of groundwater contamination by nitrate-nitrogen at a regional scale in terms of regional patterns in precipitation, depth to groundwater, and soil texture. At local scale, variations in nitrate leaching to groundwater may more strongly be controlled by management practices such as the amount and timing of N fertilizer application than by local variations in precipitation, depth to groundwater, or soil texture. To conclude, these authors affirm that the rigorous validation of models at the scale of large regions, basins or continent is difficult for a variety of reasons: part of the difficulty in validating models for large regions is due to the challenging issues of model structure, non-linearity, non-uniqueness, spatial and temporal variability and scale-transition errors.

2.8 Conclusions

In this chapter we introduce and discuss issues and concepts that further will be used in the thesis.

We shortly introduce index based methodologies for assessing spatially distributed environmental functions. We use multi-criteria decision making (MCDM) approaches to assess the spatial distributed environmental function related to groundwater vulnerability against pollution. Among several MCDM approaches to assess groundwater vulnerability, DRASTIC (Aller et al.1987) is a very popular tool. We choose the DRASTIC approach due to the lower data requirements associated with the approach and its suitability to make large scale assessments. To this regard, Honnungar (2009) affirms that the DRASTIC approach has proven to be particularly useful for large-scale assessments and has been utilized all across the world to delineate vulnerability at regional, state and national scales.

We also discuss the nitrate in groundwater issue. Indeed, we further used in this thesis nitrate as an empirical proxy of groundwater vulnerability. Using observations of nitrate pollution of groundwater can therefore be used to validate groundwater vulnerability models. Erwin and Tesoriero (1997) affirms that nitrate contamination has indeed been an indicator of overall groundwater quality (in US. Environmental Protection Agency, 1996). Nitrate in drinking water resources is further a potential health risk (Erwin and Tesoriero, 1997). Recent studies have elucidated the human health risk, such as cancer risk, associated with poor groundwater quality (Gao et al. 2012; Fabro et al. 2015; Wheeler et al. 2015; Wongsanit et al. 2015). The World Health Organization's guideline has indicated that the ingestion of more than 50 mgL^{-1} nitrate in potable water can be harmful to human health (WHO, 2004).

We finally elaborated on the scale issues when assessing complex environmental functions. Scale and scaling issues are indeed of paramount importance when framing the different methodologies used to assess groundwater vulnerability for pollution.

Chapter 3 Description of the study area

3.1 Regional layout

Geography is key to understanding any region of the world. The African continent accounts for one fifth of the total land area of the Earth. It is the second largest of the continents, comprising 54 countries, of which 47 are in sub-Saharan Africa (SSA), with a wide range of hydrological conditions (Groundwater Governance, 2014) and differing geographical, economic and cultural characteristics (ADB, 2014). The south-east of the continent is largely a high plateau country and the north-west mainly consists of plains and shallow river basins. The Sahara Desert occupies about half of the continent north of the equator. The extreme north and south have a Mediterranean climate with winter rain and summer drought. Between the tropics the rains are concentrated in the summer months, and near the equator they occur in two seasons of the year. According to Ateawung (2010), the Africa' relief is characterised by two broad, elevated regions of Eastern and Southern Africa, having an average height of 1015 m above sea level. Widely regarded as the place where the human race originated, according to ADB (2014), Africa has around 1 billion people today and will have an estimated 2.5 billion in 2060. The continent's population has undergone great changes over time, and this changing population has in turn altered African landscapes and ecosystems. While environmental change is not new to Africa, pace of change has accelerated, as it has in many other parts of the world. According to Groundwater Governance (2014), it is not always possible to separate information about SSA from information for the continent as a whole. According to Braune and Adams (2013), politically, SSA consists of all African countries that are fully or partially located south of the Sahara (excluding Sudan), making up 74 per cent of the continent's area and 85 per cent of the population. The countries of the sub-Saharan region are organised into the Economic Communities of West Africa (ECOWAS), East Africa (EAC), Central Africa (ECCAS), and Southern Africa (SADC). Madagascar was omitted from this study due to the lack of complete data for the region. In Africa, clusters of large towns and cities are concentrated in regions of economic importance, particularly the Nile Delta, the Maghreb, southern Nigeria and the economic heartland of South Africa, which together contain roughly half of Africa's population on about 2 per cent of its land area (Braune and Adams, 2013). According to these authors, the rural population is densely populated over relatively small areas of the continent with wide areas still sparsely populated, with fewer than 4 persons per km². Rural settlements in many small villages characterized by an agricultural economy thus still dominate Tropical Africa. The map in Figure 3-1 illustrates the settlement pattern in Africa.

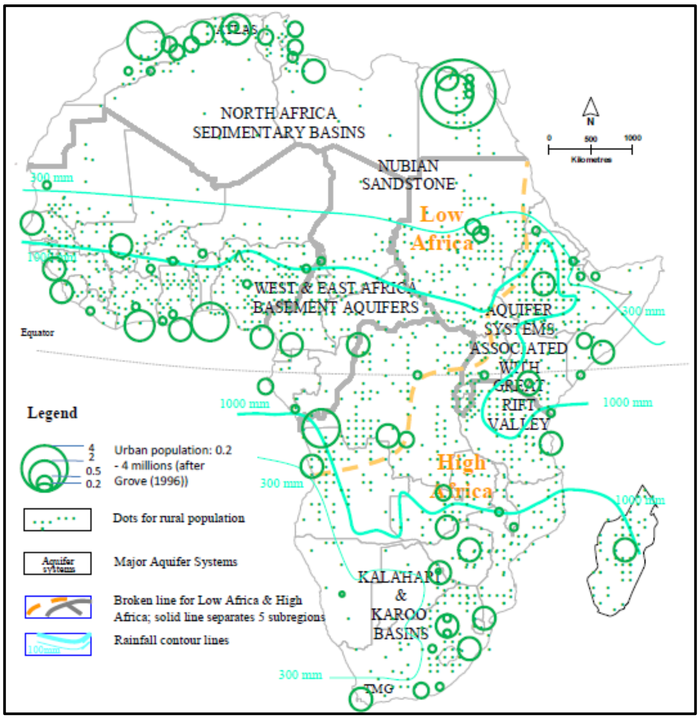


Figure 3-1: Human geographic conditions in Africa (Braune and Adams, 2013)

3.2 Climate and rainfall in Africa

Africa is one of the region's most vulnerable to climatic changes. It is the world's second driest continent after Australia (UNEP, 2010). Approximately 66 per cent of Africa is classified as arid or semi-arid (see Figure 3-2), with extreme variability in rainfall (UNEP, 2002). The distribution of rainfall varies in space and time, with a consequent overall unreliability of water supplies. For example, the humid region of Central Africa, which comprises 20 per cent of the continent's land area, receives 37 per cent of its total rainfall. In contrast, the arid region of North Africa, occupying a similar area, receives less than 3 per cent (Goulden et al., 2009). In some places temporal variations are as high as 40 per cent around the mean (UNECA et al., 2000). Rainfall variability in Africa can result in extreme events such as flooding or severe droughts over years or decades. According to Church (2011), the Sahel, the semi-arid belt that lies across Africa south of the Sahara and north of the tropical regions, has experienced the greatest change in rainfall patterns anywhere in the world since measurements began. Africa's rainfall and climate variability have had serious impacts on social and economic development. Africa is highly dependent on rain-fed agriculture and fluctuations in rainfall can have significant impacts on food production and security (Church, 2011). There are three main deserts, the Sahara in the north and the Kalahari and Namib deserts in Southern Africa. More than 40 per cent of Africa's population lives in arid, semi-arid and dry sub-humid areas, where demand for water and other ecosystem services is on the rise (Ingram et al., 2002; De Rouw, 2004; Sultan et al., 2005). As a result of high temperatures everywhere in Africa, except at high altitudes and during winter in the extreme north and south, rates of evaporation from the soil and water surfaces are high, varying from about 750 mm in the more humid and cooler regions to more than 2,000 mm. This has a major impact on the hydrological cycle in terms of infiltration, groundwater recharge and runoff production, as well as on most human uses of water, particularly irrigation (Grove, 1996, cited in Xu and Braune, 2010).

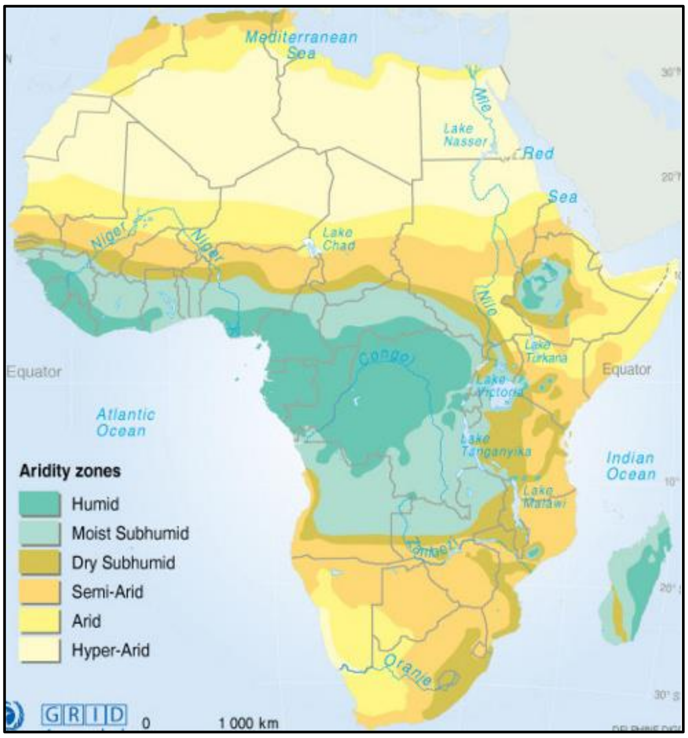


Figure 3-2: Aridity zones of climate classes for the African continent (Church, 2011)

3.3 Surface water

Africa's surface water resources comprise a total of 63 international rivers basins, covering 64 per cent of its land area and containing 93 per cent of total surface water resources (UNEP, 2010). These river basins are also home to some 77 per cent of the population according to UNEP (2010). Surface water resources in Africa are predominantly transboundary, with most situated in the central and southeastern regions of the continent, reflecting the spatial pattern of rainfall. According to the Royal Society of Chemistry (2010), around 50 per cent of Africa's total surface water resources are generated in the Congo basin alone. The most important river is the Nile, which drains north-east and empties into the Mediterranean Sea. The Congo drains much of Central Africa and empties into the Atlantic Ocean. The Niger is the principal river of Western Africa and the continent's third-longest river after the Nile and the Congo, and empties into the Atlantic Ocean. Southern Africa is drained by the Zambezi River. Africa's largest lakes are Lake Victoria, the world's second-largest freshwater lake, and Lake Tanganyika, the second-deepest lake in the world. Some of the world's largest dams are found in Africa, such as the Volta, Kariba and Cahora Bassa. According to Church (2011), surface water resources provide benefits ranging from hydropower generation, irrigation, inland fisheries, tourism, and recreation, to water supply for domestic, industrial, and mining operations. A new map (Figure 3-3) showing major surface water features (rivers and lakes) in Africa was developed by the British Geological Survey (BGS) by combining three separate open source datasets, the Africa Groundwater Atlas, the World Wildlife Fund's Digital Chart of the World, and the FAO (Food and Agriculture Organization of the United Nations).

While the availability of rainwater and freshwater from rivers and lakes will likely become more erratic and thus less reliable as a result of climate change, groundwater is likely to be less affected than surface resources by climate variability, higher temperatures, and evaporation (from ClimDev-Africa, Policy Brief 5, n.d.).

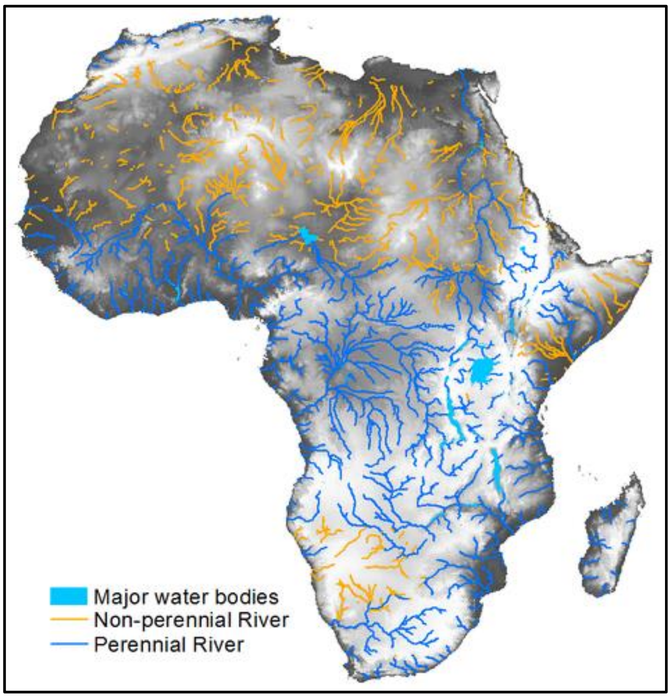


Figure 3-3: Rivers and major surface water bodies in Africa (BGS, 2015)

3.4 Geological and hydrogeological context

The African continent encompasses various climatic regions and a large geological diversity. Geology has a profound influence on groundwater conditions. The geology of the African continent contains 14 lithological classes with varying coverage: unconsolidated sediments (35.1 per cent), metamorphic rocks (27.6 per cent), siliciclastic sedimentary rocks (16.4 per cent), carbonates sedimentary rocks (9.4 per cent), mixed sedimentary rocks (6.4 per cent), basic volcanic rocks (3.3 per cent), acid plutonic rocks (1.1 per cent), water bodies (0.9 per cent), evaporites (0.6 per cent), intermediate volcanic rocks (0.6 per cent), basic plutonic rocks (0.2 per cent), intermediate plutonic rocks (0.1 per cent), and acid volcanic rocks (0.1 per cent), (Hartmann and Moosdorf, 2012). Lithology describes the geochemical, mineralogical and physical properties of rocks (see Figure 3-4).

Groundwater occurrence depends primarily on geology, geomorphology, and rainfall (both current and historic). The interplay of these three factors gives rise to complex hydrogeological environments with substantial variations in the quantity, quality, ease of access, and renewability of groundwater resources. It is widely accepted that hydrogeological conditions are the major determinant of groundwater availability. Across Africa, MacDonald et al. (2012) distinguish five important hydrogeological environments:

- Precambrian crystalline basement rocks, which occupy 34 per cent of African land area and comprise crystalline rocks with very little primary permeability or porosity.
- Consolidated sedimentary rocks, which occupy 37 per cent of land area, mainly across uninhabited areas. Sandstone basins can store considerable volumes of groundwater and support high yielding boreholes of 10-50 litres per second.
- Volcanic rocks, which occupy only 4 per cent of land area and are found in East and Southern Africa, where they underlie some of the poorest and most drought-stricken areas of Africa.
- Unconsolidated sediments from some of the most productive aquifers in Africa, which cover approximately 25 per cent of land area. They have high porosity and can store large volumes of groundwater.
- Unconsolidated sediments in river valleys, which are highly significant aquifers in Africa. They probably cover less than 1 per cent of land area, but are present in most river valleys.

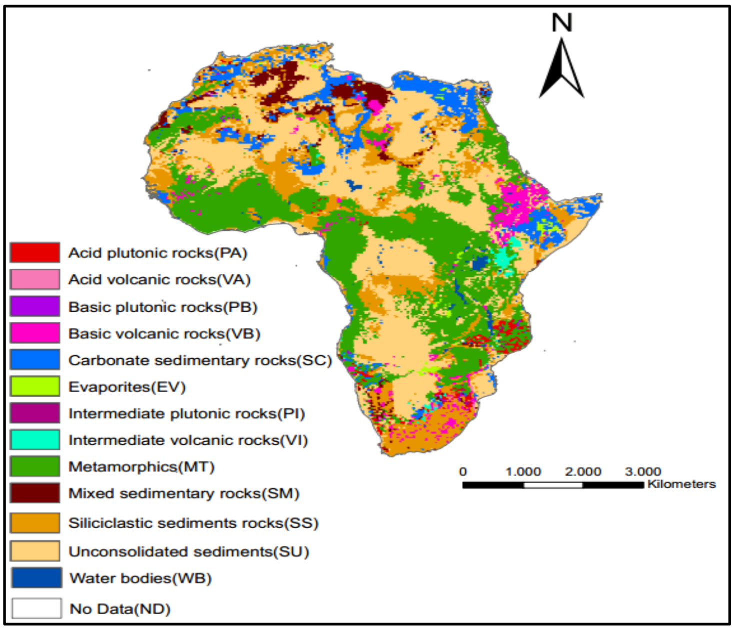


Figure 3-4: The lithological context of the African continent (from Hartmann and Moosdorf, 2012)

Groundwater and aquifers are highly important in Africa, especially for dry countries in the northern and southern sub-regions. Groundwater plays an important role in providing water for people and animals in rural areas of Africa, and is perhaps the only practical means of meeting the needs of rural communities in arid and semi-arid regions (Robins et al. 2006). Widespread but limited groundwater represents only 15 per cent of the continent's renewable water resources, but it is the source of drinking water for three-quarters of the continent's population (UNECA et al., 2000). The largest groundwater reserves in Africa are found in large sedimentary aquifer systems in Libya, Algeria, Sudan, Egypt and Chad (MacDonald et al., 2013). Groundwater development has tended to flourish most in the drier western, eastern and south-eastern parts of Africa, where annual precipitation is less than 1,000 mm per year (Foster et al., 2006). Most countries in the desert areas of Africa, such as Libya, Egypt, Algeria, Tunisia, Morocco, Namibia, and Botswana, receive very little precipitation and therefore rely heavily on groundwater resources.

The cities of Lusaka, Windhoek, Kampala, Addis Ababa and Cairo are highly dependent on groundwater for municipal water, and groundwater also contributes to the supply of other cities such as Lagos, Abidjan, Cape Town and Pretoria (Robins et al., 2006). According to Braune and Xu (2010), in general, groundwater represents the only source of water in North Africa. In other examples, groundwater provides for 80 per cent of domestic and livestock demand in Botswana (SADC et al., 2008) and meets 80 per cent of the needs of Namibia's rural population (Ndengu, 2002). These examples show that groundwater is generally cheaper to develop compared to alternatives. While aquifers are usually protected from contamination, pollution from human activities on the surface is of growing concern. In addition, naturally occurring fluoride (F) and arsenic (As) can cause significant problems. Groundwater is less prone to evaporation than are surface water bodies, so it is a more reliable water source, especially during droughts (cited in UNEP, 2010). Finally, groundwater is a source of seepage into water bodies such as rivers and lakes, and this interaction in the water cycle is important for maintaining the integrity of ecosystems. However, some of Africa's important aquifers are losing water faster than the rate of recharge, for example those found in large sedimentary basins, such as Lake Chad, and under the Sahara Desert (Stock, 2004). Pavelic et al. (2012), affirms that past and present climatic conditions, particularly rainfall patterns, dictate rates of recharge and hence long-term replenishment and aquifer sustainability.

3.5 Transboundary aquifer distribution and current knowledge

Africa is heavily reliant on groundwater resources, with an estimated 75 per cent of the population dependent on this resource for basic water supplies (Altchenko and Villholth, 2013). However, with population growth, climate change and the need to combat growing food insecurity, demand for groundwater is set to increase in the future. The focus on transboundary aquifers (TBAs) comes from the recognition of the increasing stress on available water resources. TBAs are major groundwater systems that span more than one country. The definition of a TBA is given by Stephan (2009) as 'an aquifer or aquifer system, parts of which are situated in different states' (see Figure 3-5). According to UNECA et al. (2011), an international transboundary aquifer can be defined as 'an aquifer system with physical boundaries that extend over one or more administrative arrangements'.

Africa is known for its large proportion of water systems that are shared between nations. Most of the major aquifers systems in Africa are shared by two or more countries, and therefore TBAs represent highly important groundwater resources in Africa. Altogether, at least eighty of the important aquifers that are known in Africa are TBAs (Altchenko et al., 2013). According to AGW-Net (2014), the 80 identified TBAs together represent approximately 42 per cent of the continental land area and 30 per cent of the population. The most significant of these are found in arid and semi-arid regions, but the total number (including non-shared aquifers) is not known. Cooperation among countries to develop TBAs will be needed if such resources are to be developed effectively. To this regard, on 16 December 2013, the UN General Assembly adopted an international resolution on the "Law of Transboundary Aquifers" referred to as "A/RES/68/118". The resolution noted the major importance of the subject of the law of transboundary aquifers in the relations of States and the need for reasonable and proper management of transboundary aquifers, a vitally important natural resource, through international cooperation for present and future generations. The resolution of the General Assembly includes nineteen (19) law or articles on transboundary aquifers. A few examples of these laws are: (Article 10) Protection and preservation of ecosystems; (Article 12) Prevention, reduction and control of pollution; (Article 13) Monitoring; (Article 14) Management.

TBAs encompass a wide variety of characteristics, in size as well as geological setting, recharge rate, and population density. Table 3-1 shows the evolution in the number of TBAs inventoried over the last decade by ISARM (Internationally Shared Aquifer Resources Management), WHYMAP (World-wide Hydrogeological Mapping and Assessment Programme) and the International Groundwater Resources Assessment Centre (IGRAC). A significant increase in number is noticeable in Southern Africa and Western/Central Africa, primarily due to the activities of ISARM in both areas. As a United Nations Centre, IGRAC is taking a global lead in assessing and providing information on transboundary aquifers. There are many initiatives looking at various aspects of transboundary groundwater, including global baseline assessments and more detailed regional or aquifer assessments. Ashton and Turton, (2009), affirms that there are also a number of transboundary aquifers which require strategic management in terms of groundwater resources and water quality.

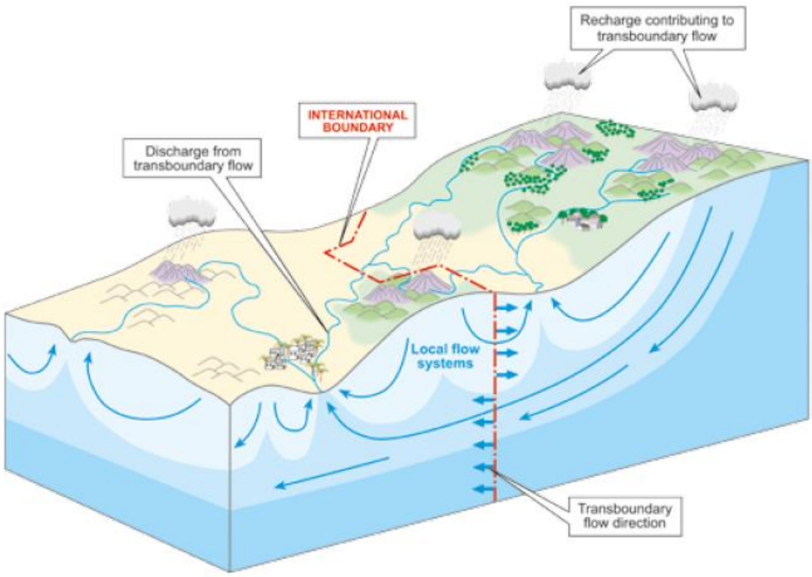


Figure 3-5: Transboundary groundwater (cited in AGW-Net, 2014)

Table 3-1: Evolution of the number of TBAs in Africa inventoried and mapped by various efforts and subdivided into regions (Altchenko and Villholth, 2013)

African region[a]	UNESCO, 2004	WHYMAP, 2006	IGRAC, 2009	IGRAC, 2012a	Altchenko and Villholth, 2013
North Africa	6	6	7	9	15
Western and Central Africa (excluding SADC[b] countries)	9	9	9	22	22
Eastern Africa (excluding SADC countries)	5	5	5	6	8
Southern Africa (SADC countries)	18	20	20	34	35
Total	38	40	41	71	80

[a]United Nations sub-region definition (UN data, 2013).
[b]Southern African Development Community.

3.6 Resource availability

3.6.1 Groundwater storage

Understanding and characterising Africa's groundwater pollution and groundwater-to-nitrate contamination requires an understanding of the spatial distribution of groundwater storage, aquifer permeability and annual rate of recharge. Groundwater is Africa's most precious natural resource, providing reliable water supplies to at least a third of the continent's population (MacDonald, 2010). However, the African continent is not blessed by a large quantity of groundwater resources; it is the world's second-driest continent after Australia and water resources are limited. Total groundwater storage in Africa is estimated at 0.66 million km^3 with a range in uncertainty of between 0.36 and 1.75 million km^3 (MacDonald et al., 2012). According to these authors, not all of this groundwater storage is available for abstraction, but the estimated volume is more than 100 times estimates of annual renewable freshwater resources on Africa. Figure 3-6 shows groundwater storage across Africa, which has been estimated by MacDonald et al. (2012) by combining the saturated thickness and effective porosity of aquifers. We observe that large sedimentary aquifers in North Africa contain a considerable proportion of Africa's groundwater. Many of the large, North African aquifers are not actively recharged, but were recharged more than 5000 years ago when the climate of the area was wetter (Scanlon et al., 2007). Abstraction from these aquifers is considered to be mining fossil groundwater. According to MacDonald et al.(2013), away from the arid areas of Africa, groundwater recharge generally occurs on at least decadal timescales (Taylor et al., 2012), and ongoing monitoring can assist in identifying whether abstraction for irrigation is in excess of long term recharge and would deplete groundwater storage (MacDonald et al.,2013). For example, countries such as– Libya, Algeria, Sudan, Egypt and Chad – in this region have the largest groundwater reserves and fossil groundwater.

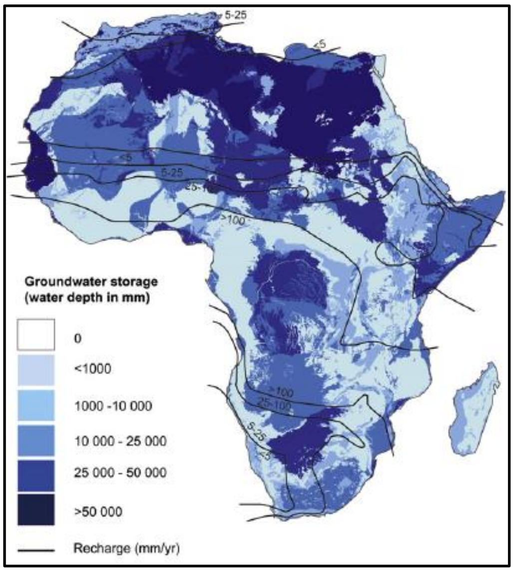


Figure 3-6: Groundwater storage map for Africa, expressed as water depth in millimetres, with modern annual recharge for comparison (MacDonald et al., 2012)

Despite the importance volume of groundwater estimated by MacDonoald et al. (2012) for Africa and mentioned above, the water resources are influenced by the evaporation/evapotranspiration. To this regard, by modeling global-scale groundwater recharge, Döll and Fiedler (2008) affirms that total internally renewable water resources of a country are equal to the sum of net cell runoff of all cells within the country. They can be smaller than the groundwater resources, or even negative. The latter is the case in Botswana, Egypt and Malawi, where more water evapotranspirates from land, wetlands and lakes than falls as precipitation inside the country. Döll and Fiedler (2008) added the groundwater resources of Chad, Mali, Senegal, Sudan, The Gambia, Uganda and Zambia are larger than the total internally renewable water resources due to evaporation of external water from open water surfaces. According to them, other semi-arid countries that are strongly affected by evaporation from surface waters (e.g., Burkina Faso and Central African Republic), groundwater use may have the potential to decrease evaporation from surface waters and thus to increase total water resources.

3.6.2 Aquifer productivity

The accessibility of groundwater resources is as important as overall storage in determining how far groundwater can support nations and communities in adapting to climate change and population growth (Calow et al., 2010). Generally, groundwater is accessed and abstracted by drilling boreholes, and the yield of the borehole limits the rate at which groundwater can be abstracted. Figure 3-7 is a groundwater productivity map and indicates what boreholes yields can reasonably be expected in different hydrogeological areas. The ranges indicate the approximate interquartile yield range of boreholes that have been sited and drilled using appropriate techniques, rather than those drilled at random. The most productive and high-storage aquifers that have been mapped in Africa are the large sedimentary basins in North Africa.

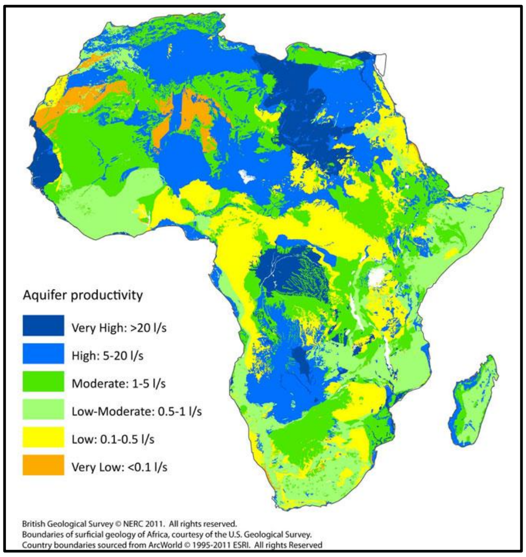


Figure 3-7: Groundwater productivity map (MacDonald et al. 2011)

3.7 Pressures on water quality in Africa

Groundwater is considered the major source of water supply and provides water for domestic use, agriculture and industry in Africa. It represents approximately 75 per cent of Africa's total drinking water and is an integral component of the water cycle. In many countries in SSA, groundwater plays an important role in providing domestic supplies to the rural population. For example, according to SADC statistics, groundwater is the primary drinking water source for both humans and livestock in the driest areas of the SADC, and it is estimated that about 60 per cent of the population depends on groundwater resources for domestic water. In addition to small-scale groundwater use in rural areas, there is pronounced use in many urban centres. The large cities in SSA that are groundwater-dependent are shown in Figure 3-8. Even in cases where groundwater is a small fraction of total water use, it represents a stable source of water (particularly in dry years) and this is one of its important characteristics. In addition to the large cities shown Figure 3-8, several urban centres not included in this map also depend on groundwater and many small towns are dependent on groundwater for their water supply. However, in many areas in recent years, extracting groundwater has become more difficult because of over-exploitation. Growing populations and rising economies have resulted in increasing consumption of water and discharge of wastewater, which causes heavy pollution (Omosa et al., 2012). For example, groundwater that is subject to unplanned and excessive abstraction in coastal cities is inducing saltwater intrusion, resulting in permanent damage to coastal aquifers. According to Steyl and Dennis (2010), it is also clear that the majority of urban centres are located in coastal regions, and as such may be impacted by saline intrusion. Comte et al., (2016) affirms that the management of coastal groundwater poses further challenges due to its vulnerability to seawater contamination, and because of the specific physical and socio-economic characteristics of the coastal zone.

In terms of quality, Africa has an adequate groundwater reservoir for future generations. However, agriculture can severely degrade groundwater resources. The water quality of groundwater is becoming a major concern (UNEP, 2011; Takem et al., 2010) and continuous abstraction together with anthropogenic activities represent the main sources of groundwater pollution in Africa. For example, in Sub-Sharan of Africa the issue of the vulnerability of critical urban groundwater sources to anthropogenic contamination has to date received little attention compared to other regions globally Lapworth et al. (2017). To illustrate the problem of nitrate pollution in urban centres in SSA, Lapworth et al. (2017) represented on the Figure 3-9 the mean nitrate recorded per urban groundwater study, compared with the DRASTIC risk aquifer vulnerability (from Ouedraogo et al. 2016) and maximum population density in the settlement studied. Figure 3-10 shows a growing low-income urban population in Africa. According to Pravettoni (2011), the slum areas tend to lack infrastructure such as pipe-borne water and sewerage, and services such as garbage collection and waste management are often non-existent. In the context of rural in Africa, MacDonald and Calow (2009) argue that increasing use and construction of household latrines pose a considerable threat to groundwater supplies. At the multi-country level, the map of Figure 3-11 shows the eleven countries studies on the project, "Assessment of the Pollution Status and Vulnerability of Water Supply Aquifers of African Cities" realised by UNEP (from M'mayi, 2014). Indeed, contaminants can migrate vertically to the aquifer and then to the borehole or, more dangerously, horizontally through permeable soils to poorly constructed supplies, particularly in African informal settlements (See Figure 3-12, Figure 3-13, and Figure 3-14). Also, current intensive agriculture practices lead to excess nitrate in soil and groundwater. Fertiliser use and irrigation returns can degrade water quality by increasing nitrate concentrations and salinity (Scanlon et al., 2007; Ó Dochartaigh et al., 2010). Furthermore, the production process that modern mining entails has the potential to affect the environment in several ways, e.g. through acid rock drainage, contamination of ground and surface water, and emission of air pollutants according to U.S. Environmental Protection Agency (2000), Environment Canada (2009) and Natural Resources Canada (2010) cited in Aragon and Rud (2012). Furthermore, Aragon and Rud (2012) affirms that mining operations can also affect water quality when waters (natural or wastewater) infiltrate through surface materials into the groundwater and pollutes it with contaminants such as metals, sulphates and nitrates. A few examples in relation with mining activities and nitrate pollution were found in Africa. By studying nitrate pollution from open-pit mines in the Limpopo province of South Africa, Bosman (2009) found a serious nitrification (57 mg/l) of a community drinking water supply near an open-pit mine, which was identified as the cause of the contamination, after other potential sources. ActionAid (2008) analysed water samples taken at three sites in Ga-Molekane village (Limpopo province in South Africa), near community for drinking water next to the river. They found that water was unfit for human consumption, containing high concentrations of total dissolved salts, sulphate and nitrate.

Although the possible cause could be raw sewage seeping into the groundwater recharge zone, the report noted that the most probable cause was mining activities. In addition, a second water sample was taken at Ga-Pila village in the same province, in a seep made by the community for their drinking water next to the river. This sample showed the water to be unfit for human consumption, because it contains high concentrations of total dissolved salts, sulphate and nitrate. The report found that it could be safely deduced that the cause of contamination was mining activities. According to MacDonald et al. (2013), elevated nitrate concentrations in the water environment can have a major impact on ecosystems and detrimental health effects for humans. Nitrate is the most important pollutant in Africa (Xu and Usher, 2006) and concentrations in groundwater have dramatically increased in the last decade. The allowable upper limit for nitrate in drinking water (50 mg/L as NO_3^-, according to WHO value) has already been exceeded in many parts of Africa.

Despite all the pressures on groundwater bodies, stemming from different sources (including urbanisation, landfills, wastewater and solid wastes, and nonpoint agricultural agrochemicals), the use of fertilisers (organic and inorganic) to ensure high crop production is continuously increasing in Africa. This has led MacDonald et al. (2013) to declare that almost all groundwater abstraction and land use activities will have some impact on groundwater. Therefore, management strategies generally focus on minimising impacts, particularly for third parties, rather than eradicating them altogether, because water pollution not only reduces available freshwater but also affects human and ecosystem health (Armstrong, 2009; Pickering and Davis, 2012; Montgomery and Elimelech, 2007).

Figure 3-8: Groundwater dependent cities in Africa (Morris et al., 2003)

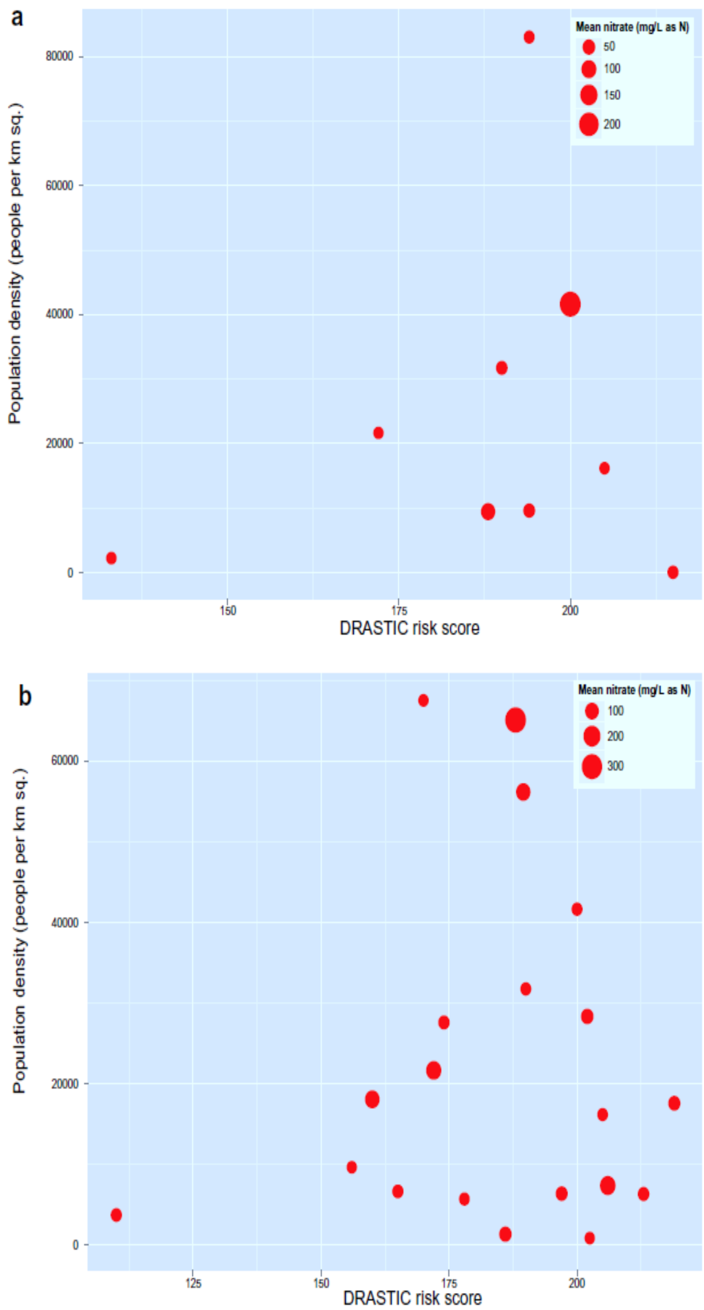


Figure 3-9: Relationship between mean nitrate levels, population density, and DRASTIC aquifer vulnerability risk score among 31 studies that a predominantly sampled boreholes and b predominantly sampled wells and springs (Lapworth et al. 2017).

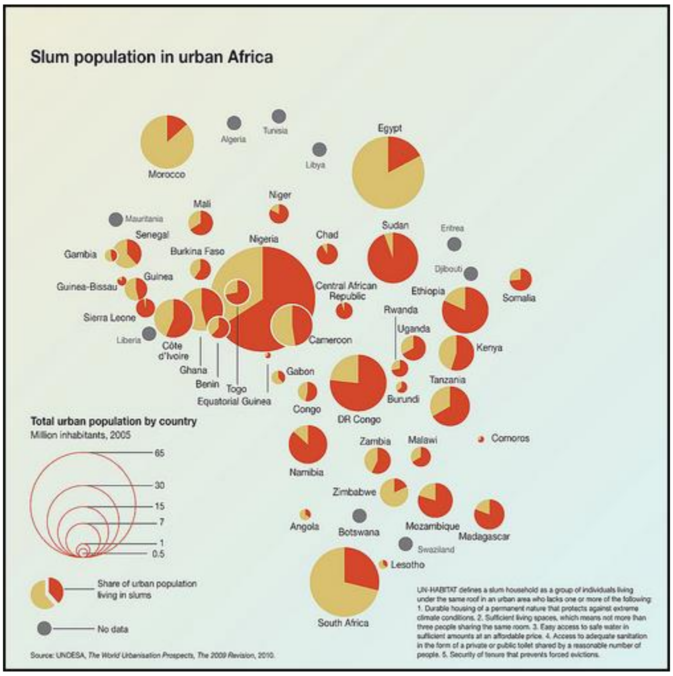


Figure 3-10: Slum population in urban Africa (from Pravettoni, 2011)

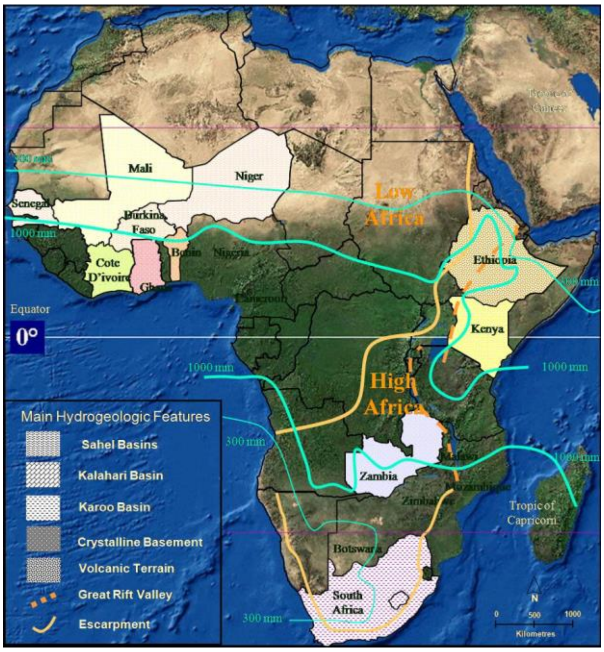


Figure 3-11: Eleven countries in the project (M'mayi/ UNEP/DEWA, 2014)

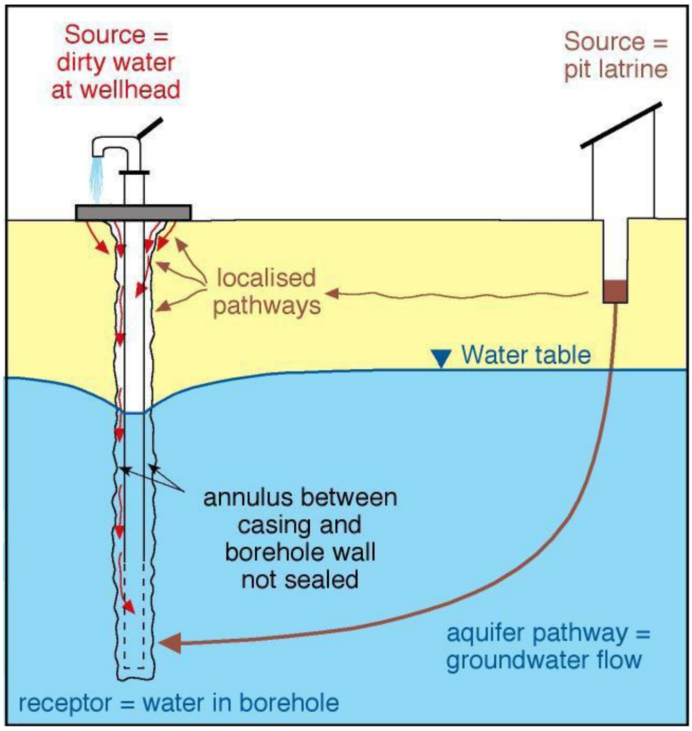


Figure 3-12: The source/pathway/receptor concept for groundwater pollution (MacDonald, n.d)

Figure 3-13: South African informal settlements (UNEP/DEWA, 2014)

Figure 3-14: Relating groundwater source vulnerability to land use: (A) a vulnerable, unlined, shallow well adjacent to the road in a lower cost housing area; (B) a shallow well and a borehole with protective headworks, located in gated properties within higher cost areas; (C) a fully-sealed public water supply borehole within a secure compound in the peri-urban Mukobeko wellfield in Zambia (Sorensen et al., 2015a).

As an example, Figure 3-15 shows the temporal evolution of nitrate concentrations in the groundwater system for the city of Abidjan, Ivory Coast. Observations of evolving average annual levels of drilling water nitrate in Abidjan over 11 years, from 1992 to 2002, show a steady increase. The author (Ahoussi et al., 2013), concludes that the temporal distribution of water nitrate levels in groundwater demonstrates that nitrate levels have risen for decades. This increase in nitrate levels is related to population growth and increased urbanisation, highlighting the significant pressure exerted by human activities on the city's groundwater, which contribute to the degradation of its quality. Another example, Figure 3-16 shows the spatial distribution of nitrate concentrations in country scale of Burkina Faso. We observe that higher levels of nitrate concentration is found in everywhere on the map and boreholes/wells have a nitrate concentration above the WHO standard. Table 3-2 presents an overview of typical problems caused by groundwater pollution in Africa, as proposed by Wang et al. (2014).

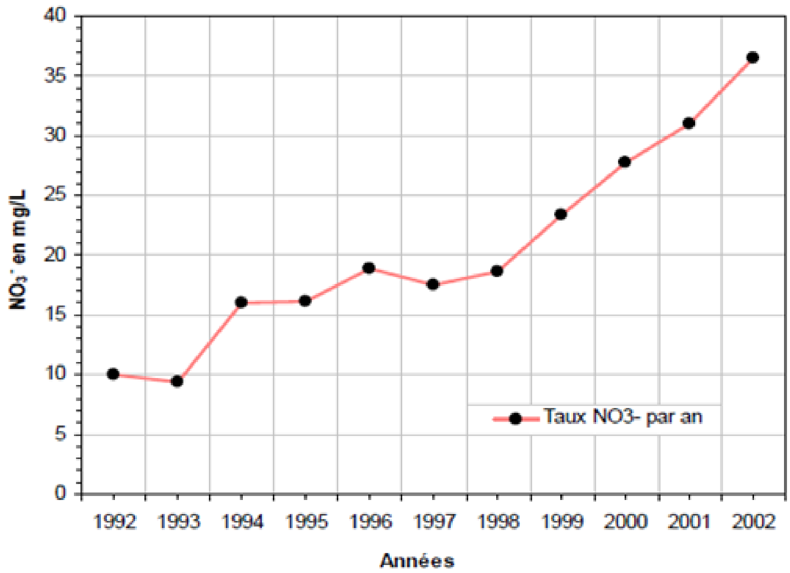


Figure 3-15: Evolution in average levels of drilling water nitrate in Abidjan city (Ahoussi et al. 2013)

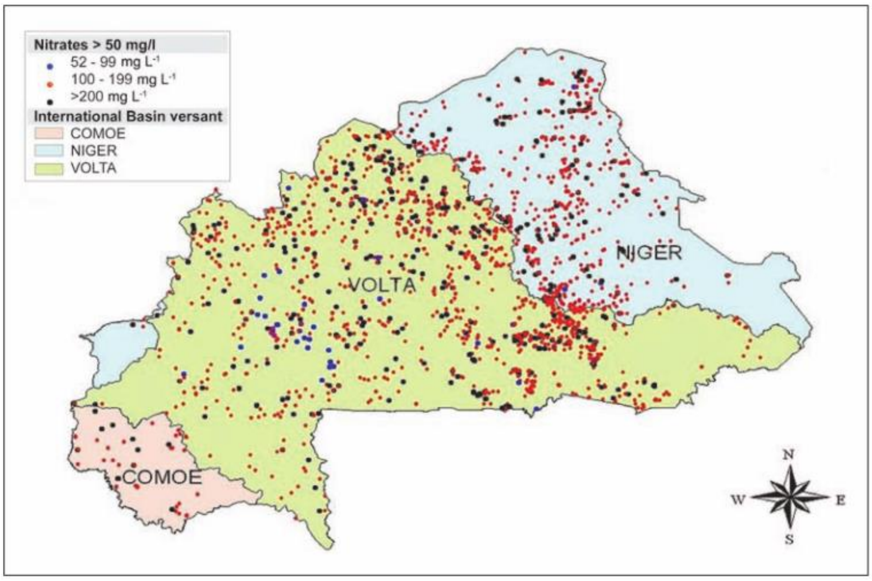


Figure 3-16: Groundwater nitrate distribution in Burkina Faso (Pavelic et al. 2012)

Table 3-2: Typical problems of groundwater pollution (Wang et al. 2014)

City/country	Problems of groundwater pollution
Port-Harcourt, Nigeria	Over 80 per cent of drinking water is reliant on groundwater, but the shallow water table makes it prone to pollution, for example by untreated wastewater. This increases the risks of water-borne diseases (UNEP, 2010).
Nairobi, Kenya	1. Nairobi's upper aquifer is particularly vulnerable to pollution from human activities such as landfills and dumpsites, leakage from underground storage of petroleum and chemicals, and infiltration from polluted streams (Li et al., 2011). 2. Industrial wastewater and pesticides lead to groundwater pollution.
Kisumu, Kenya	Although groundwater is easily available (groundwater levels are 2–5m from the soil surface), the water supply in this area is still dependent on surface water because groundwater is susceptible to contamination due to inadequate drainage and overflowing pit latrines (Parkman et al., 2008).
Thiaroye, Dakar, Senegal	Concentrations of NO_3^- in groundwater can be over 50 mg/L, which is due to the overuse of agricultural fertilisers (UNEP, 2011).
Ghana	Chemicals in borehole water from 38 per cent of samples exceed the WHO guidelines. Typical contaminants are nitrate (NO_3^-), manganese (Mn) and fluoride (F^-) (Rossiter et al., 2010).
Bolama Island, Guinea-Bissau	Around 79 per cent of wells show moderate to heavy faecal contamination (Bordalo et al., 2007).
Addis Ababa, Ethiopia	Toxicant leachate from dumped solid waste is a major factor in groundwater contamination.
Northern Mali and Zambia	Arsenic pollution, both geogenic or anthropogenic, is a common contaminant in groundwater. This is also a global challenge.
Kampala, Uganda	1. Pit-latrines deteriorate groundwater quality (UNEP, 2011). 2. Dilapidated pipelines result in the contamination of groundwater (ibid).
Sirte, Libya	Groundwater is becoming salted because of water intrusion from the Mediterranean Sea. The salt water results in higher costs of desalination (Gossel et al., 2010).

Chapter 4 Mapping the groundwater vulnerability for pollution at the pan African scale[1]

[1] Based on:
Ouedraogo, I., *Defourny, P., Vanclooster, M. (2016). Mapping the groundwater Vulnerability for pollution at the pan-African scale. Science of the Total Environment, Vol. 544, p. 939-953.DOI: 10.1016/j.scitotenv.2015.11.135*
Ouedraogo, I., *and Vanclooster, M. (2016). Shallow groundwater poses pollution problem for Africa. In: SciDev.Net. 4 pp, http://hdl.handle.net/2078.1/169630*

4.1 Abstract

We estimated vulnerability and pollution risk of groundwater at the pan-African scale. We therefore compiled the most recent continental scale information on soil, land use, geology, hydrogeology and climate in a Geographical Information System (GIS) at a resolution of 15 km x 15 km and at the scale of 1:60,000,000. The groundwater vulnerability map was constructed by means of the DRASTIC method. The map reveals that groundwater is highly vulnerable in Central and West Africa, where the water table is very low. In addition, very low vulnerability is found in the large sedimentary basins of the African deserts where groundwater is situated in very deep aquifers. The groundwater pollution risk map is obtained by overlaying the DRASTIC vulnerability map with land use. The northern, central and western part of the African continent is dominated by high pollution risk classes and this is very strongly related to shallow groundwater systems and the development of agricultural activities. Subsequently, we performed a sensitivity analysis to evaluate the relative importance of each variable on groundwater vulnerability and pollution risk. The sensitivity analysis indicated that the removal of the impact of the vadose zone, the depth of the groundwater, the hydraulic conductivity and the net recharge causes a large variation in the mapped vulnerability and pollution risk. The mapping model was validated using nitrate concentration data of groundwater as a proxy for pollution risk. Pan-African concentration data were inferred from a meta-analysis of literature data. Results show a good match between nitrate concentration and the groundwater pollution risk classes. The pan African assessment of groundwater vulnerability and pollution risk is expected to be of particular value for water policy and for designing groundwater resources management programmes. We expect, however, that this assessment can be strongly improved when better pan African monitoring data related to groundwater pollution will be integrated into the assessment methodology.

4.2 Introduction

Groundwater is an important water resource for meeting the various water demands in Africa. It is vital for supporting the socio-economic development of the continent, as well as for maintaining a wide diversity of ecosystem functions and services. However, the booming population in Africa, together with climate change, increase the pressure on the African groundwater resources considerably, both in quantity as in quality. For defining sustainable water resources management plans at the continental scale, assessments of groundwater resources and associated pressures are strongly needed (Hasiniaina et al., 2010).

Several studies have already been undertaken to improve the knowledge of African groundwater systems. At the local scale, Xu and Usher (2006) recently compiled information from the UNEP/UNESCO project "Assessment of pollution Status and Vulnerability of Water Supply Aquifers of African Cities". They confirm that groundwater in African cities is subjected to different pollution pressure exerted by several sources such as leaking sewage systems, solid waste dumpsites, household waste pits, surface water infiltration spots, peri-urban agriculture sites, petrol service stations (underground storage tanks) and wellfields. At the continent scale and sub-regional scale, studies include the development of the African groundwater map (WHYMAP, 2008; Seguin. 2008), the assessment of groundwater potential (Wright, 1992; Chilton and Foster, 1995), the assessment of basin yield, storage capacity, flow types and saturated thickness (BGS, 2011), the drought vulnerability in the SADC region (Villholth et al., 2013), the groundwater availability (UNEP, 2010; Palevlic et al., 2012) and the irrigation potential from renewable groundwater (Alchentko et al., 2014). In another continental scale, to support policy, some studies addressed the need for mapping groundwater vulnerability to pesticide leaching EU-wide (Tiktak et al.2004; Tiktak et al. 2006).

Furthermore, Abbaspour et al. (2015) developed also a continental-scale hydrology and water quality model for Europe by using a high-resolution large-scale SWAT model. Schriever and Liess (2007) introduced a screening model of generic indicator termed runoff potential (RP) to characterise the ecological risk of pesticide runoff at the EU-scale. At the global scale, more recently, studies were also undertaken. DeGraaf et al. (2014), for instance, presented the first high-resolution global scale groundwater model. Notwithstanding this recent progress, no study has been made for assessing the pan African scale groundwater vulnerability for pollution. Assessing groundwater quality at the large scale is particularly important for monitoring progress in sustainable development, such as the implementation of the UN SDG for water.

In this context, assessing the groundwater vulnerability to pollution is important for designing efficient regional scale groundwater management and protection strategies. When discussing groundwater vulnerability, a difference can be made between specific vulnerability and intrinsic vulnerability (NRC, 1993). Vulnerability is an intrinsic property of a groundwater system that depends on the sensitivity of that system to human and/or natural impacts (Vrba and Zaporozec, 1994). Specific vulnerability is used to define the vulnerability of groundwater to a particular contaminant or a group of contaminants. For specific vulnerability, specific physico-chemical properties from contaminants are considered (Gogu and Dassargues, 2000). Groundwater pollution risk can be defined as the process of estimating the possibility that a particular event may occur under a given set of circumstances (Voudouris, 2009) and the assessment is achieved by overlaying hazard and vulnerability (Gogu and Dassargues, 2000; Uricchio et al,2004). Several approaches exist for assessing groundwater vulnerability. They can be grouped into methods based on the use of (1) process-based simulation models, (2) statistical models and (3) Multicriteria decision-making (MCDM) models. Dixon et al. (2015) argue that MCDM models are often used to characterize intrinsic aquifer vulnerability (Al-Hanbali and Kondoh, 2008; Gogu and Dassargues, 2000; Farjad et al., 2012; Mimi et al., 2011). Alternatively, they can be classified according to the degree of integration of monitoring data in the vulnerability assessment (Vanclooster et al., 2014). Hence, a distinction can be made between vulnerability assessment methods based on generic data, based on groundwater monitoring data, or hybrid methods based both on monitoring and generic data.

Regional-scale groundwater vulnerability assessment models based on MCDM approach have been widely used to define intrinsic aquifer vulnerability (Honnungar, 2009). Within the Multicriteria decision-making (MCDM) models, the DRASTIC model (Aller et al. 1987) put forth by US Environmental Protection Agency (USEPA) is a prime example of using MCDM for aquifer vulnerability characterization. It is the most used method worldwide, and belong also to the overlay and index methods family. The method has been widely used for regional vulnerability assessments in many countries such as the USA (Fritch et al., 2000; Shuka et al., 2000; Kumarasamy, 2007), China (Yuan et al., 2006), Canada (Liggett et al., 2010), India (Senthilhumar et al., 2014), Turkey (Ersoy et al., 2013),Tunisia (Saida et al., 2010; 2011), South Africa (Musekiwa and Majola, 2013) and Ivory Coast (Jourda et al.,2007), among many others.

MCDM approaches similar to DRASTIC have been used elsewhere as well, and include the SINTACS method (Civita, 1990), the EPIK method (Doerfliger et al.1999), the GOD method (Foster, 1987), the SEEPAGE method (Moore and John, 1990). At large scale, two examples illustrating the use of index overlay methods in their study are: (1) Zhou et al. (2015) evaluated the vulnerability of global groundwater systems to nitrate contamination with GOD method; (2) Jaroslav (UNESCO-IHP) and Richts (BGR) (2015) used DRASTIC method to map the global groundwater vulnerability to floods and droughts at the scale of 1: 25 000 000. The DRASTIC method, as like similar index models, has many advantages: (1) the method has a low cost of application and can be applied at the regional scale, because it is based on often easily available generic data (Aller et al., 1987); and (2) the use of a high number of input data layers is believed to limit the support of errors or uncertainties of the individual data layer in the final output (Evans and Myers, 1990, Rosen, 1994). Despite its popularity, the DRASTIC method has some disadvantages (Neshat et al., 2013). First, many variables are factored into the final number (vulnerability index) that critical parameters in the groundwater vulnerability may be subdued by other parameters that have no bearing on vulnerability for a particular setting (Vrba and Zaporozec, 1994). Hence, in many cases, vulnerability can be explained with a subset of DRASTIC factors. Second, studies based on the DRASTIC method tend to overestimate the vulnerability of porous media aquifers compared to aquifers of fractured media (Rosen, 1994). Third, only few studies have been performed to validate the DRASTIC vulnerability method at the regional scale. Despite these disadvantages, the DRASTIC method can easily be deployed to make continental scale assessment of groundwater vulnerability. To this regard, Honnungar (2009) affirms that regional-scale delineation of aquifer vulnerability represents the first-step of any integrated land-water management paradigm.

The major objective of this study is to assess the groundwater vulnerability and pollution risk at the pan African scale, using the DRASTIC indicator methodology. A specific objective is to identify the quality and sensitivity of the different data layers in the regional scale vulnerability assessment and to assess the validity of the vulnerability assessment using nitrate contamination as a proxy of the vulnerability. To implement the DRASTIC indicator methodology at the pan African scale, a best available database of environmental for the continent was established.

4.3 Materials and methods

4.3.1 The DRASTIC model

In the present study, the DRASTIC method is used for evaluating groundwater vulnerability for pollution. The acronym DRASTIC corresponds to the initials of the seven variables that drives vulnerability as defined according to Aller et al. (1987) and shown in Table 4-1.

The DRASTIC vulnerability index was calculated by the addition of the different products (rating×weight of the corresponding variable), using the following the equation:

$$D_i = D_w D_{r,i} + R_w R_{r,i} + A_w A_{r,i} + S_w S_{r,i} + T_w T_{r,i} + I_w I_{r,i} + C_w C_{r,I} \quad (1)$$

where Di, is the DRASTIC index; D, R, A, S, T, I, and C are the seven variables, as defined in Table 4-1; and the subscripts r,i and w are the corresponding rating for grid cell i and weights.

Table 4-1: Weight settings for DRASTIC variables (Aller et al., 1987)

Symbol	Variable	Weight
D_w	Depth to Water	5
R_w	Net Recharge	4
A_w	Aquifer media	3
S_w	Soil type	2
T_w	Topography	1
I_w	Impact of vadose zone	5
C_w	Hydraulic Conductivity	3

The weights indicate the relative importance of each DRASTIC variable with respect to the other variables. These weights are constant (Ehteshami et al., 1991). Also, for each DRASTIC variable the designated rating varies from 1 to 10. The rating ranges were determined depending on the properties at the pan-African scale. A good knowledge of geology and hydrogeology of the research area is a prerequisite to determine the rating ranges of the parameters (Sener et al., 2009). In general, the ratings assigned in this study were similar to the typical ratings suggested in the original DRASTIC study (Aller et al., 1987). However, they have been adjusted to consider the full variability of DRASTIC variables as retrieved in the present study (Table 4-4 and Table 4-5), similarly as in the example presented by Sener et al. (2009).

Finally, for purposes of interpretation, we subdivided the possible values of the DRASTIC index calculated into five classes of vulnerability, according to the range of indices defined by Jourda et al. (2007):

- $D_i > 176$ is considered to have a very high vulnerability;
- $146 < D_i < 175$ is considered to have a high vulnerability;
- $115 < D_i < 145$ is considered to have a moderate vulnerability;
- $84 < D_i < 114$ is considered to have a low vulnerability; and
- $D_i < 84$ isconsidered to have a very low vulnerability.

4.3.2 Data acquisition and data base compilation

We constructed a GIS data base for the hydrogeology, the geology, the soil, the groundwater recharge and topography of Africa. Table 4-2 shows the metadata of the constructed GIS data base. We processed all data with ArcGIS 10.2™, QGIS™ 2.2 and Matlab™.

Data came in various spatial resolutions. Before processing the data, it is important to keep in mind data processing errors identified by Murat et al.(2004): the errors refer to data handling and integration such as format conversion, structure of data storage (raster/vector), geometric and positioning system transformation, spatial analysis (buffering, overlaying), querying, updating, etc. Notwithstanding uncertainty associated with spatial data processing, all our GIS data were converted to raster form by projecting the data into a world sinusoidal projection appropriate for the continental scale of Africa. This type of projection represents areas accurately. We resampled GIS datasets to determine the adequate spatial resolution. For example, in the case of land cover/land use and soil, the resampling was performed with the nearest neighbor method consistent with categorical scaling of the data. While, for continuous data such as topography (slope), or recharge, we resampled using the bilinear interpolation algorithm until we achieved our choice of resolution. We proposed a 15 km x 15 km resolution for this study. We consider that this resolution is a reasonable compromise between different resolutions of the different datasets, computing constraints and regional extent. We obtained the vulnerability and risk maps, after classifying and assigning relative ratings and weights, then overlaying the individual maps in a GIS. We consider that this resolution is a reasonable compromise between different resolutions of the different datasets, computing constraints and regional extent. We obtained the vulnerability and risk maps, after classifying and assigning relative ratings and weights, then overlaying the individual maps in a GIS.

4.3.3 Development of the DRASTIC variables

Figure 4-1 gives an overview of the methodology used to develop the intrinsic groundwater vulnerability map. Each variable processed in the GIS is described below.

4.3.3.1 Depth of groundwater (D)

The 'Depth to water table' (D), is the vertical distance from the land surface to the top of the saturated zone in the aquifer. It represents the distance that a potential contaminant must travel before reaching the aquifer. Consequently, the D will have an impact on the degree of interaction between the percolating contaminant and the sub-surface materials (air, minerals, water) and, therefore, on the degree and extent of the physical and chemical attenuation and the degradation process (Rahman, 2008). In general, the vulnerability for pollution decreases with D. The D was calculated from the data as presented by Bonsor et al. (2011). The original value of this variable was not continuous and was obtained in a categorical data format.

4.3.3.2 Net Recharge(R)

The 'Net Recharge', R, represents the amount of water per unit area of land penetrating the ground surface and reaching the water table. It is thus influenced by the amount of surface cover, the slope of the land surface, the permeability of the soil and the amount of water that recharge the aquifer. The dispersion and dilution of contaminants depend greatly on the volume of water available in the vadose zone as well as in the saturated zone and thus on the net recharge. High recharge areas are more vulnerable than low recharge areas. Net recharge was derived from the global-scale modeling of groundwater recharge as presented by Döll and Fiedler (2008).

Table 4-2: Data used for the creation of the seven variable data layers of the pan African DRASTIC model

Raw data	Sources	Format	Resolution/Scale	Date	Output layer
Depth to groundwater map	British Geological Survey (http://www.bgs.ac.uk/)	xyzASCII file	5km	2012	Depth of water (D)
Recharge data	P.Döll and F. Portman (University of Frankfurt)	Shapefile	0.5°x0.5°	2008	Recharge (R)
The new global lithological map database (GLiM)	Nils Moosdorf (HamburgUniversity)	File Geodatabasefeature	1:3750 000	2012	Aquifer media (A)
Soil data	ISRIC, World Soil Information	Raster	1km×1km	2014	Soil type(S)
SRTM90	UCL/ELIe-Geomatics (Belgium) and CGIAR/CSI	Raster	90mx90m	2000	Topography (T) or slope (%)
The new global lithological map(GLiM)	Nils Moosdorf (HamburgUniversity)	File Geodatabasefeature	1:3750 000	2012	Impact of Vadose zone(I)
Global HYdrogeologyMaPS (GLYMPS) of permeability and porosity	T;P;Gleeson (McGill University)	File Geodatabasefeature	Average size of polygon ~100km2	2014	Hydraulic Conductivity(C)
Land cover/land use map	UCL/ELIe-Geomatics (Belgium)	Raster geotiff	300mx300m	2014	Land Use(LU)

4.3.3.3 Aquifer media (A)

The 'Aquifer media', *A*, refers to type of consolidated or unconsolidated material which hosts the aquifer (Esroyet al., 2013). *A* was inferred from three main data sources: (1) the high resolution global lithological database (GliM) of Hartmann and Moosdorf (2012); (2) the global permeability estimates of Gleeson et al.(2011); and (3) the African hydrogeology and rural water supply map of MacDonald et al. (2008). The analysis of the global permeability has permitted to identify parent material for each hydrolithologic unit. The GLiM data bases encompass 16 lithological classes, is similar to the number of classes as used in the study of Dürr et al. (2005). In this work, we assumed that the lithological map represents the geology. Aquifer media were determined of each of the five hydrolitholigies, defined as broad lithologic categories with similar hydrogeological characteristics (Gleeson et al., 2011). These categories are unconsolidated sediments, siliciclastic sediments, carbonate rocks, crystalline rocks and volcanic rocks (Gleeson et al., 2014). Aquifer media and Impact of vadose zone were inferred from GLiM and global permeability data. The vulnerability of the aquifer will increase if the grain size and the fractures or openings within the aquifer will increase (Alwathafet al., 2011).

4.3.3.4 Impact of the vadose zone (I)

The role of the unsatured zone above the water table is integrated in the I variable. It is an important variable in the estimation of vulnerability, because it influences the residence time of pollutants in the unsaturated zone, and hence the attenuation probability. Similar to the A variable, the method used to identify the vadose zone material depend on GLiM data and the African hydrogeological map, based on each parent material type that is the same as for aquifer media. The weights and ratings for I are shown in Table 4-5 and Figure 4-9, and correspond to the map layer created for the vadose zone.

4.3.3.5 Topography (T)

The'Topography', T, determines the runoff and infiltration capacity of the surface water into the soil, and hence the capacity to introduce pollutants into the soil. If the slope is important, more runoff will be generated and hence groundwater contamination risk will be low. However, flat areas tend to retain water for a long time, therefore increasing the potential for migration of contaminants. The T was inferred from the 90 meter Shuttle Radar Topography Mission (SRTM90) database. The slope values were generated with the SRTM 90 by using the Spatial Analyst software of ArcGIS10.2TM. The slope layers were resampled and reclassified with the ratings into six classes.

4.3.3.6 Soil media (S)

Soil is the first media the contaminant passes through when it percolates into the ground. According to Lee, (2003), soil has a significant impact on the amount of recharge that can infiltrate into the ground, and hence on the ability of a contaminant to move vertically into the vadose zone. For this study, the soil map of Africa was inferred from the data processed by Hengl et al. (2014).

4.3.3.7 Hydraulic conductivity (C)

The 'Hydraulic conductivity', C, is a measure of the ability of the aquifer to transmit water when submitted to a hydraulic gradient. It determines the migration velocity of pollutants, and hence the residence time and attenuation potential. High conductivity values will be associated to high contamination risks (Rahman A., 2008). We inferred the hydraulic conductivity map from the global hydrogeological map of permeability and porosity, as produced by Gleeson et al. (2014). This global permeability map is given in log permeability (log (k)). From our case, the hydraulic conductivity is more useful. We converted k permeability into K hydraulic conductivity as follows:

$$K= \quad k*rho*g/mu \qquad (2)$$

where K (m/s) is hydraulic conductivity which depends on fluid viscosity and density, rho (kg/m^3) is the density of the fluid, normally water=999.97 kg/m^3, g (m/s^2) is the acceleration due to gravity=9.8 m/s^2; and mu (kg/m.s or Pa.s) is the viscosity of the fluid. Hence, following Gleeson et al., (2014), we use the following conversion:

$$K=k*1e+7 \qquad (3)$$

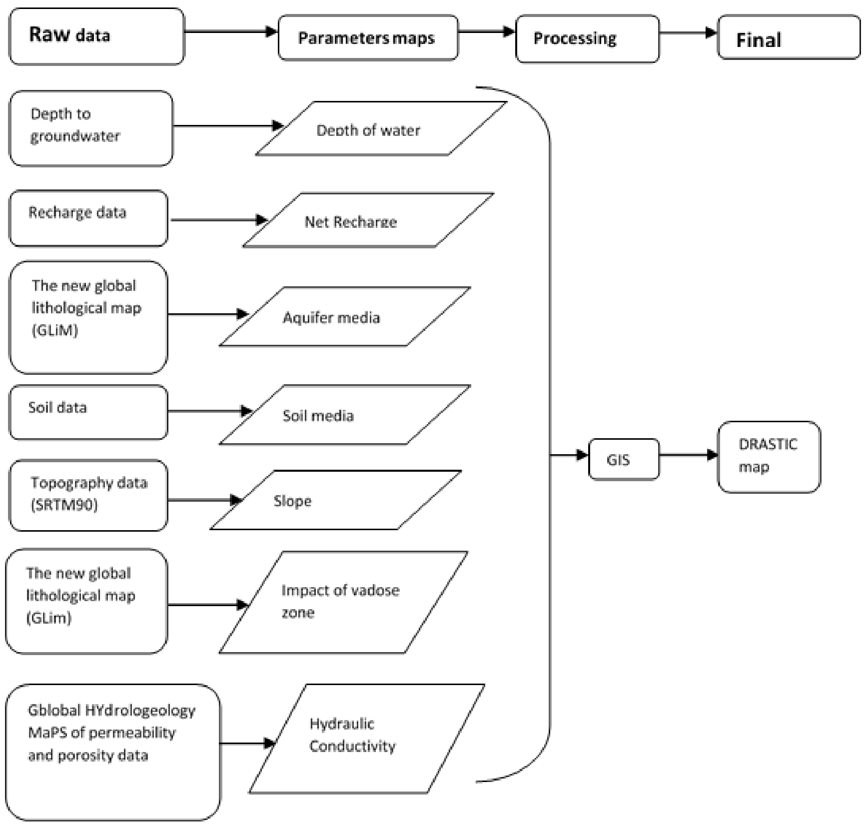


Figure 4-1: Flow chart of the methodology used to develop the groundwater vulnerability map using the DRASTIC model in GIS

4.3.4 Sensitivity analysis

One of the major advantages of the DRASTIC model is the fact that a high number of input data layers is used (Evan & Myers, 1990). Indeed, increasing the number of data layers limits the impact of errors or uncertainties of the individual parameters on the final output (Rosen, 1994). Some scientists agreed that groundwater vulnerability assessment can be studied without considering all the factors of the DRASTIC model (Merchant, 1994); yet this opinion is not shared by others (e.g. Napolitano and Fabbri 1996). We, therefore, performed a sensitivity analysis that provides information on the influence of rating and weights assigned to each of the factors considered in the model (Gogu and Dassargues 2000). Two sensitivity analyses tests were performed: the map removal sensitivity analysis introduced by Lodwick et al. (1990), and the single parameter sensitivity analysis introduced by Napolitano and Fabbri (1996).

The map removal sensitivity identifies the sensitivity of the vulnerability map towards removing one or more maps from the analysis and is computed by the following equation:

$$Si = (|Di/N - D'i/n|/Di) \times 100, \qquad (4)$$

where Si is the sensitivity index, Di is the unperturbated vulnerability index, D'i is the perturbated vulnerability index, i is the grid cell index, and N and n are the number of data layers used to calculate Di and Di'. We considered the vulnerability index obtained using all the seven parameters as an unperturbated vulnerability index and the vulnerability computed using fewer parameters layers as the perturbated vulnerability.

The single-parameter sensitivity measure was developed to evaluate the impact of each of the DRASTIC parameters on the vulnerability index. It allows comparing the “effective” weight with their “theorical” weight (Babiker et al., 2005). The “effective” weight of each parameter in each subarea is computed using the following equation:

$$Wi = (P_{r,i} \times P_w / Di) \times 100 \quad (5)$$

where Wi refers to the “effective” weight of each parameter, $P_{r,i}$ and P_w are the rating value and the weight of each parameter respectively, and Di is the overall vulnerability index.

4.3.5 Development of groundwater risk map

The groundwater pollution risk corresponds to the potential of a groundwater body for undergoing groundwater contamination (Farjad et al., 2012). The risk of pollution is determined both by the intrinsic vulnerability of the aquifer, which is relatively static, and the existence of potentially polluting activities at the soil surface. These latter activities are time dynamic and can be controlled (Saidi et al, 2010). Land use information is often used as a proxy for pollution pressure at the soil surface. In this study, the high resolution land cover/land use map was obtained from the GlobCoverdataset (Mayaux et al., 2013). We used the land use categories as defined by Mayaux et al. (2013). Land use is thus grouped into five classes namely (1) forests, (2) woodlands, shrub lands and grasslands, (3) agriculture, (4) bare soil and (5) other land-cover classes (water bodies and cities). We generated the groundwater pollution risk map by combining the intrinsic groundwater vulnerability map with the land use map, using the additive model of Secunda et al. (1998).

Hence, the land use (L) is incorporated here into the risk model as an eighth parameter. Using the following DRASTIC equation, modified from Secunda et al. (1998):

$$MD_i = D_i + L_{r,i} \times L_w \quad (6)$$

where MD_i is the modified DRASTIC index for risk assessment, D_i is the DRASTIC index and $L_{r,i}xL_w$ is the multiplication of rating for grid cell i and weight for land use.

In order to evaluate the groundwater pollution risk map at the pan African scale, the land use/land cover map was combined with the DRASTIC vulnerability map. The weight (Lw =5) used for the land use layer is the value defined by Secunda et al. (1998). The land cover/land use map (Figure 4-2) was geo-referenced and also converted to a raster grid format. The twenty two classes of land cover/land use were reclassified into six major classes: forest/tree, croplands, grassland/shrubland, bare areas, and urban area and water bodies (Figure 4-3). Subsequently, land cover/land use was rated according to the values in Table 4-3.

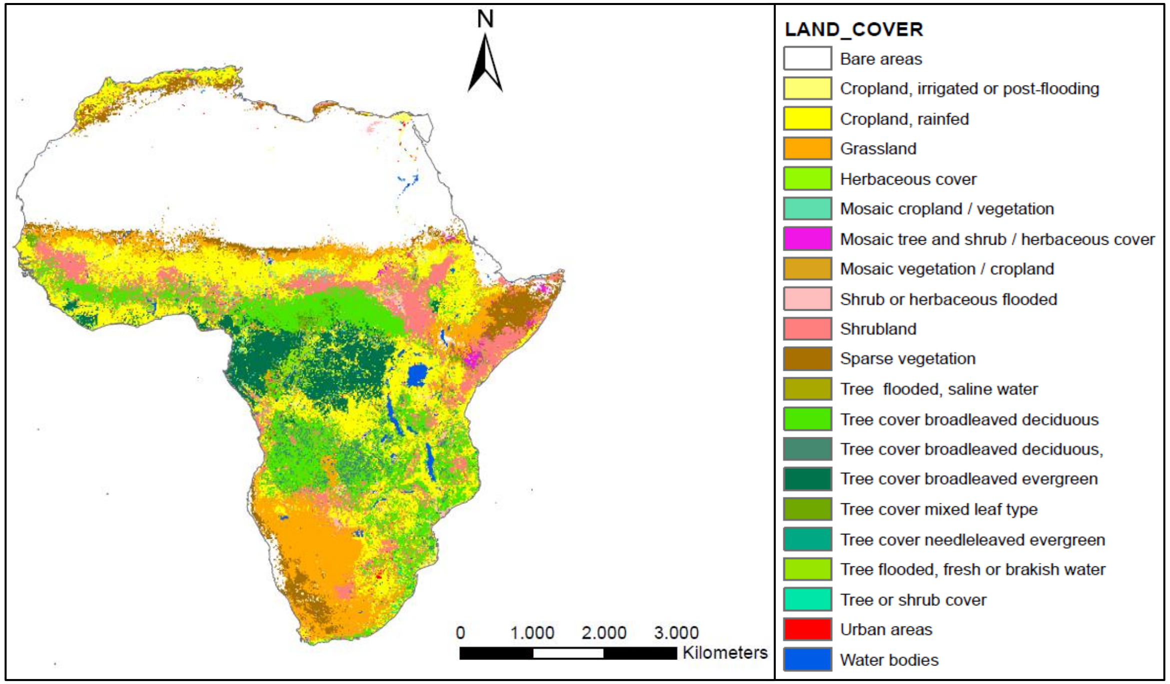


Figure 4-2: Land cover/ land use map for Africa (modified from Defourny et al. 2010)

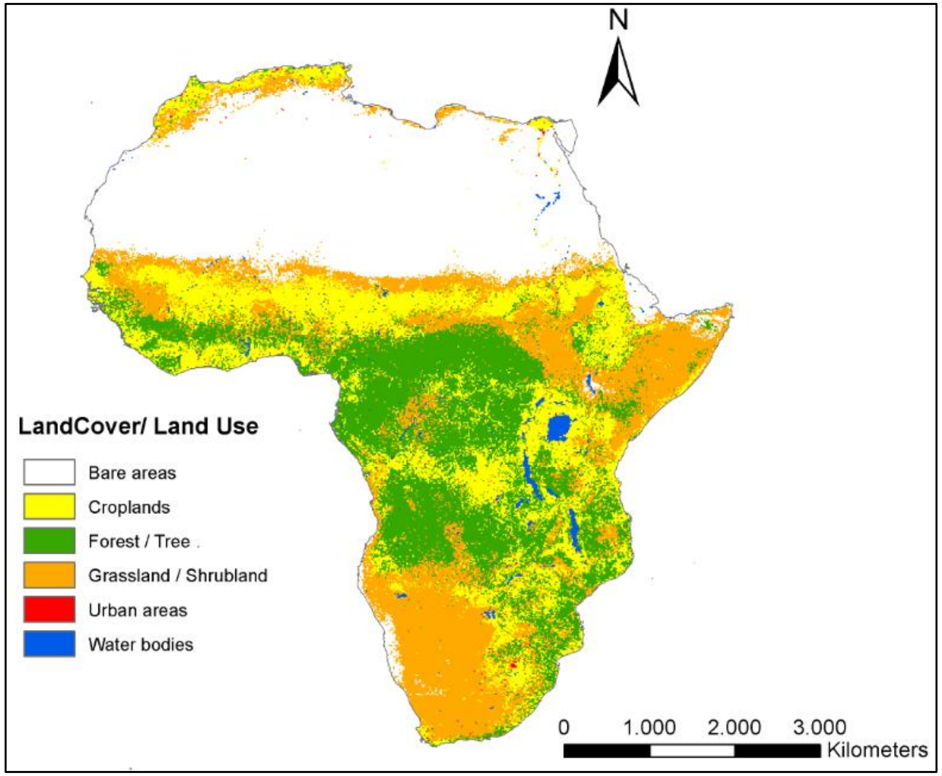


Figure 4-3: Reclassify categories of land cover/land use map (modified from Defourny et al. 2010)

Table 4-3: Rating of Land use in this study:
[a]after: Bataineh et al; [b]after: Dickerson, (2007), [c]after:Secunda et al., (1998),[d]after: from Shrirazi et al., (2012).

Land Cover/Land use	Rating
[a]Urban	8
[b]Croplands	10
[b]Grassland/Shruland	4
[c]Tree/Forest	1
[a]Water bodies	3
[d]Bare areas	1

4.3.6 Validation using observed nitrate concentration data

The above mentioned modified DRASTIC model is an indirect method for evaluating vulnerability and pollution potential of groundwater systems on a regional scale. This method heavily relies on accessible generic data and should therefore be validated. Indeed, the use of methods that are not validated can result in erroneous conclusions and subjective vulnerability assessment (Leal and Castillo, 2003). However, since intrinsic and specific vulnerabilities only measure the likelihood that groundwater systems may be degraded, or become degraded in the future, it cannot be measured directly in-situ. This challenges the empirical validation of vulnerability mapping (Andrea et al. 2005). In this study we implement the approach as presented by Sulmon et al. (2006), and compare the vulnerability patterns with proxies of vulnerability that can be measured in-situ. In this paper, we use the degradation of groundwater systems by nitrates as a proxy for vulnerability. We select nitrate in groundwater as a proxy since anthropogenic activities like agriculture or urban development are the principle causes of groundwater pollution by nitrates. Also, many groundwater monitoring programs include nitrate as a monitoring parameter, and therefore nitrate contamination data are widely available at the regional scale. The spatial patterns of nitrate contamination are therefore closely related to the spatial patterns of anthropogenic activities and are therefore good proxies for the spatial patterns of overall vulnerability. In our study, we compared groundwater nitrate concentration inferred from a meta-analysis with the aforementioned modified DRASTIC vulnerability risk map. Existing groundwater nitrate contamination data were collected from 250 studies. This allowed identifying the minimum (185 cases), maximum (206 cases) and mean (92 cases) of nitrate concentration of groundwater systems in Africa. Most studies are situated in the agricultural belt surrounding the African mega-cities where population density is high, or close to the coastal zones.

The validation of the groundwater vulnerability map was made through the nitrate distribution analysis and the vulnerability classes. ArcGIS10.2 was used to distribute spatially the minimum, mean and maximum nitrate concentrations in Africa and were compared with the various degrees of vulnerability maps.

4.4 Results and discussion

4.4.1 Ratings of DRASTIC parameters and aquifer vulnerability

Ratings and weights of each parameter of DRASTIC are illustrated in Table 4-4 and Table 4-5, which vary from 1 to 10, with higher values describing greater pollution.

The *D* map is represented in Figure 4-4. The rate varies from 0 to more than 250 m bgl across the African continent. The heights are shallow mostly in Central Africa, West Africa, Southern Africa and some areas of North Africa. These areas are more susceptible to contamination according the DRASTIC assumptions. The high values of *D* are located in large sedimentary aquifers in North Africa (Libya, Algeria, Egypt and Soudan). These aquifers contain a considerable proportion of Africa's groundwater. The assigned *D* ratings vary between 1 to 10, according the classification of Aller et al. (1987). The highest scores of 9 and 10 are assigned where the depths are in the class 0-7 m and 7-25 m, respectively. The lowest depths are assigned a rating of 1.

The *R* map is shown in Figure 4-5. Africa has areas with low net recharge rate (<50 mm/year) for which a rating of 1 is assigned, and areas with high recharge ranges (>225 mm/year), particularly in Central Africa and a portion of western Africa for which a rating of 9 is assigned.

The *A* map is shown in Figure 4-6. The ratings in Table 4-5 are assigned as commonly found in previous studies. A rating of 10 is assigned to carbonate rocks because their permeability value is most likely influenced by the presence of karst phenomena (Gleeson et al., 2011; Graaf et al., 2014). According Gleeson et al. (2011), volcanic rocks correspond to permeable basalt. A rating of 9 is assigned to these aquifer types. The major aquifer media in unconsolidated sediments are clay, sand and gravel. A rating of 8 is assigned to these media, considering that sand and gravel layers are dominant over clay layers, following the study of MacDonald et al. (2008). A low rating of 3 is assigned to crystalline rocks, because they are identified as fracture igneous/metamorphic rocks. Following Hartmann and Moosdorf (2012), we considered water bodies as an "other rock type", and we have assigned a rating of 8 for water bodies.

The texture based *S* map is represented in Figure 4-7. Soils are mapped in seven different classes. The dominant textures at the continental scale are sandy clay, loam and clay loam. The silty clay and sandy soil types appear in a lower proportion. The highest rating, 9, is assigned to the sandy soil and the lowest rating, 1, to the clayey soil. There is no information available on soils for the Sahara region; thus this part was rated equal to 0.

The *T* map representing the surface slope is shown in Figure 4-8. A gentle slope (0-4 %) is dominating the largest part of Africa. A rating score of 9 and 10 is assigned to this class, indicating that there is a large probability of pollution infiltration. The highest slopes are located in East Africa and areas associated with the high mountain range. A rate of 1 is assigned to areas where slopes are larger than 18 %, indicating their minimal potential effect on the groundwater vulnerability.

The *I* map is shown in Figure 4-9. The data used to define this parameter is the same as that used for the *A* map. Although the same hydrolithology is used for both A and I parameters, the maps are different because the crystalline rocks (igneous/metamorphic rocks) of the vadose zone are assigned a rating of 4 for *I* (Aller al., 1987). The weights and ratings for *I* are shown in Table 4-4.

The *C* map is shown in Figure 4-10. The hydraulic conductivity calculated is inferred from the global permeability database and has been classified in six classes (Figure 4-10). In general, the variability of the *C* parameter is not high. Low hydraulic conductivity values, inferior to 0.01 m/day are dominating in Southern Africa. We assigned a rating of 1 to this class. The continent is dominated by the hydraulic conductivities values varying between 0.04-0.13 m/day and 0.13-0.34 m/day, so we assigned respectively the ratings of 4 and 6. The horn of Africa and North Africa shows high conductivity values ranging between 0.57–2.82 m/day. The maximum rating score of 10 is assigned to these areas.

The resultant DRASTIC map is shown in Figure 4-11. DRASTIC classes have been grouped together into very low, low, moderate, high and very high vulnerability intervals.

Table 4-4: Rate and weight of the seven DRASTIC parameters (Aller et al., 1987)

Depth of Groundwater (m)		Net Recharge (mm)		Topography (%)		Hydraulic Conductivity (m/day)		Soil media	
Interval	ratings	Interval	ratings	Interval	Ratings	Interval	ratings	Soil classes	Ratings
0-7	10	0-45	1	0-2	10	<=0.010426	1	Clay	1
7-25	8	45-123	3	2-4	9	0.010426-0.038255	2	Clay loam	3
25-50	5	123-224	6	4-8	8	0.038255-0.12701	4	Loam	5
50-100	3	224-355	8	8-12	5	0.12701-0.34525	6	Loamy sand	7
100-250	2	>355	9	12-18	3	0.34525-0.569221	8	Sandy clay	2
>250	1			>18	1	0.569221-2.819372	10	Sandy clay loam	4
								Sandy loam	6
								Silty clay loam	3
								Sand	9
Weight:5		Weight: 4		Weight: 1		Weight: 3		Weight: 2	

[a] based on literature

Table 4-5: Rate and weights (A=3 and I=5) of aquifer media and impact of the vadose zone (Aller et al., 1987)

Lithology classes[a]	Hydrolithology classes[b]	Bedrock material	A and I ratings
Unconsolidated sediments	Unconsolidated		A(8) and I(7)
	c.g.unconsolidated	Alluvial deposits, dune sands	
	f.g.unconsolidated	Loess (Aeolian sediment), organic sediment	
Siliciclastic sediments	Siliciclastic sedimentary	Limestone, sandstone,	6
	c.g. siliciclastic sedimentary	Dolomite, siltone, salt	
	f.g.sedimentary	Conglomerate, shale	
Mixed sedimentary rocks	Carbonate	Karst limestone	10
Carbonate sedimentary rocks			
Evaporites			
Acid volcanic rocks	Volcanic	Permeable basalt	9
Intermediate volcanic rocks			
Basic volcanic rocks			
Acid plutonic rocks	Crystalline	Igneous/ metamorphic rocks	A(3) and I(4)
Intermediate plutonic rock			
Basic plutonic rocks			
Metamorphic rocks			
Water bodies	« Others rock »	-	8

[a]Hartmann and Moosdorf(2012); [b]Based on Gleeson et al.(2011)

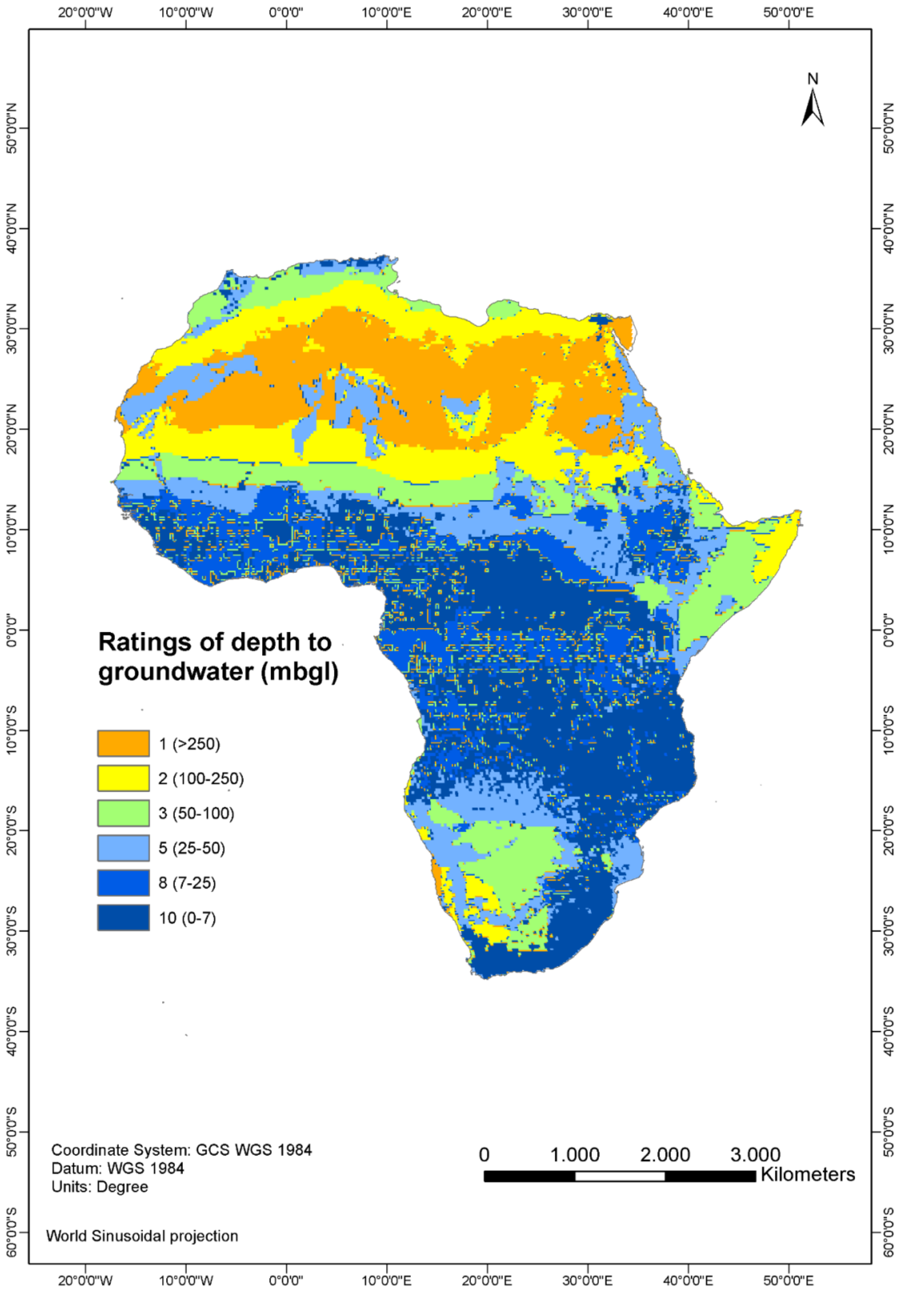


Figure 4-4: DRASTIC rating for the depth to groundwater (D).

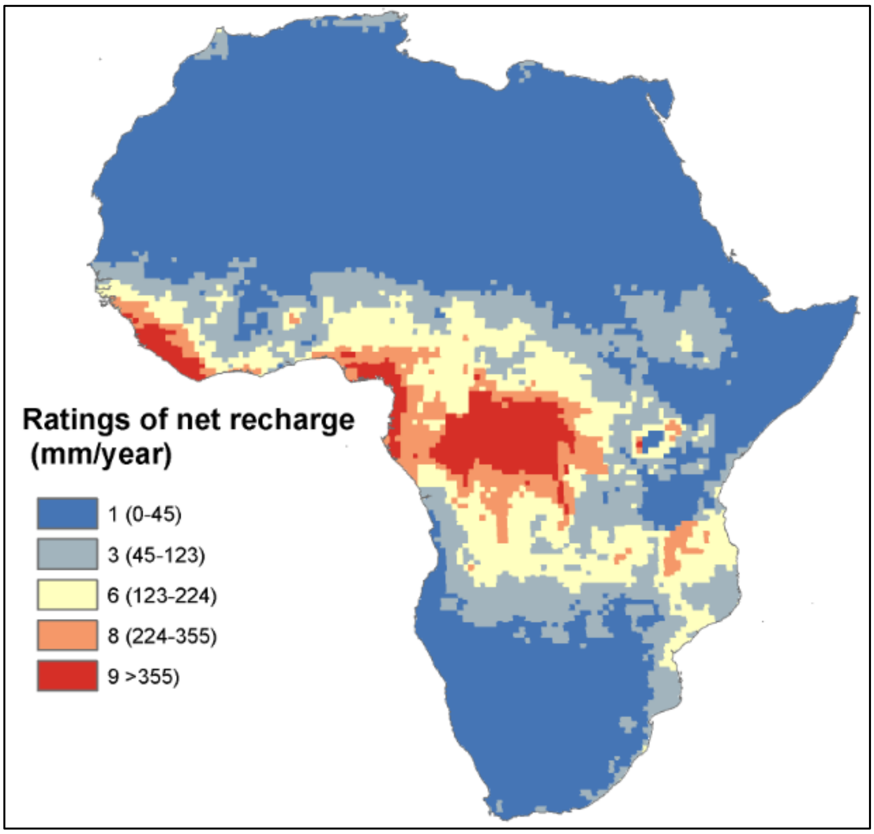


Figure 4-5: DRASTIC ratings for the net recharge (R) for Africa

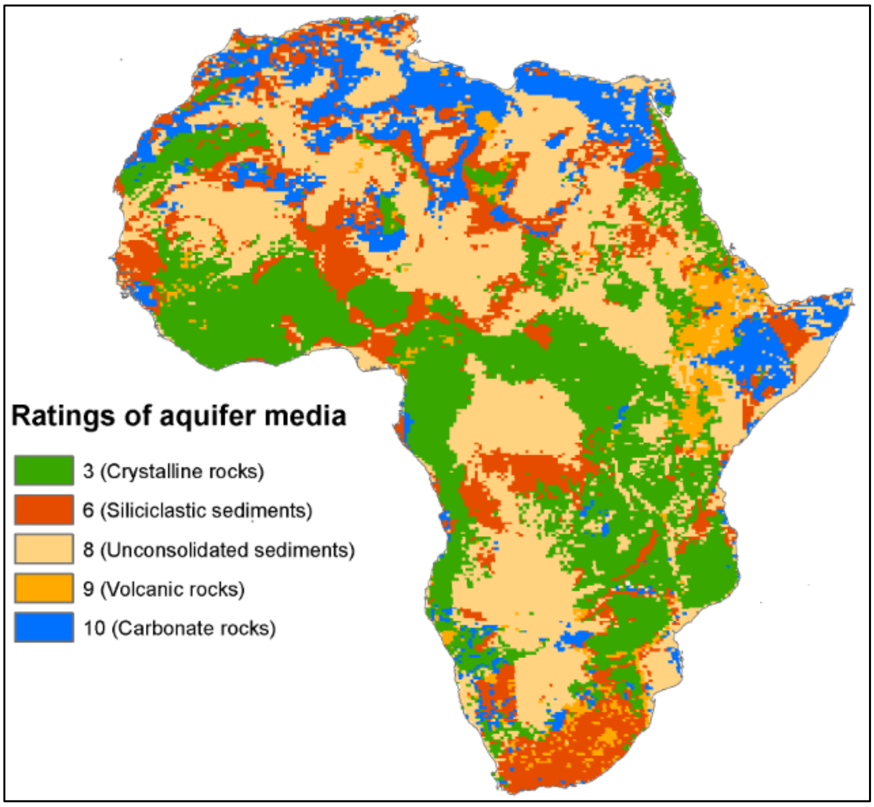


Figure 4-6: DRASTIC rating for the Aquifer type (A) for Africa.

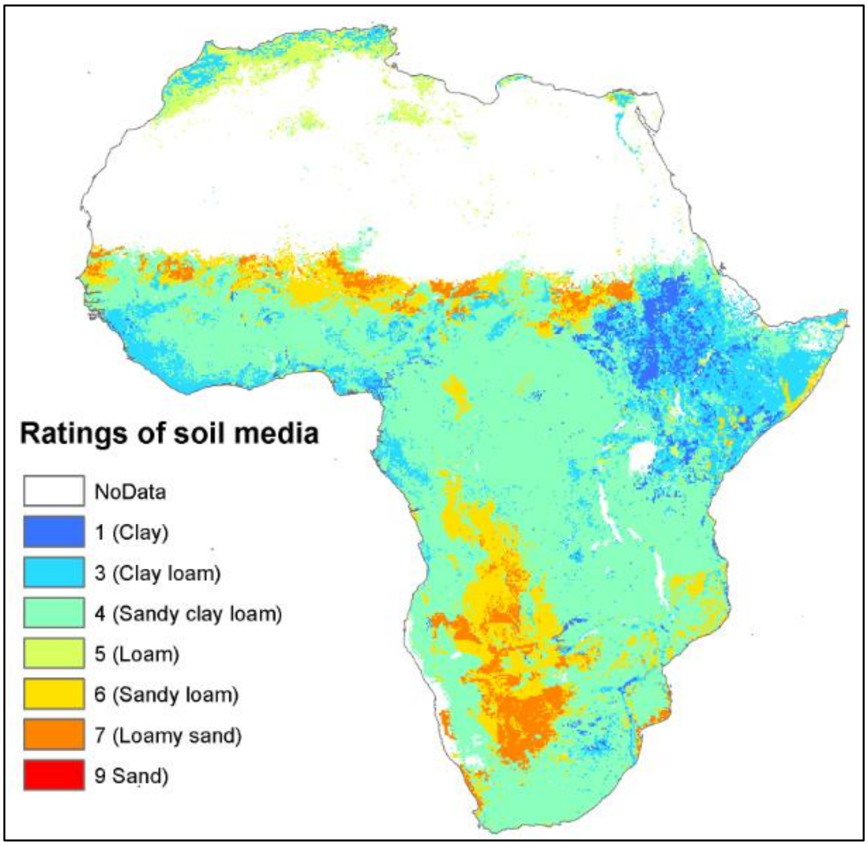


Figure 4-7: DRASTIC rating for Soil media (S) for Africa

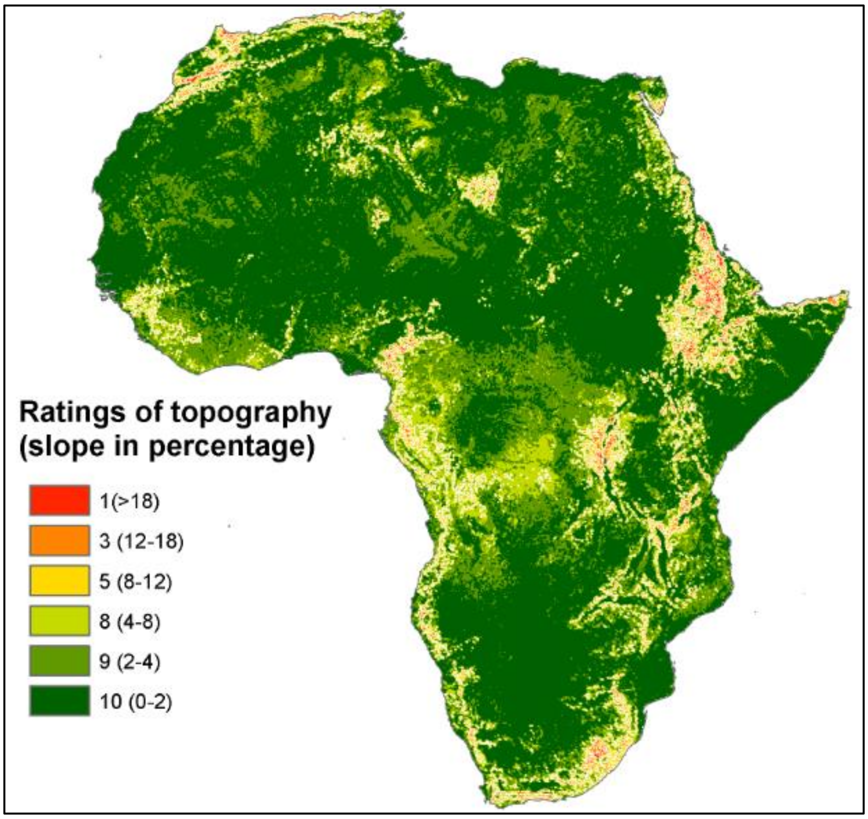


Figure 4-8: DRASTIC rating for the Topography (T) for Africa.

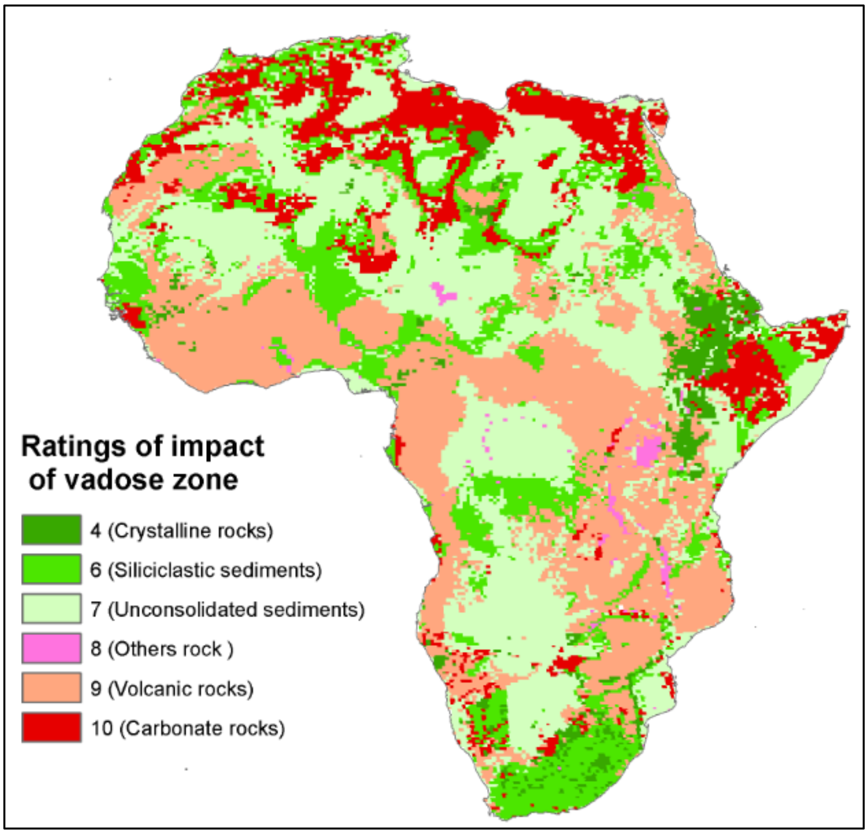


Figure 4-9: DRASTIC rating for the Impact of vadose zone (I) for Africa

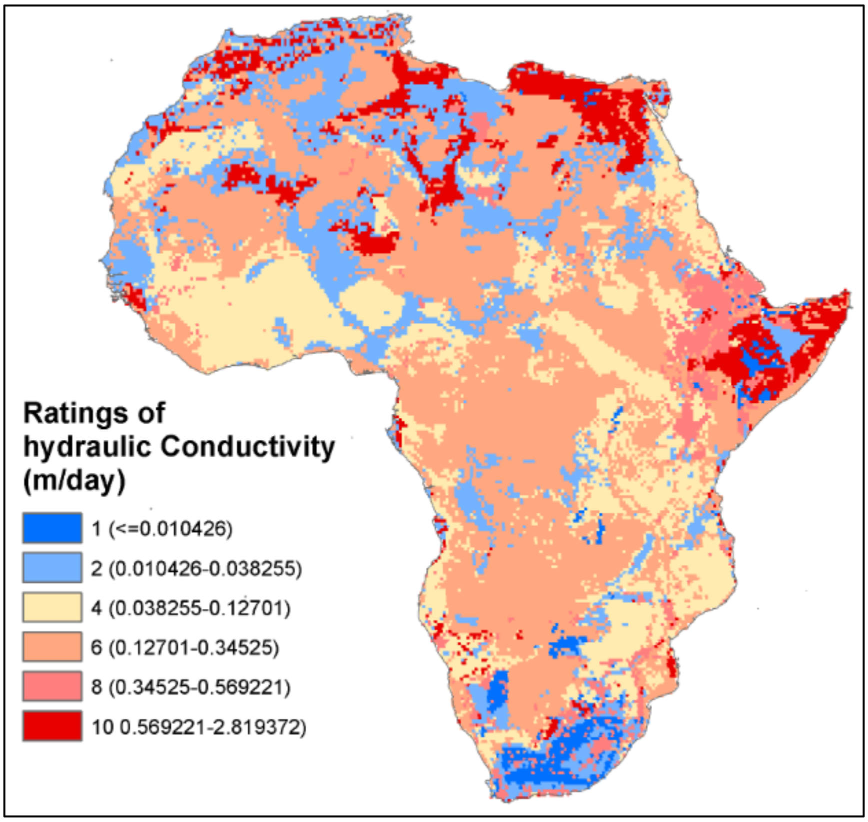


Figure 4-10: DRASTIC rating for the hydraulic conductivity (C) for Africa

4.4.2 Sensitivity of the DRASTIC model

4.4.2.1 Summary of the DRASTIC parameters

The Table 4-6 shows a statistical summary of the seven rated parameters of the DRASTIC model. On average, the *T* parameter (mean =9.12) has the highest rate values. The *I* (mean = 7.68), *A* (mean=6.36), *D* (mean=5.34) *and* C (mean=5.16) parameter have a moderate rate value. The *S* (mean =2.85) and *R* (mean =2.73) parameter imply a low rate value. The coefficients of variation (CV) indicate that a high contribution to the variation of vulnerability is expected by the variability in *R* (92.30%), *S* (76.49%) and *D* (65.16%). A moderate contribution is expected due to variability of *C* (42.67%) and *A* (39.62%), while the impact of the variability of *I* (20.05%) and *T*

(18.53%) is expected to be the lowest. In this research, vadose zone and aquifer media are composed of the same material. This could explained why A and I have the same maximum values (Max=13).

Table 4-6: Statistical summary of the DRASTIC parameters map

	D	R	A	S	T	I	C
Minimum	1	1	3	0	1	4	1
Maximum	10	9	13	9	10	13	10
Mean	5.34	2.73	6.36	2.85	9.12	7.68	5.16
SD	3.48	2.52	2.52	2.18	1.69	1.54	2.20
CV(%)	65.16	92.30	39.62	76.49	18.53	20.05	42.67

SD: refers to the standard deviation and CV: coefficient of variation.

4.4.2.2 Map removal sensitivity analysis

The results of the map removal sensitivity analysis computed by removing one or more data layers at a time are presented in Table 4-7 and Table 4-8. Table 4-7 reveals that the I map is the layer that affects strongly the final vulnerability index. This is mainly due to the high theoretical weight assigned to this parameter (weight =5). In contrast, Table 4-7 reveals that the *T* map, A map and C map affects the least the variation index (mean variation = 0.63%, 0.63% and 0.40%, respectively). This is due to the low weight (weight=1) associated to T and C. The variation in vulnerability observed after the removal of the *D*, and *R* map is moderate (mean = 1.28 %, and 1.21 % respectively).

Table 4-8 illustrates the variation of the vulnerability index due to the removal of one or more data layers at a time from the DRASTIC model computation. The layer which causes less variation in the final vulnerability index is removed first. It appears from the Table 4-7 that after removing the hydraulic conductivity layer, T, the variation index has the least average value (mean=0.63%), while the highest variation is associated with the removal of the D and I parameters (mean=11.31%

and mean=17.21% respectively). This average variation index changes as more data layers are removed from the computation. The removal of some layers (D, and I) affects the vulnerability assessment and this is demonstrated by all sensitivity tests.

Table 4-7: Statistics of map removal analysis

Parameters removed	Variation index (%)			
	Minimum	Maximum	Mean	SD
D	0	5	1.28	1.57
R	0	12	1.21	1.23
A	0	4	0.63	0.63
S	0	3	1.15	0.78
T	0	3	0.63	0.53
I	0	8	2.32	1.25
C	0	3	0.40	0.55

One parameter is removed at a time. SD refers to the standard deviation

Table 4-8: Statistics of map removal sensitivity

Parameters used	Variation index (%)			
	Mean	Minimum	Maximum	SD
D, R, A, S, T, I	0.63	0	3	0.53
D, R, A, S, I	1.14	0	4	1.11
D, R, S, I	3.2	0	8	1.98
D, R, I	6.84	0	30	3.13
D, I	11.31	0	46	5.34
I	17.21	0	47	7.50

One or more parameters are removed at a time. SD refers to the standard deviation

4.4.2.3 Single-parameter sensitivity analysis

While the map removal sensitivity analysis presented in previous section has confirmed the significance of the seven parameters in the assessment of the DRASTIC vulnerability index at the pan Africa scale, the single parameter sensitivity analysis allows the comparison between the effective and theoretical weights. The effective weight of the DRASTIC parameter is a function of the theoretical weight and the interaction with the other six parameters of the DRASTIC model (Babiker et al., 2005). The comparison is given in Table 4-9. The effective weight of the DRASTIC parameters obtained in this study exhibited some deviation from the theoretical weights. The *I* parameter tends to be the most effective parameter in the vulnerability assessment. His mean effective value of 31.12 % is higher than the theoretical weight of 21.7 %. This result is in agreement with the map removal sensitivity analysis for this parameter. The effective weight of the D parameter (19.71 %) is less than to its theoretical weight 21.7 %. The effective weights for *A* and *T* (15.76 %, 7.19 %) are higher then their theoretical weight (13.0 %, 4.3 %). The significance of the vadose zone, aquifer media and topography layers highlights the importance of obtaining accurate, detailed and representative information about these factors. The other DRASTIC parameters reveal lower effective weights compared to their theoretical weights. Parameters A, I and C are based effectively on the same datasets, which explains their contribution to adding up more 50% of the effective weight of the intrinsic vulnerability.

Table 4-9: Statistics of single parameter sensitivity analysis

Parameters	Theoretical weight	Theoretical weight (%)	Effective weight (%)			
			Mean	Min	Max	SD
D	5	21.7	19.71	2	70	11.52
R	4	17.4	7.25	2	32	5.94
A	3	13.0	15.76	4	39	7.43
S	2	8.7	3.92	0	17	3.32
T	1	4.3	7.19	0	13	2.31
I	5	21.7	31.12	11	60	7.49
C	3	13.0	12.07	1	33	5.44

SD refers to the standard deviation

4.4.3 Mapping of groundwater pollution risk

The result of groundwater pollution risk map is shown in Figure 4-12. We classified Africa into five zones corresponding to a very low, low, moderate, high and very high groundwater pollution risk. We observe a very low and low risk for the Sahara desert where large sedimentary basins are found. Indeed, the absence of important anthropogenic activities in combination with very low and low vulnerability zones result in very low and low contamination risks. We calculate high to very high vulnerability zones for regions in North Africa and a few zones of Eastern Africa and Southern Africa. A large part of Southern Africa shows a low risk for pollution. In general, high risk areas for pollution in Africa are lowlands where agricultural development is important. A region with a low pollution risk does not mean that it is free from groundwater contamination, but that it is relatively less susceptible to contamination compared to other regions.

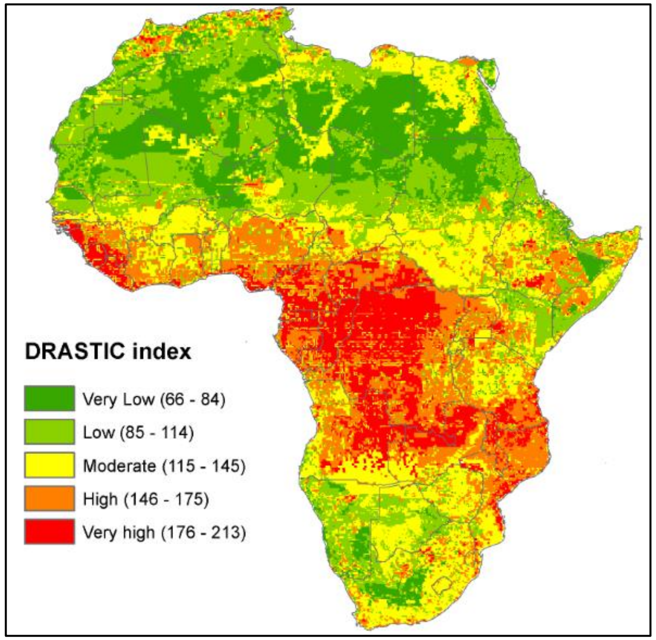


Figure 4-11: Groundwater intrinsic vulnerability map of Africa.

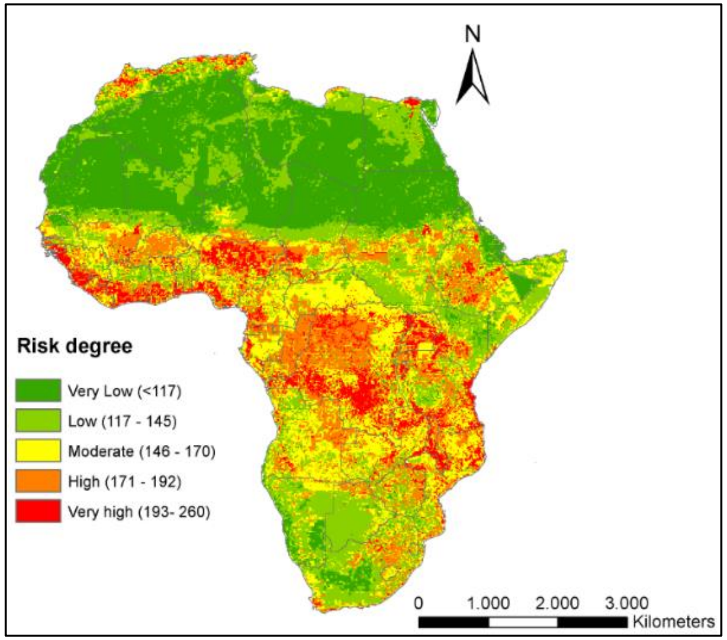


Figure 4-12: Risk map of groundwater pollution for Africa

The intrinsic vulnerability map indicated that Central Africa and a portion of West Africa are dominated by very high and high intrinsic vulnerabilities. The low depth of groundwater in these regions and the high recharge explains this high intrinsic vulnerability. The large sedimentary basins in North Africa are characterized by a low intrinsic vulnerability. The large depths of water and very low recharge rates explain these low intrinsic vulnerabilities. It also appears that in some regions like Southern Africa and Eastern Africa, a very high and high vulnerability of groundwater are also due to the shallow depths of groundwater systems. The topography parameter had the highest mean rating value for assessing the intrinsic vulnerability of Africa groundwater. The impact of vadose zone, the aquifer media and depth to groundwater had a moderate mean rating value while the soil media, the net recharge and the hydraulic conductivity had a low mean rating value respectively on vulnerability. The map removal sensitivity analysis test indicated that the vulnerability index is highly sensitive to the removal of the impact of vadose zone, the depth to groundwater and recharge layers. The index is less sensitive to the removal of hydraulic conductivity parameter. The single-parameter sensitivity analysis showed that the impact of vadose zone, the aquifer media and topography are the most significant environmental parameters which dictate the intrinsic vulnerability of African aquifers. Consequently, this highlights the importance of obtaining accurate, detailed, and representative information for the different parameters explaining intrinsic vulnerability of groundwater systems (Bouchaou et al., 2009).

We also created the first pan African groundwater pollution risk map. Areas under very high and high pollution risk are mainly characterized by shallow groundwater systems. At the opposite, low contamination risks are observed for the large sedimentary basins in North Africa, a little portion of Eastern and Southern Africa. Indeed, these groundwater systems situates at larger depths. The risk map of groundwater pollution in Africa shows that water resources are mainly under pressure in large agricultural basins.

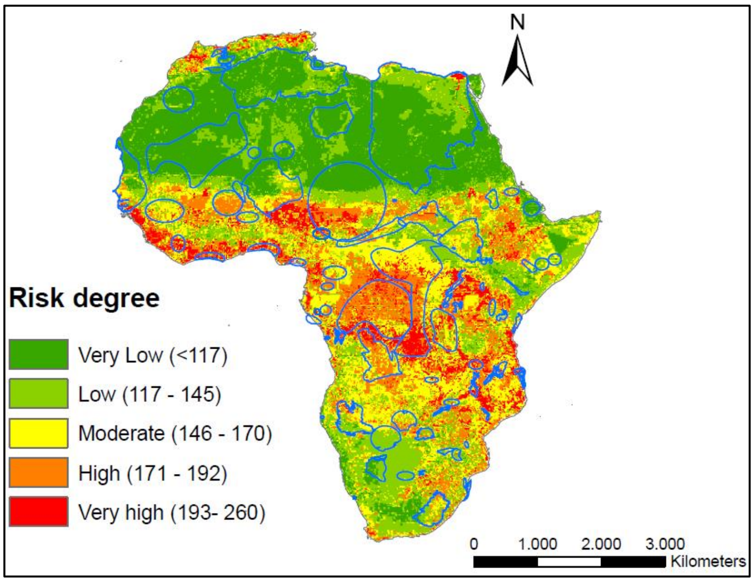


Figure 4-13: Risk map overlaying Transboundary aquifers (TBAs) defined by Altchenko and Villhoth (2013)

The eight model parameters of the groundwater pollution risk model were constructed, classified and encoded employing various maps from several sources and at different mapping scales. Figure 4-12 has the merit to produce a very valuable map for managing and protecting groundwater at the regional scale. So, water directors can use the vulnerability map to support the design of groundwater development or protection programs. Figure 4-13 for example give the utility of this risk map for transboundary aquifers management (International Network of Basin Organizations (INBO), Global Water Partneship (GWP)).

4.4.4 Validation of the groundwater vulnerability map

4.4.4.1 Spatial concentrations of nitrate

The spatial distribution of the nitrate mean groundwater concentration inferred from the meta-analysis is illustrated in Figure 4-14. In the meta-analysis database, 206 studies related to the maximum concentration of nitrate, 185 studies to the minimum concentration of nitrate, and 92 studies to the mean concentration of nitrate have been analysed. This meta-analysis reveals that nitrate concentration varies between zero and 4625 mg/L. We selected the mean nitrate concentration as proxy for risk and superimposed on the previously developed risk map.

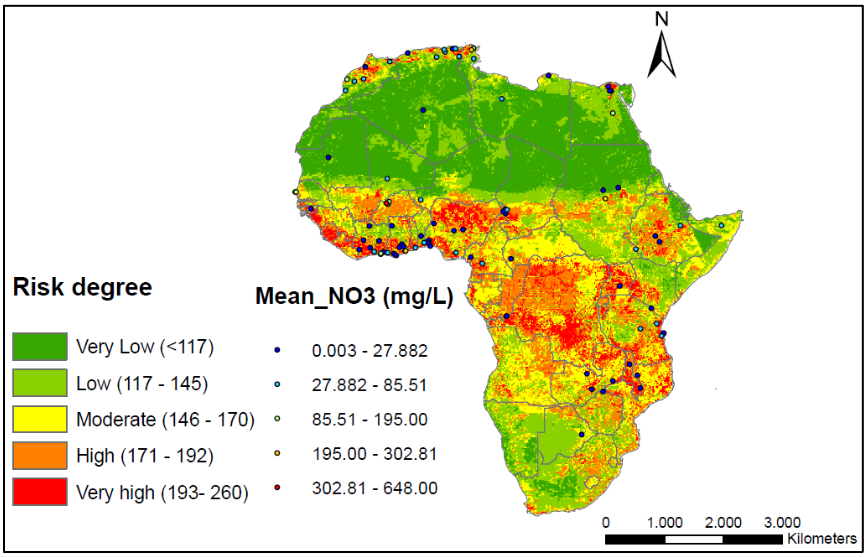


Figure 4-14: Spatial distribution of mean nitrate concentration in groundwater

4.4.4.2 Regression of aggregated nitrate concentration data with estimated groundwater risk

We also aggregated the observed maximum nitrate concentration for each vulnerability class and compared it with vulnerability and risk. In this approach, the DRASTIC index has been used as surrogate of the vulnerability map and regressed against the extracted nitrate concentration. Figure 4-15 and Figure 4-16 illustrate that the aggregated maximum nitrate concentration data are positively related to the intrinsic vulnerability (R^2= 0.89) and the risk for pollution (R^2= 0.65) respectively. This suggests that the generic model for mapping vulnerability and groundwater pollution risk is consistent with observed nitrate inferred from the literature. We chose the maximum concentration values of nitrate as aggregate values to show the trend of our groundwater vulnerability model, because the sample size is larger for the maximum concentration. Also, sample data of maximum concentration cover the complete study area. However, the aforementioned results shows that further validation using more measurement data is recommended.

Furthermore, by analysing the Figure 4-15, we can conclude that the intrinsic vulnerability at the pan-African scale divided into 5 classes, could be grouped into three categories with very low and low classes as 1st category, moderate and high classes the 2nd category and 3rd category corresponding to the very high class of vulnerability index. While, the risk pollution map represented by Figure 4-16 could be regrouped into two categories at the continental scale, with 1st category including very low and low class of risk degree and 2nd category representing the moderate, high and very high classes.

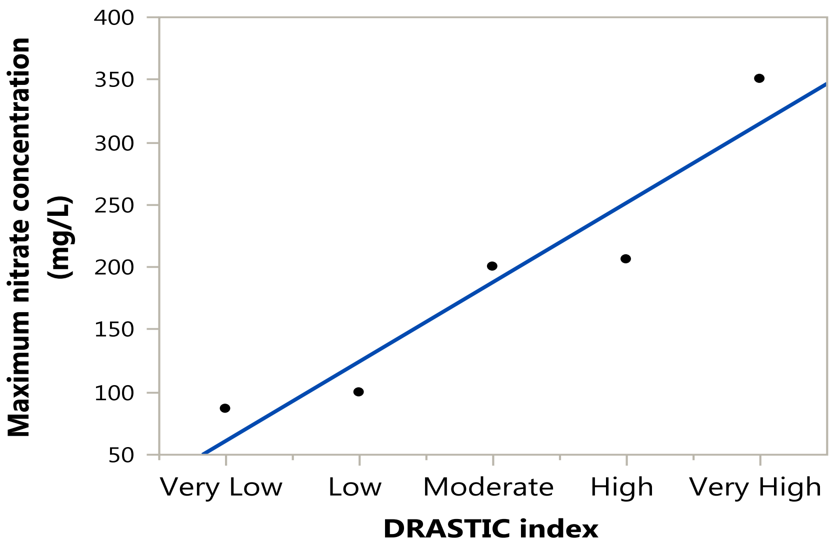


Figure 4-15: Relation between nitrate maximum and DRASTIC with R^2=0.89

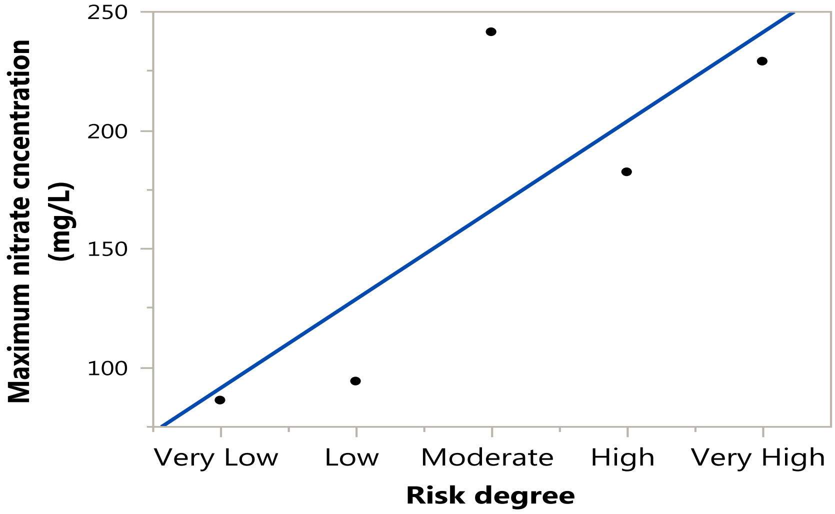


Figure 4-16: Relation between nitrate maximum and risk degree with R^2=0.65

4.4.5 Limitations of vulnerability assessment

Although the method DRASTIC is good and used worldwide (most popular approach to groundwater vulnerability assessments, because it is relatively inexpensive, straightforward, and uses data are commonly available or estimated, and produces an end product that can easily be interpreted and incorporated into the decision-making process); it also has disadvantages. To be effective, DRASTIC requires calibration against real groundwater observation (Worrall and Besien, 2005). The DRASTIC index provides only a relative evaluation tool and is not designed to provide absolute answers (Gogu and Dassargues, 2000). Furthermore, as pointed out by Foster (1998) cited in Abdullahi (2009), the method has some general shortcomings such as that it underestimates the vulnerability of fractured aquifers, and that the weighting system is not scientifically based. In spite of the limitations in fractured aquifers observed by Foster (1998), Murat et al. (2003) used 2 methods (DRASTIC and GOD) to study aquifer vulnerability in two hydrogeological settings in Canada. In their study at local and regional scale, they concluded that: "it is clear through this comparative study that vulnerability maps vary significantly with the selected vulnerability evaluation method and the type of investigated hydrogeological setting. DRASTIC appears to be the method that provides the best results in both the superficial granular and confined/semi- confined fractured rock contexts studied. Also, by applicability of regional-scale MCDM (Multi-criteria decision-making) based on intrinsic aquifer and vulnerability assessment, Honnungar (2009) addressed the limitations that arise due to spatial and temporal variability of input (data and resolution), data processing methods (sampling and interpolation methods), subjectivity in assigning weights and ratings by decision makers, non-integration of intrinsic and specific vulnerability, and non-linear relationships between the hydrogeological parameters. Thus, through the research of Honnungar (2009), we acknowledge that our continental-scale groundwater vulnerability assessment presents also some limits. Other limitations of DRASTIC were outlined in Cotonou/Benin where seawater intrusion is as great a risk as surface contamination (Xu and Usher, 2006).

In addition to these limitations, groundwater vulnerability assessments have also some uncertainties. To this regard, NRC (1993) affirms that uncertainty is inherent to all vulnerability assessments. Loague et al. (1999) adds that, in general assessments of groundwater vulnerability at the regional scale rest upon soil, climate, and chemical data that are extremely sparse and contain considerable uncertainty. In a study on a propose to monitor uncertainty associated with spatial data processing for aquifer vulnerability mapping and GIS, Murat et al.(2004) affirm uncertainty monitoring may be complex and subjective and in fact it is rarely done on a regular basis mainly because it requires much more efforts compared to simply running the model.

4.5 Conclusion

We assessed the intrinsic vulnerability and risk for groundwater pollution at the pan African scale. We deployed the empirical index model DRASTIC into a GIS. The GIS provides an effective analysis environment and a strong capacity for handling large amounts of spatial data. We identified the seven environmental DRASTIC parameters (Depth to water (D), net Recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of vadose zone (I), and hydraulic Conductivity (C)) from available generic data, and compiled them into a 15 km resolution geo-database for the African continent. We classified and coded these parameters to create an intrinsic groundwater vulnerability map. Subsequently, we combined the intrinsic vulnerability map with a high resolution land use/land cover map to assess the groundwater pollution risk. We show that the DRASTIC index varies between 66 to 213. We classified this index into 5 classes, ranging from very low to very high.

Despite the lack or limit of groundwater pollution data at the continental scale, the intrinsic vulnerability and risk map was tested and validated using nitrate concentration data as proxies for vulnerability and risk. Nitrate concentration data were inferred from a literature meta-analysis. High nitrate concentrations detected in literature coincide with high intrinsic vulnerability and high pollution risks. This illustrates the consistency between the calculated vulnerability and groundwater pollution risk using generic data on the one hand, and the observed contamination on the other hand. However, the explained variability in the boxplots and scatter plots is still rather low, showing that quite some scope exist to calibrate and to improve the proposed vulnerability and groundwater risk mapping procedure. This should be based on a better understanding of the factors explaining the contamination at the pan African scale. When the availability of lack monitoring data will become operational, she allowing to consolidate the calibration and validation of the presented mapping methodologies.
Vulnerability assessments are a general planning and decision-making tool. They should not be mistaken for a scientifically precise prediction for future contamination. Rather, they are a general assessment of the risk that contamination may occur in groundwater. As with any risk analysis, there is no guarantee that contamination does or doesn't occur.

The maps that were designed in this study can increase awareness of citizens and regulators in areas where groundwater pollution is likely to be significant. In addition, they could prompt national or international authorities to foster targeted local investigations. In fact, environmental management needs to be operatively performed at regional, country and local scales, but investment policies can be addressed at continental or even global scales by international agencies and authorities (e.g., AMCOW, African Development Bank Group (AfDB), Danish Cooperation for Environment and Development

(DANCED), Swiss Agency for Development and Cooperation (SDC), UNICEF). The map should serve efforts to raise awareness within the African Minister's Council on Water (AMCOW), particularly AMCOW Groundwater Commission on the strategic importance and vulnerability of groundwater resources throughout Africa. In other words, the study will support AMCOW to help African countries towards a situation where groundwater resources are valued, protected and utilized sustainably by empowered stakeholders for the achievement of the UN Sustainable Development Goal 6.

Chapter 5 A meta-analysis and statistical modelling of nitrates in groundwater at the African scale[2]

[2] *Based on:* ***Ouedraogo, I.,*** *and Vanclooster, M. (2016). A meta-analysis and statistical modelling of nitrates in groundwater at the African scale. In: Hydrology and Earth System Sciences, Vol. 20, no.6, p. 2353-2381. DOI: 10.5194/hess-20-2353-2016.*

5.1 Abstract

Contamination of groundwater with nitrate poses a major health risk to millions of people around Africa. Assessing the space-time distribution of this contamination, as well as understanding the factors that explain this contamination is important to manage sustainable drinking water at the regional scale. This study aims to assess the variables that contribute to nitrate pollution in groundwater at the African scale by statistical modelling. We compiled a literature database of nitrate concentration in groundwater (around 250 studies) and combined it with digital maps of physical attributes such as soil, geology, climate, hydrogeology and anthropogenic data for statistical model development. The maximum, medium and minimum observed nitrate concentrations were analysed. In total, 13 explanatory variables were screened to explain observed nitrate pollution in groundwater. For the mean nitrate concentration, 4 variables are retained in the statistical explanatory model: (1) depth to groundwater (shallow groundwater, typically <50m); (2) recharge rate; (3) aquifer type; and (4) population density. The first three variables represent intrinsic vulnerability of groundwater systems towards pollution while the latter variable is a proxy for anthropogenic pollution. The model explains 65 % of the variation of mean nitrate contamination in groundwater at the African scale. Using the same proxy information, we could develop a statistical model for the maximum nitrate concentrations that explains 42 % of the nitrate variation. For the maximum concentrations, other environmental attributes such as soil type, slope, rainfall, climate class and region type improve the prediction of maximum nitrate concentrations at the African scale. As to minimal nitrate concentrations, in the absence of normal distribution assumptions of the dataset, we do not develop a statistical model for these data. The data based statistical model presented here represents an important step toward developing tools that will allow to accurately predict nitrate distribution at the African scale and thus

may support groundwater monitoring and water management that aims to protect groundwater systems. Yet they should be further refined and validated when more detailed and harmonized data becomes available and/or combined with more conceptual descriptions of the fate of nutrients in the hydrosystem.

5.2 Introduction

Nitrate contamination of groundwater is a common problem in many parts of the world. Elevated nitrate concentrations in drinking water can cause methemoglobinemia in infants and stomach cancer in adults (Yang et al., 1998; Knobeloch et al., 2000; Hall et al., 2001). As such, the World Health Organization (WHO) has established a maximum contaminant level (MCL) of 50 mg L^{-1} NO_3 (WHO, 2004). Nitrate in groundwater is generally from the anthropogenic origin and associated with leaching of nitrogen from agriculture plots or from waste and sewage sanitation systems. The heavy use of nitrogenous fertilizers in cropping system is the largest contributor to anthropogenic nitrogen in groundwater worldwide (Suthar et al., 2009). In particular, shallow aquifers in agricultural fields are highly vulnerable to nitrate contamination (Böhlke, 2002; Kyoung-Ho et al, 2009). According to Spalding and Exner (1993), nitrate may be the most widespread contaminant of groundwater.

In Africa, groundwater is recognized as playing a very important role in the development agenda. According to Xu and Usher (2006), degradation of groundwater is the most serious water resources problem in Africa. The two main threats are overexploitation and contamination (MacDonald et al., 2013). Furthermore, Xu and Usher (2006) showed that the major sources of groundwater contamination are related to on-site sanitation, to the presence of solid waste dumpsites, including household waste pits, to infiltration of surface water, to agricultural activities, to the presence of petrol service stations (underground storage tanks), and to the mismanagement of wellfields. Nitrate contamination of groundwater is a problem that commonly occurs in Africa, as illustrated in the studies for Algeria (Rouabhia et al., 2010; Messameh et al., 2014), Tunisia (Hamza et al., 2007; Anane et al., 2014), Morocco (Bricha et al., 2007; Fetouani et al., 2008; Benabbou et al., 2014), Senegal (Sall and Vanclooster, 2009; Diédhiou et al., 2012), Ivory Coast (Loko et al., 2013; Eblin et al., 2014), Ghana (Tay and Kortatsi, 2008; Fianko et al., 2009), Nigeria (Wakida and Lerner, 2005; Akoteyon and Soladoye, 2011; Obinna et al., 2014), South Africa (Maherry et al., 2009; Musekiwa and Majola, 2013), Ethiopia (BGS, 2001a; Bonetto et al., 2005) and Zambia (Wakida and Lerner, 2005). Several of these studies showed that pollution from anthropogenic activities is the main source of high and variable nitrate levels. For example, Comte et al. (2012) illustrates that the groundwater situated in the Quaternary sandy aquifer of the peninsula of Dakar is under strong anthropogenic pressure from the city of Dakar, resulting in important nitrate loadings. Such contamination problems are often retrieved in many metropoles in Africa. Notwithstanding the availability of all these studies at the local, regional or country level, no comprehensive synthesis of nitrate contamination of groundwater at the scale of the African continent has been presented in the literature. Assessing large-scale groundwater contamination with nitrates is important for the planning of the large-scale groundwater exploitation programs and for designing transboundary water management policies. It yields also important baseline information for monitoring progress in the implementation of the United Nations Sustainable Development Goals (UN SDGs) for water. According to Saruchera and Lautze (2015), transboundary water cooperation has emerged as an important issue in the post-2015 United Nations (UN) Sustainable Development Goals (SDGs). This study will increase awareness of citizens, international agencies and authorities (e.g. FAO, UNEP, and OECD; Water Sanitation for Africa (WSA)) of the environmental factors likely to be significant to groundwater contamination. However, making an appropriate African scale synthesis of nitrate contamination of groundwater remains a scientific and technical challenge, given the heterogeneity of the nitrate monitoring programmes and the absence of administrative and institutional capacity to collect and diffuse the data at the African scale. A concept that partially helps to solve this urgent data management problem is the concept of groundwater vulnerability. Groundwater vulnerability for nitrate contamination is an expression of the likelihood that a given groundwater body will be negatively affected by nitrate contamination. Given that the vulnerability is a likelihood, it is only an expression of the potential degradation of groundwater and hence a proxy of groundwater contamination by nitrates. Groundwater vulnerability can be assessed based on available generic data. It does therefore not depend on a strong and operational Africa groundwater quality monitoring capacity. In this chapter, we propose and implement a methodology for assessing the vulnerability of groundwater contamination by nitrates at the African scale. We further consider nitrate in this study as a proxy for overall groundwater pollution, which is consistent with the view of the US EPA (EPA, 1996).

In general, there are three categories of models for the assessment of groundwater vulnerability: (1) index methods or subjective rating methods, (2) statistical methods and (3) process-based modelling methods. Index-and-overlay methods are one set of subjective rating methods that utilize the intersection of regional attributes with the qualitative interpretation of data by indexing parameters and assigning a weighting scheme. The most widely used index method is DRASTIC (Aller et al., 1985). Unfortunately, index methods are based on subjective rating methods (Focazio et al., 2002) and should preferably be calibrated using measured proxies of vulnerability (Kihumba et al., 2015; Ouedraogo et al., 2016). When a groundwater monitoring dataset is available, formal statistical methods can be used to integrate groundwater contamination data directly in the vulnerability assessment. Finally, process-based methods refer to approaches that explicitly simulate the physical, chemical and biological processes that affect contaminant behaviour in the environment. They comprise the use of deterministic or stochastic process-simulation models, eventually linked to physically based field observations (e.g. Coplen et al., 2000). Physically process-based methods are typically applied at small scales, mostly to define well protection zones, rather than to assess groundwater vulnerability at broader scales (Frind et al., 2006). A well-known example is the use of a physical based groundwater model (e.g. MODFLOW, Harbaugh et al., 2000) that solve the governing equations of groundwater flow and solute transport. Such models have explicit time steps and are often used to determine the timescales of contaminant transport to wells and streams, in addition to the effects of pumping. However, they also have many parameters that require estimation. In this chapter, we use statistical models to assess the vulnerability of groundwater systems towards nitrate pollution.

Formal statistical methods have often be deployed to assess the vulnerability of groundwater at national and regional scales. They are also often used to discriminate contaminant sources and to identify factors contributing to contamination (Kolpin, 1997; Nolan and Hitt, 2006). Many authors used multiple linear regression (MLR) techniques. For example, Bauder et al. (1993) investigated the major controlling factors for nitrate contamination of groundwater in agricultural areas using MLR of land uses, climate, soil characteristics, and cultivations types. MLR was also used to relate pesticide concentrations in groundwater to the age of the well, land use around the well, and the distance to the closest possible source of pesticide contamination (Steichen, et al., 1988). Boy-Roura et al. (2013) used MLR to assess nitrate pollution in the Osona region (NE Spain). Amini et al., (2008a, b) used MLR and Adaptive Neuro-Fuzzy Inference System (ANFIS), a general non-linear regression technique, to study the global geogenic fluoride contamination in groundwater and the global geogenic arsenic contamination in groundwater respectively. MLR has the strong advantage that regression coefficients can directly be interpreted in terms of the importance of explaining factors. Many studies linking nitrate occurrence in groundwater to spatial variables have employed logistic regression (Hosmer and Lameshow, 1989; Eckardt and Stackkelberg, 1995; Tesoriero and Voss, 1997; Gardner and Vogel, 2005; Winkel et al., 2008; and Mair and El-kadi, 2013). According to Kleinbaum (1994), MLR is conceptually similar to logistic regression. Other authors have used more sophisticated approaches such as Bayesian methods (Worrall and Besien, 2005; Mattern et al., 2012) and, more recently, classification and regression tree modelling approaches (Burow et al., 2010; Mattern et al., 2012). However, to our knowledge, a statistical model of groundwater nitrate contamination at the African scale does not exist yet.

In the present study, we used MLR techniques to assess the vulnerability of nitrate groundwater pollution at the African scale. To this end, we compiled at the African scale groundwater pollution database from the literature and combined it with environmental attributes inferred from a generic data basis. The generic data basis was developed in a former study to assess vulnerability using the DRASTIC index method (Ouedraogo et al., 2016). MLR models were subsequently identified to explain quantitatively the log transformed observed nitrate contamination in terms of generic environmental attributes and finally, the regression models were interpreted in terms of characteristics of contaminants sources and hydrogeology of the African continent.

5.3 Data and methods

5.3.1 Nitrate contamination data

For a large part of Africa, there is very little, or no systematic monitoring of groundwater. In the absence of data systematic monitoring program, we compiled nitrate pollution data at the African scale from different literature sources. We considered approximately 250 published papers on nitrate contamination of groundwater in Africa. We consulted the web of sciences (Scopus™, Sciences Direct™, Google™, and Google Scholar™) and available books. Figure 5-1 shows the spatial distribution of the considered field studies. Table 5-1 outlines criteria used in the web search.

Table 5-1: Criteria used to identify nitrate data studies within web data bases.

Search engine	**Search criteria**
Google, Google Scholar, and Google Books	Groundwater pollution + Africa Nitrate in groundwater + "African country name" or "African capital city name" Groundwater quality + Africa Nitrate and agricultural practices in Africa Groundwater vulnerability + "African country name" Pollution des eaux souterraines par les nitrates+ ''nom du pays Africain'' (in French) Pollution des eaux souterraines + "nom du pays Africain" (in French) Nitrate concentrations under irrigated agriculture + "African country name"
Web of Sciences, Scopus and Sciences Direct	Groundwater pollution by nitrate + "African country name" Nitrate in groundwater + "Africa capital city name" Pollution des eaux souterraines par les nitrates + "nom du capital des pays"(in French) Groundwater contamination by nitrate + "Africa countries" or "African capital city name" Africa irrigated agriculture + nitrate Groundwater contamination by nitrate + "Africa country name" or "African capital city name" Nitrate concentrations under irrigated agriculture + "African country name" Groundwater vulnerability to nitrate contamination + "Africa country name" or "African capital city name"
Books	Groundwater pollution in Africa (Xu and Usher, 2006)

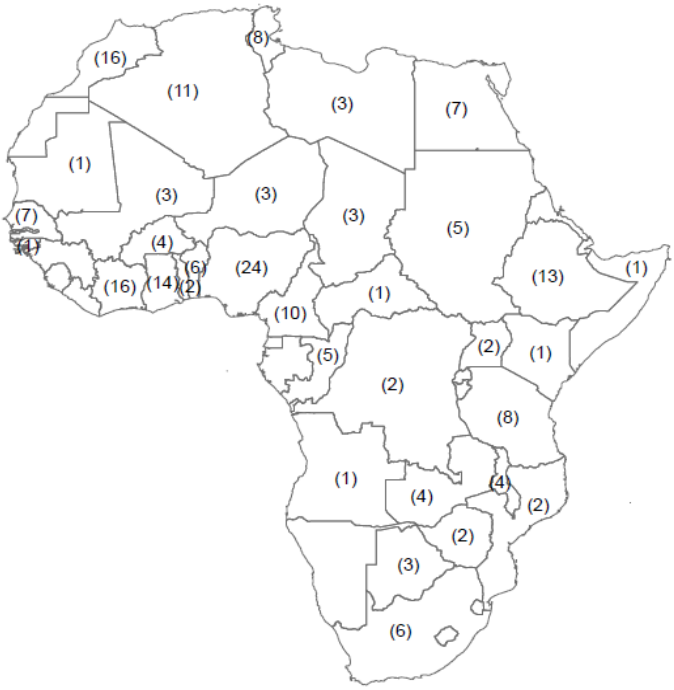


Figure 5-1: Distribution of studies identified across Africa

5.3.2 Data quality evaluation

We used the following additional criteria to select the study: the publication should explicitly report on nitrate concentrations in groundwater; and the publication should be published after 1999. Also, when many articles have been published on the same field site, we used only the most recent study. We excluded older studies before 1999 since the intensity of human activities is expected to be significantly different after 1999. We eliminated 37 articles because no quantitative data on nitrate concentration were reported. For the considered data set, 206 studies report on the maximum concentration of nitrate, 187 studies on the minimum concentration of nitrate, and 94 studies on the mean concentration of nitrate. Out of the 94 datasets for which mean values were reported, 12 field sites have nitrate concentration smaller than 1 mg/L. We present the locations and references of the considered field studies in Table 5-2. In case spatial coordinates were not reported in the selected paper, we allocated the coordinates of the field study in Google Earth using the www.gps-coordintes.net and www.mapcoordinates.net applications. As an example, we present in Figure 5-2 the identified locations and reported maximum nitrate values of the selected studies. The absence of exact spatial coordinates in many studies will, therefore, generate a positioning error in the analysis. However, given the extent of the study, i.e. the African continent, we consider that this positioning error will not have significant effects on the overall results. The groundwater pollution risk in Figure 5-2 corresponds to the potential of a groundwater body for undergoing groundwater contamination (Farjad et al., 2012). The risk of pollution is determined both by the intrinsic vulnerability of the aquifer, which is relatively static, and the existence of potentially polluting activities at the soil surface. These latter activities are time dynamic and can be controlled (Saidi et al, 2010). We generated the groundwater pollution risk map by combining the intrinsic groundwater vulnerability map with the land use map, using the additive model of Secunda et al. (1998). Details of these procedures are given by Ouedraogo et al. (2016).

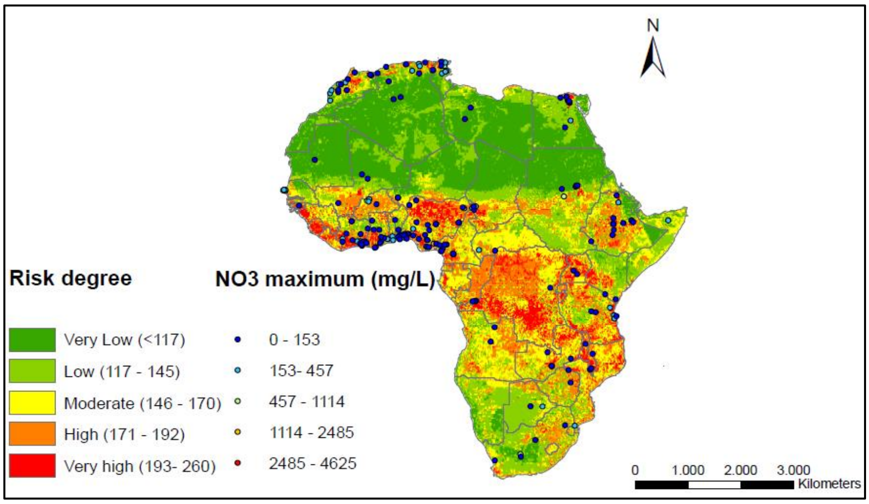


Figure 5-2:The locations and the maximum values of nitrate in Africa superimposed on risk pollution map as generated in the previous generic vulnerability study of Ouedraogo et al. (2016)

5.3.3 Determination of spatial explanatory variables

Table 5-3 lists the environmental attributes and data sources that we considered for explaining the observed nitrate contamination. These variables represent both anthropogenic and natural factors and were derived from multiple sources of information. The attributes are related to recharge, geology, hydrogeology, soil texture, land use, topography and pollution pressure and were partially inspired by the DRASTIC vulnerability mapping approach. We compiled all explanatory variables in a common GIS environment (ArcGIS 10.3™), using a common projection and resolution (15 km x 15 km) at the 1:60.000.000 scale. This spatial resolution was chosen because we have considered that she was a reasonable compromise between different resolutions of the different datasets, computing constraints and regional extent. Indeed, this grid cell dimension has been used to map the vulnerability and risk pollution maps at the African scale (Ouedraogo et al. 2016). Generic variables at the grid scale were extracted to build our explanatory variables in this study. Most of these variables were categorical, but some were continuous.

Groundwater recharge is considered as a primary explaining variable because recharge is the primary vehicle by which a contaminant is transported from the ground surface to groundwater. Groundwater recharge to an unconfined aquifer is a function of precipitation, runoff, and evapotranspiration. The latter is related to vegetation and/or soil type. Groundwater recharge to a confined aquifer is generally more complex, as consideration must be given to the location of the recharge zone and the influence of any confining layers, vertical gradients, and groundwater pumping (Todd Engineers and Kennedy/Jenks Consultants, 2010). In this study, we derived the African recharge map from the global-scale groundwater recharge model of Döll and Fiedler (2008). We also considered independent climate data as alternative proxies of recharge. Hence, we considered the climate and region type data class as defined by Trambauer et al. (2014). We also considered the rainfall map as generated from the UNEP/FAO World and Africa GIS Data Base. The spatial resolution of this latter dataset is approximately 3.7 km.

Subsequently, we selected a set of environmental attributes related to aquifer type, groundwater position and the substrate that protects the aquifer. The depth to groundwater represents the distance that a contaminant must travel through the unsaturated zone before reaching the water table or to the first screen. We mapped the depth to water based on the data presented by Bonsor et al. (2011). The slope of the land surface is important with respect to groundwater vulnerability because it determines the potential of a contaminant to infiltrate into the groundwater or be transported horizontally as runoff. We inferred the slope from the 90-meter Shuttle Radar Topography Mission (SRTM90) topographic map, using the Spatial Analyst software of ArcGIS10.2™. We derived the aquifer type and the impact of vadose zone material from the high resolution global lithological database (GliM) of Hartmann and Moosdorf (2012). We determined aquifer type and unsaturated lithological zone for each of the five hydro-lithological and lithological categories as defined by Gleeson et al., (2014). These categories are: unconsolidated sediments, siliciclastic sediments, carbonate rocks, crystalline rocks, and volcanic rocks (Gleeson et al., 2014). We constructed the soil type map from the 1 km resolution soil grid database developed by Hengl et al. (2012). We determined the hydraulic conductivity of aquifers from the Global Hydrogeology MaPS (GHYMPS) dataset (Gleeson et al., 2014). For the determination of the land use at the African scale, we used the high-resolution land cover/land use map from the GlobCoverdataset (Defourny et al., 2014). There are twenty-two (22) classes of land cover that represents Africa in this dataset. We aggregated these 22 classes into 6 similar classes (water bodies, bare area, grassland/shrubland, forest, urban, croplands) as represented in the Figure 5-3 and then regrouped them in 5 groups (water bodies, forest/bare area, grassland/shrubland, croplands, urban area).

Finally, we considered a set of variables related to possible pollution pressure. We considered the application of fertilizer in the agricultural sector as a possible explanatory variable. We generated the nitrogen fertilizer application map from the Potter et al. (2010) data set. The values shown on this map represent an average application rate for all crops over a 0.5° resolution grid cell. Following this study, the highest N fertilizer application rate (i.e. 220 kg ha^{-1}) is found in Egypt's Nile Delta. We further considered population density as a proxy of pollution source. We considered the population density map for the year 2000, as produced by Nelson (2004).

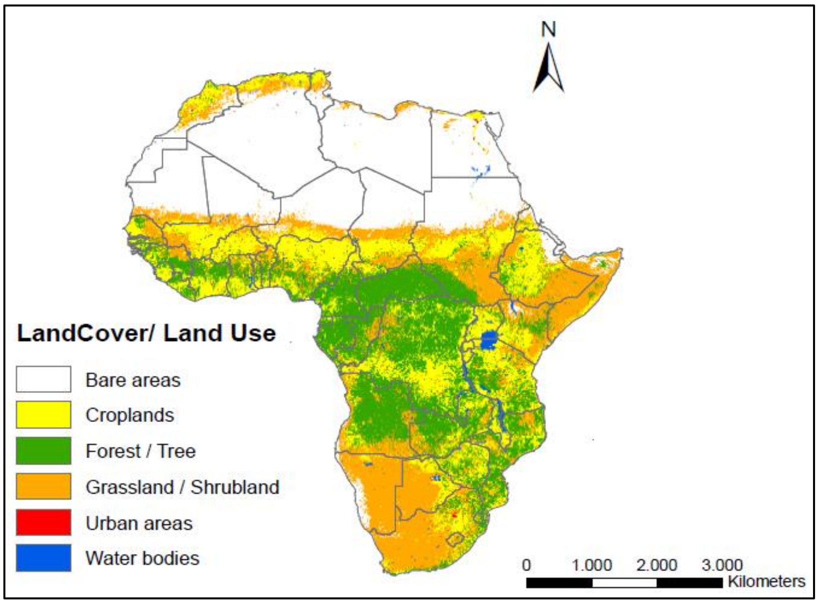


Figure 5-3: Land Cover/Land Use map of Africa (modified from Defourny et al., 2014)

Table 5-2: Localisation of study sites considered in the meta-analysis

Country	Localisation	Number of studies per country	References
Algeria	North east of Algeria	11	Labar et al.(2012a)
	Ouargla phreatic aquifer in Algeria: Valley of OuedM'y a		Semar et al.(2013)
	Nord-Algerian aquifer (Mitidija)		Sbargoud (2013)
	Medja area		Rouabhia et al.(2010)
	Biskra		Messameh et al.(2014)
	Case Skikda		Labar et al.(2012b)
	El Eulma		Belkhiri and Mouni (2012)
	Mostaganem, Mecheria, Naama, Tiaret, Bechar, and Adrar		Bahri and Saibi, (2012)
	Southern Hodna		Abdesselam et al.(2012)
	Tlemcen		Abdelbaki et al.(2013)
	Merdja plain		Rouabhia et al.(2009)
Angola	Angola	1	Angola Water Works (2013)
Benin	Cotonou	6	Totin et al.(2013)
	Beninese coastal basin		Totin et al.(2010)
	Municipality of Pobè		Lagnika et al.(2014)

Country	Localisation	Number of studies per country	References
	Dongo-pont		Bossa et al.(2012)
	Cotonou		BGS (2003b)
	Cotonou		Xu and Usher (2006)
Bostwana	Rural Bostwana	3	Batisani (2012)
	Kalahari		Stadler et al.(2004)
	Eastern fringe of the Kalahari near Serowe		Stadler et al.(2008)
Burkina Faso	Burkina Faso	4	BGS (2002)
	Burkina Faso		Pavelic et al.(2012)
	Sourou Valley		Rosillon et al.(2012)
	Ouagadougou		Xu and Usher (2006)
Cameroon	Mingoa River basin/Yaounde	10	Tabue et al.(2012)
	Bafoussam		Mpakam et al.(2009)
	Coastal zone of Cameroon/Douala		Nougang et al.(2011)
	Logon Valley/Chad-Cameroun		Sorlini et al.(2013)
	Anga's river		Kuitcha et al.(2013)
	Rio del Rey Basin/South Western Coast		Wotany et al.(2013)
	Mingoa/Yaounde catchment		Tabue et al.(2009)

Country	Localisation	Number of studies per country	References
	2 areas of Cameroon and Chad in the Lake Chad basin		Ngatcha and Daira (2010)
	Dschang Municipality		Temgoua (2011)
	Cameroon		Xu and Usher (2006)
Central African Republic	Bangui area	1	Djebebe-Ndjiguim et al.(2013)
Congo-Brazzaville	Brazzaville	5	Matini et al. (2012)
	Brazzaville		Barhe and Bouaka (2013)
	Souht East Brazaville		Laurent et al. (2010)
	Souht East Brazaville		Laurent and Marie (2010)
	South West Brazzaville		Matini et al.(2009)
Egypt	Alexandria	7	Abd El-Salam and Abu-Zuid (2015)
	Helwan		Abdalla and Scheytt (2012)
	Nile Valley		Abdel-Lah and Shamrukh (2001)
	Tahta		Easa and Abou-Rayan (2010)
	Kafr Al-Zayet District		Masoud (2013)
	Nile Delta aquifers / Western Nile Delta		Sharaky et al.(2007)
	Cairo, Egypt / province of Giza		Sadek and El-Samie (2001)

Country	Localisation	Number of studies per country	References
Ethiopia	Dire Dawa	13	Abate (2010)
	Ethiopia		BGS (2001a)
	Raya valley		Bushra (2011)
	Adis Ababa		Engida (2001)
	Addis Ababa		Kahssay et al.(2010)
	Koraro/Tigray		Nedaw (2010)
	Ethopia		Pavelic et al.(2012)
	Bulbule and Zway		Bonetto et al.(2005)
	Haromaya Watershed, Eastern Ethiopia		Tadesse et al.(2010)
	Akaki		Tegegn (2012)
	Adis Ababa		Xu and Usher (2006)
	Dire Dawa of Sabian area		Tilahun and Merkel (2010)
	Wondo Genet District, Southern Ethiopia		Haylamicheal and Moges (2012)
Ghana	Ga East	14	Ackah et al.(2011)
	Sawla-Tuna-Kalba District		Cobbina et al.(2012)
	Akatsi, Adidome and Ho Districts		Ansa- Asare et al.(2009)
	Ghana		BGS (2000a)

Country	Localisation	Number of studies per country	References
	Six districts in the eastern region of Ghana		Fianko et al.(2009)
	Kwahu West District		Nkansah et al.(2010)
	Ga-East District of Accra(Taifa)		Nyarko (2008)
	Ghana		Obuobie and Barry (2010)
	Ghana		Pavelic et al.(2012)
	Densu basin		Tay and Kortatsi (2008)
	Contamination in Ghana		Xu and Usher (2006)
	Western Region of Ghana		Affum et al.(2015)
	Gold Mining area in Ghana/Tarkwa		Armah et al.(2012)
	Lower Pra Basin of Ghana		Armah (2010)
Guinea-Biseau	Boloma	1	Bordalo and Savva-Bordalo (2007)
	Bonoua		Abenan et al.(2012)
	Bondoukou region		Ahoussi et al.(2012)
	Bonoua aquifer (South-East Ivory Coast)		Ake et al. (2010)
	Abidjan District		Douagui et al. (2012)
	Adiaké Region		Eblin et al. (2014)
	Abidjan and Korhogo		Kouame et al. (2013)

Country	Localisation	Number of studies per country	References
Ivory Coast	Abidjan aquifer	16	Xu and Usher (2006)
	South-West Ivory Coast		Yao et al. (2013)
	N'zi-Comoé (Centre East Ivory Coast)		Kouassi et al. (2010)
	Guiglo-Douekoué (West Ivory Coast)		Kouassi et al. (2012)
	N'zi, N'Zianouan municipality(South Ivory Coast)		Ahoussi et al. (2012)
	Bandama basin at Tortiya(Nothern Ivory Coast)		Drissa et al. (2013)
	Abia Koumassi village/Abidjan		Loko et al. (2013a)
	Slums of Anoumabo (Marcory) and AdjouffouPort-Bouet		Osemwegie et al. (2013)
	Catchment Ehania, South-Eastern Ivory Coast		Dibi et al. (2013)
	Hiré , South-West of Ivory Coast		Loko et al. (2013b)
Kenya	Kisaumi, Mombasa	1	Xu and Usher (2006)
Libya	North-East Libya	3	Nair et al. (2006)
	Alshati		Salem and Alshergawi (2013)
	North East Jabal Al Hasawnah		Sanok et al. (2014)

Country	**Localisation**	**Number of studies per country**	**References**
Malawi	Lake Chilwa basin	4	Xu and Usher (2006)
	Chikhwawa		Grimason et al. (2013)
	Upper Limphasa River/Nkhata-Bay district		Kanyerere et al. (2012)
	Blantyre		Mkandawire (2008)
Mali	Bamako city	3	Xu and Usher (2006)
	Mali		Pavelic et al. (2012)
	Timbuktu		Cronin et al. (2007)
Mauritania	Mauritania	1	Friedel (2008)
Morocco	Oued Taza	16	Ben Abbou et al. (2014)
	Taldla plain		Aghzar et al. (2002)
	Marrakesh		Alaoui et al. (2008)
	Meknès region		Belghiti et al. (2013)
	Oum Azza of Rabat		Benabbou et al. (2014)
	Phreatic aquifer of M'nasra		Bricha et al. (2007)
	Taldla plain		EL Hammoumi et al. (2013)
	Mzamza-Chouia		Asslouj et al. (2007)
	Berrechid plain		EL Bouqdaoui et al. (2009)
	Taldla plain		El Hammoumi et al. (2012)
	Triffa plain		Fekkoul et al. (2011)

Country	Localisation	Number of studies per country	References
	Triffa plain		Fetouani et al. (2008)
	Essaouira Basin		Laftouhi et al. (2003)
	Phreatic aquifer of Martil		Lamribah et al. (2013)
	Casablanca		Smahi (2013)
	Souss-Massa basin (South-west Morocco)		Tagma et al(2009)
Mozambique	Lichinga	2	Cronin et al. (2007)
	Maputo city		Muiuane (2007)
Niger	Niamey	3	Chippaux et al.(2002)
	Niamey		Hassane (2010)
	Niamey		Abou (2000)
Nigeria	Uzouwani (South Eastern Nigeria)		Ekere (2012)
	Lagos		Adelekan and Ogunde (2012)
	Ondo State		Akinbile (2012)
	Southwestern Abeokuta		Aladejana and Talabi (2013)
	Lagos		Anthony (2012)
	Lagos-State		Balogun et al. (2012)
	Nigeria		BGS (2003a)
	Konduga town		Dammo et al. (2013)
	Abuja		Dan-Hassan et al. (2012)

Country	Localisation	Number of studies per country	References
	Nigeria	24	Edet et al. (2011)
	Edo State/ South-South		Imoisi et al. (2012)
	Jimeta-Yola (Northeastern of Nigeria)		Ishaku (2011)
	Eastern Niger Delta		Nwankwoala and Udom (2011)
	Anambra State		Obinna et al. (2014)
	Lagos		Ojuri and Bankole (2013)
	Afikpo basin		Omoboriowo et al. (2012)
	Benue State		Ornguga (2014)
	Nigeria		Palevlic et al.(2012)
	Niger Delta		Rim-Rukeh et al. (2007)
	Igbokoda, Southwestern Nigeria		Talabi (2012)
	Lagos		Wakida and Lerner (2005)
	Nigeria		Xu and Usher (2006)
	Abia state		Obi and George (2011)
	Eti-Osa, Lagos		Akoteyon and Soladoye (2011)
Republic Democratic of Congo	Kahuzi-Biega Nationals Parks	2	Bagalwa et al. (2013)
	Kinshasa		Longo (2009)
Senegal	Dakar Region	7	Brandvold (2013)

Country	Localisation	Number of studies per country	References
	Thiaroye		Madioune et al. (2011)
	Niayes region		Sall and Vanclooster (2009)
	Dakar		Wakida and Lerner (2005)
	Dakar		Xu and Usher (2006)
	Dakar		Diédhiou et al. (2012)
	Yeumbeul/Dakar		BGS (2003b)
Somalia	Somaliland and Puntland	1	FAO-SWALIM (2012)
South Africa	South Africa	6	Maherry et al. (2009)
	Philippi/Western Cape		Aza-Gnandji et al. (2013)
	Mpumalanga Province		Mpenyana-Monyatsi and Momba (2012)
	South Africa		Musekiwa and Majola (2013)
	South Africa		Pavelic et al. (2012)
	Hex River Valley; Sandveld; Hertzogville		Xu and Usher (2006)
Sudan	Southern Suburb of the Ondurman	5	Abdellah et al. (2013)
	Khartoun		Ahmed et al. (2000)
	Karrary		Salim et al.(2014)
	Karrary		Taha (2010)
	Khartoum		Idriss et al. (2011)

Country	Localisation	Number of studies per country	References
Tanzania	Tanzania	8	BGS (2000b)
	Dar es Salam		De Witte (2012)
	Dodoma		Kashaigili (2010)
	Kilimandjaro region		McKenzie et al. (2010)
	Dar es Salam		Mjemah (2013)
	Dar es Salam		Mtoni et al.(2013)
	Tanzania		Palevlic et al. (2012)
	Temekedistric/Dar es Salam		Napacho and Manyele (2010)
Tchad	N'djamena	3	Guideal et al.(2010)
	Lake Chad basin		Seeber et al. (2014)
	Chad basin		Ngatcha and Daira (2010)
Togo	Agoè-Zongo	2	Kissao and Housséni (2012)
	Gulf/South of Togo		Mande et al.(2012)
Tunisia	North-east of Tunisia (Korba aquifer)	8	Zghibi et al.(2013)
	Cap Bon		Anane et al. (2014)
	Cap Bon		Charfi et al.(2013)
	Djebeniana		Fedrigoni et al.(2001)
	Metline-Ras Jebel-Raf Raf/North-East		Hamza et al., 2007

Country	Localisation	Number of studies per country	References
	Sfax-Agareb		Hentati et al.(2011)
	El Khairat aquifer		Ketata et al.(2011)
	Chaffar/ South of Sfax		Smida et al.(2010)
Uganda	Uganda	2	BGS (2001b)
	Kampala/Bwaise III		Kulabako et al.(2007)
Zambia	Petauke Town	4	Mbewe (2013)
	John Laing and Misisi de Lusaka		Xu and Usher (2006)
	Copperbelt Province/(North Western Province; Lusaka Province ; Central Province ; Southern Province)		Nachiyunde et al.(2013)
	Lusaka		Wakida and Lerner (2005)
Zimbawe	Kamangara	2	Dzwairo et al.(2006)
	Epworth at Harare		Zingoni et al.(2005)

Table 5-3: Explanatory variables used in the MLR analysis.

Explanatory variables	Type	Units or Categories	Spatial resolution/Scale	Date	Data source(s)
Land Cover/Land Use	Categorical data	-	300 m	2014	[1]UCL/ELIe-Geomatics (Belgium)
Population density	Continuous point data	people/km^2	2.5 km	2004	ESRI : www.arcgis.com/home
Nitrogen application	Continuous point data	kg/ha	0.5° x 0.5°	2009	[2]SEDAC : www.sedac.ciesin.columbia.edu
Climate class data	Categorical data	-	0.5°	1997	Global-Aridity values (UNEP, 1987)/ (UNESCO-IHE, Delft, The Netherlands)
Type of regions	Categorical data	-	0.5°	2014	Global-Aridity values (UNEP, 1987)/ (UNESCO-IHE, Delft, The Netherlands)
Rainfall class	Categorical data	mm/year	3.7 km	1986	UNEP : http://www.grid.unep.ch
Depth to groundwater	Categorical data	m	0.5° x 0.5°	2012	British Geological Survey: www.bgs.ac.uk/
Aquifer type	Categorical data	-	1:3750 000	2012	[3]GLiM data (Hamburg University)
Soil type	Categorical data	-	1 km × 1 km	2014	ISRIC, World Soil Information: www.isric.org/content/soilgrids
Unsaturated zone(impact of vadose zone)	Categorical data	-	1:3750 000	2012	GLiM data (Hamburg University)
Topography/Slope	Continuous point data	Percentage (%)	90 m	2000	UCL/ELIe-Geomatics (Belgium) and [4]CGIAR/CSI
Recharge	Continuous point data	mm/year	5 km	2008	Global-scale modelling of groundwater recharge (University of Frankfurt)
Hydraulic conductivity	Continuous point data	m/day	Average size of polygon ~100km^2	2014	[5]GLHYMPS data (McGill University)

[1]Université Catholique de Louvain/Earth and Life Institute/Environmental sciences; [2]Socioeconomic Data and Applications Center (SEDAC); [3]The new global lithological map database GLiM: A representative of rock properties at the Earth surface; [4]Consultative Group for International Agricultural Research (CGIAR)/ Consortium for Spatial Information (CSI); [5]A glimpse beneath earth's surface: Global Hydrogeology MaPS (GLHYMPS) of permeability and porosity.

5.3.4 Statistical model description

We used Multiple Linear Regression (MLR) as the statistical method for identifying the relationship between the observed nitrate concentrations in groundwater and the set of independent variables given in Table 5-3. MLR is based on least squares, which means that the model is fitted such that the sum of squares of differences of predicted and measured values is minimized (Koklu et al., 2009; Helsel and Hirsh. (1992)). The MLR model is denoted as by Eq. (1):

$$y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \varepsilon_i \qquad i=1, m, \qquad (1)$$

where y_i is the response variable at location i, β_0 is the intercept, β_j are the slope coefficients of the explanatory categorical or continuous variables x_{ij}, n the number of variables and m is the number of locations or wells (number of studies here). ε_i is the regression residual. In this study, the response variable is the log transformed nitrate concentration in groundwater. The log transformation was needed to stabilize the variance and to comply with the basic hypothesis of MLR. The log transformed nitrate concentration is a continuous monotonic increasing function; it is, therefore, reasonable to accept that factors that contribute to the log transformed nitrate load will also contribute to the nitrate load. The explanatory variables were defined using a stepwise procedure, using the Akaike Information Criterion (AIC) as test statistic (Helsel and Hirsch, 1992). We evaluated model performance based on the significance level of estimated coefficients, the coefficient of determination (R^2), the mean square error (MSE), the probability plots of model residuals (PRES), the plots of predicted versus observed values and the Akaike Information Criterion (AIC). High values of R^2 and low values of RMSE, PRES and AIC indicate a better performance of the model. To validate the model obtained by the stepwise procedure, the standard regression diagnostics were assessed. To test the heteroscedasticity in the model residuals, we use the Breusch-Pagan (BP) test by implementing with "lmtest" package.

A Student statistic t test was finally used to check the statistical significance (with p-values <0.10) of variables in the final model. We assessed tolerance to examine if multicollinearity exists between variables. In this study, we performed the statistical analyses using the R version 3.1.1 (R Development Core team, 2015).

5.4 Results

5.4.1 Normality of the dependent variable

Prior to analysis, we carefully checked the data using descriptive statistics, such as boxplots and correlation analysis. The observed nitrate concentrations through meta-analysis range from 0 mg/L to 4625 mg/L for all categories, i.e. mean, maximum and minimum values of nitrate groundwater contamination. Descriptive statistics are summarized in Table 5-4. The average mean nitrate concentration is 27.85 mg/L. The positive skewness of the mean nitrate concentration data and the kurtosis suggest that the mean nitrate concentration is not normally distributed. In contrast, the lognormally transformed mean nitrate concentration obeys normality, as demonstrated by means of the non-parametric Shapiro-Wilk test (p-value=0.1432>0.05). The histogram of mean and log transformed concentration is shown in the Figure 5-4. We also checked the minimum and maximum nitrate concentration for normality (see Appendix A and B respectively).

Table 5-4: Summary statistics of original and log (ln) transformed nitrate data.

Statistic	**Maximum NO_3^- concentration**	**Maximum ln(NO_3^-) concentration**	**Mean NO_3^- concentration**	**Mean ln(NO_3^-) concentration**	**Minimum NO_3^- concentration**	**Minimum ln(NO_3^-) concentration**
Number of data (-)	206	206	82	82	185	185
Minimum (mg/l or ln(mg/l))	0.08	-2.52	1.26	0.231	0	0
Maximum (mg/l or ln(mg/l))	4625	8.43	648	6.473	180	5.19
Median (mg/l or ln(mg/l))	73.64	4.29	27.58	3.317	0.55	0.43
Mean (mg/l or ln(mg/l))	190.05	3.99	54.85	3.169	8.91	1.08
Variance ($(mg/l)^2$ or $ln(mg/l)^2$)	183778.94	3.39	163.92	43.901	537.07	1.78
CV (-)	225.56	46.18	8085.08	1.935	260.08	123.04
Standard Deviation (mg/l or ln(mg/l))	428. 69	1.84	89.91	1.391	23.17	1.33
Kurtosis	60. 24	0.90	23.99	-0.167	25.57	0.37
Skewness	6.75	-0.74	4.31	-0.294	4. 56	1.2

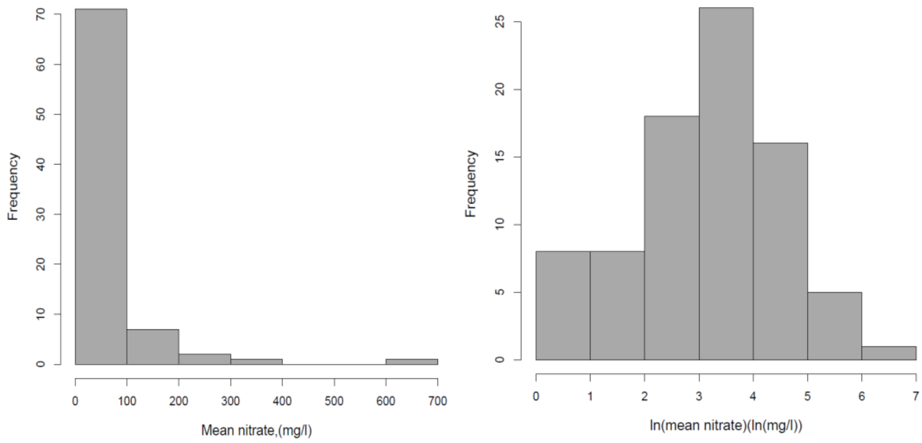


Figure 5-4: Histograms of observed mean nitrate concentration (mg/l) and logtransformed mean nitrate concentration (ln (mg/l))

5.4.2 Correlation between nitrate in groundwater and explanatory variables

Land Cover/Land Use is in general an important factor controlling groundwater contamination. Thus, the box plot distribution of log transformed mean nitrate concentration for different land use classes is presented in Figure 5-5. Groundwater in agricultural and urban areas is clearly more susceptible to nitrate pollution as compared to forest/bare area land use. Also, water bodies are susceptible to nitrate contamination but this result is likely spurious since only two studies support this category. We performed a similar analysis on the log transformed maximum and minimum nitrate concentration. The corresponding boxplots results can be obtained from the authors upon request. High values for log transformed maximum nitrate concentration are also found in urban and cropland areas. High values for log transformed minimum nitrate concentration are detected in croplands fields. All analyses confirm that the highest nitrate pollution is retrieved in urban areas, immediately followed by agricultural areas.

The relation between the log transformed mean nitrate concentration and the population density is given in Figure 5-7a. We observe an increasing nitrate in groundwater related to increasing population. This explicit relationship between population density and nitrate concentration has a Pearson's correlation of 0.632. This obviously confirms the importance of studying the population as a potential polluting parameter and its relevant correlation to nitrate occurrence in the groundwater at the African scale.

Nitrogen fertilizer contributes significantly to an increase in crop yields, but excess nitrogen fertilizer generally pollutes groundwater (Green et al., 2005; Nolan et al., 2002). In the case of Africa, the impact of the nitrogen fertilizer application rate on log transformed mean nitrate concentration is illustrated in Figure 5-7b. Pearson's correlation give a low relation (r=0.09). The analysis in this figure confirms that no clear relationship existing between fertilizer load and groundwater nitrate contamination. This can be linked to the relatively low fertilizer use in Africa, as compared to other continents. Indeed, most studies have nitrogen fertilizer dressings that are below 50 kg/ha. According to the FAO (2012), Africa accounts only for about 2.9 percent of the world fertilizer consumption in 2011.

The distribution of the log transformed mean nitrate concentration data with depth is shown in Figure 5-7c. Apparently, no clear relationship exist between depth to groundwater and nitrate contamination. Pearson's correlation give a poor correlation (r=0.004). However, careful analysis of this figure shows clearly that shallower wells (7-25 m bgl and 25-50 m bgl) are associated with higher values of log-transformed mean nitrate concentration, in contrast to the low values of log transformed nitrate concentrations found in the deeper groundwater systems (>250 m bgl).

The relationship between the log transformed mean nitrate concentration and groundwater recharge can also be observed in Figure 5-7d. This figure shows that nitrate concentration in the groundwater decreases with recharge. This may due to dilution of nitrate charge. We observe on this figure high nitrate concentrations in the very low recharge class (0-45 mm/year). This may be due to irrigation water return that feeds the groundwater and that is not integrated into the recharge calculations. The analysis of Pearson's correlation between recharge and log transformed mean nitrate give a r=-0.292.

In this study, the aquifer systems for Africa are divided into five categories based on the lithological formations. Figure 5-6 shows the relation between mean log transformed nitrate concentration and aquifer system type class. The carbonates rocks, the unconsolidated sediments, and the siliciclastic sedimentary rocks represent respectively the first, the second and the third class in terms of nitrate contamination. The crystalline rock and volcanic rock aquifer classes are less contaminated. The high concentrations in the unconsolidated aquifer systems is a particular point of concern since this class is the most representative in terms of groundwater exploitation. The high concentrations in the carbonates rocks and fractured basalt can be explained by their high vulnerability related to the presence of solution channels and fractures.

We performed similar correlation analysis on the log transformed maximum concentration and log transformed minimum concentration respectively. The different box plot diagram are reported in appendix section (see figures A 3 to A 8 and figures B 3 to B 7). Results of these analyses are coherent with the results for log transformed mean nitrate concentration.

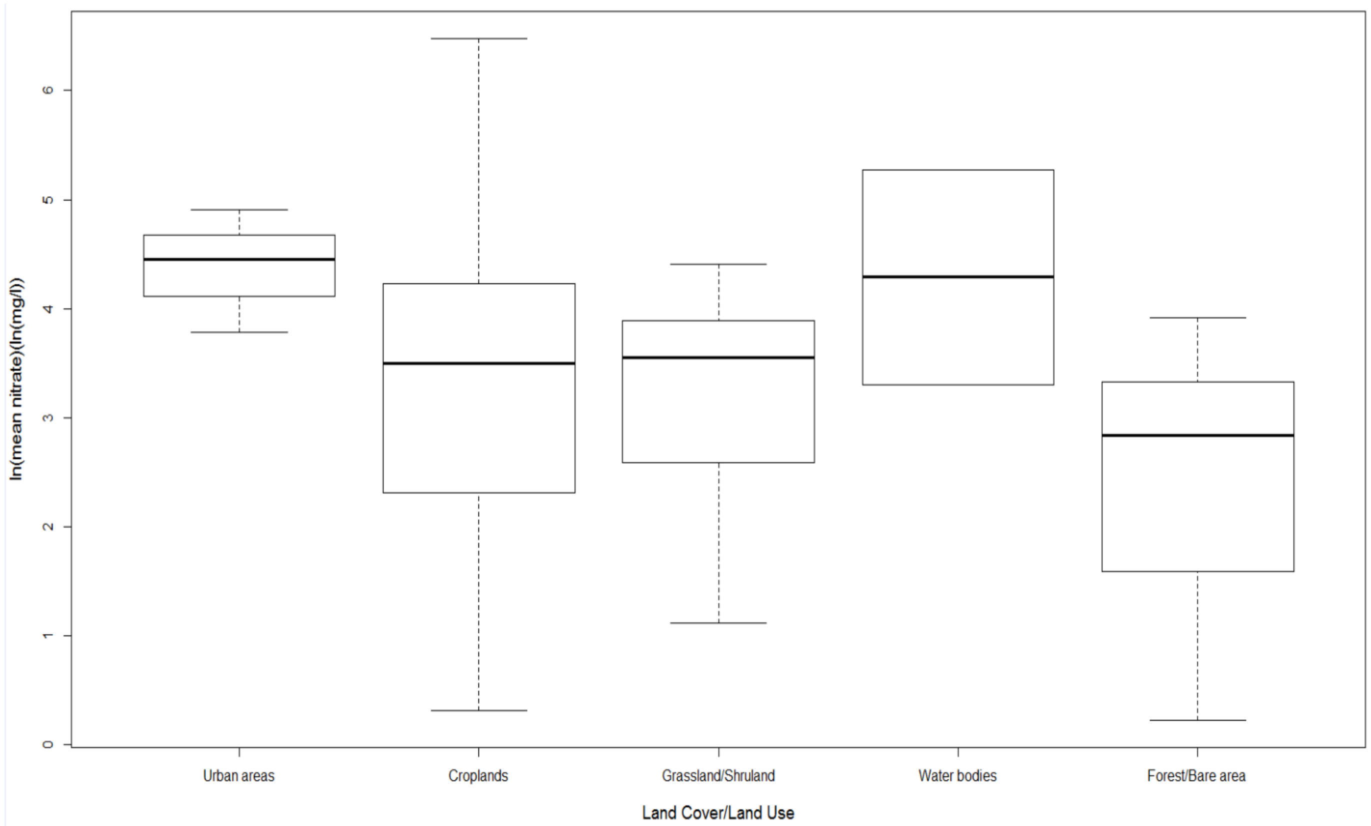


Figure 5-5: Log transformed mean nitrate concentration for different land use classes

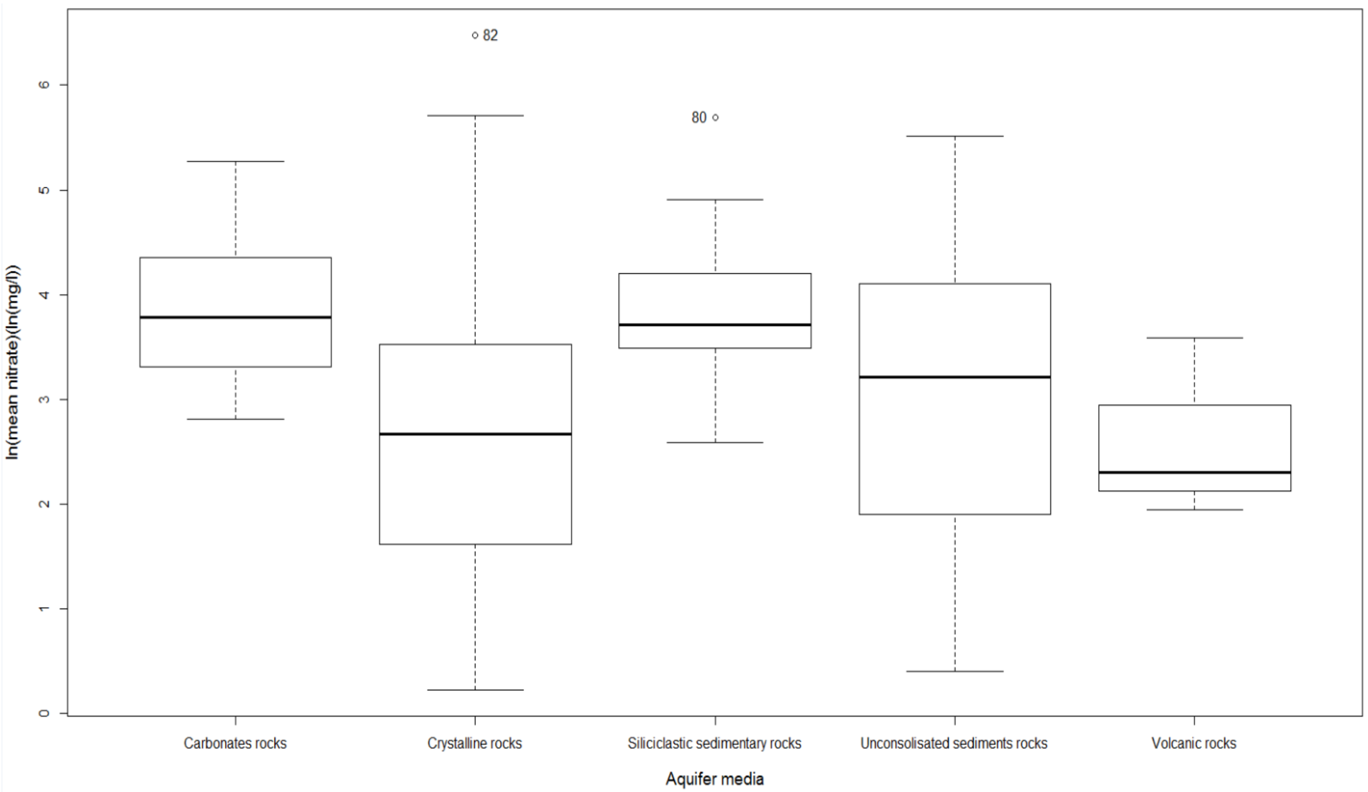


Figure 5-6: Log transformed mean nitrate concentration for different aquifer system classes

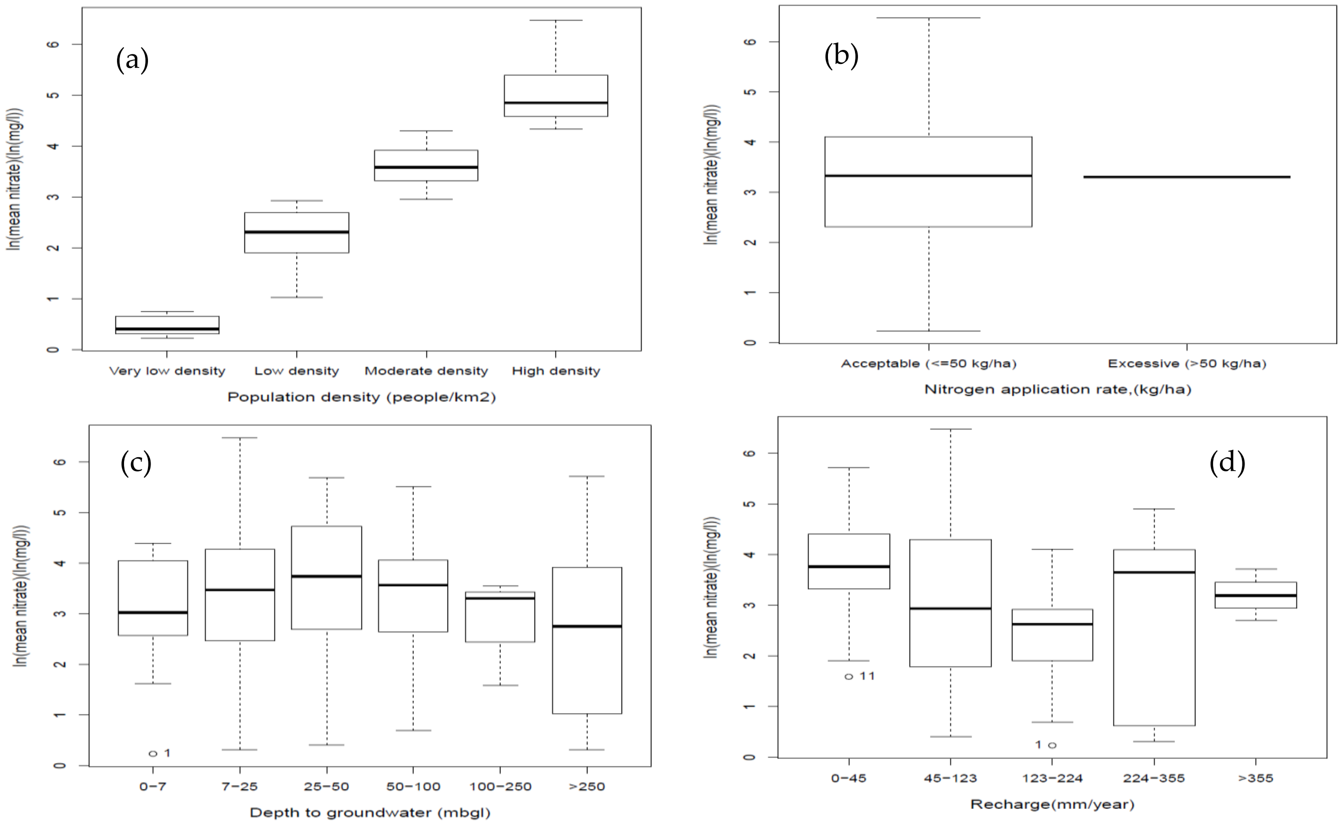


Figure 5-7:Log transformed mean nitrate concentration for different population density classes (a), nitrogen application rate classes (b), groundwater depth classes (c) and recharge classes (d).

5.4.3 Development of the multi-variate statistical model

We developed a set of multiple variable regression models for the log transformed mean and maximum nitrate concentration in terms of above mentioned explanatory variables. A positive regression coefficient indicates a positive correlation between a significant explanatory variable and a target contaminant while a negative coefficient suggests an inverse or negative correlation. We retained only explanatory variables with p-values ≤ 0.1.

The best model that explains the log transformed mean nitrate concentration includes only 4 explanatory variables: (1) depth to groundwater, (2) recharge, (3) aquifer type, and (4) population density. Table 5-5 summarizes the results of this linear regression model. This model can explain 65 percent of the log transformed mean nitrate concentration observations. The sign of the parameter coefficient indicates the direction of the relationship between independent and dependent variable (Boy-Roura et al., 2013). The lower the p-value, the more significant is the model parameter.

The regression analysis confirms the strong relationship between population density and log transformed mean nitrate concentration. As the p-value is far below 0.05, we are more than 95 % confident that the population density strongly affects the nitrate occurrences in groundwater.

The aquifer medium is another important explanatory variable for log-transformed mean nitrate concentration. Three categories of aquifer media are significantly explaining the dependent variables: carbonates rocks, crystalline, and unconsolidated sediments rocks. Indeed, the analyse of regression coefficients shows that the likelihood of nitrate contamination decreases with the presence of unconsolidated sediments and crystalline rocks. Other aquifer types tested include siliciclastic sedimentary rocks and volcanic rocks aquifers were found not statistically significant in the model. However, the aquifer media type is an important variable to assess groundwater vulnerability and to bring information about the hydrogeological system in the assessment. It allows differentiating the vulnerability in terms of aquifer lithology. Variables such as hydraulic conductivity could be surrogates for aquifer media because hydraulic conductivity data were developed based on the lithological formation. Nevertheless, they were not statistically significant in the final model.

The third variable represents the depth to groundwater. The three first classes (0-7; 7-25 and 25-50 m bgl) of groundwater depth are all statistically significant. The water table corresponding to the 0-7 m class has the strongest statistical significance. The positive parameter coefficient indicates large contamination for shallow groundwater depths. By analysing the table of the coefficients, we observe that the largest groundwater depth class (100-250 m bgl) is not statistically significant (p-value >0.05). We can conclude that the shallow groundwater systems at an African scale are most vulnerable to nitrate pollution.

The fourth variable included in the final model is the recharge. The recharge rate in the 45-123 mm/year and 123-224 mm/year class are statistically significant. In general, these rates correspond to semi-arid and dry sub-humid regions. The high concentrations in these areas can be due to intensive agricultural activities.

Other explanatory variables such as rainfall or land cover/land use were not considered in the final model. Indeed, notwithstanding a variable such as land cover/land use strongly influences observed log transformed mean nitrate concentration (Figure 5-5), it is related to other variables such as population density. Hence, to avoid multicollinearity in the final model, the land cover/land use variable is no longer included in the final model.

Table 5-5: Optimal linear regression model for explaining the log transformed mean nitrate concentration

Coefficients:				
	Estimate	Std. Error	t value	Pr (>|t|)
(Intercept)	3.348e+00	6.624e-01	5.055	3.56e-06 ***
Depth [0-7]	1.160e+00	3.895e-01	2.977	0.00404 **
Depth [7-25]	6.563e-01	3.693e-01	1.778	0.08002*
Depth [25-50]	1.114e+00	4.755e-01	2.342	0.02216 **
Depth [50-100]	6.536e-01	4.005e-01	1.632	0.10744
Depth [100-250]	4.258e-01	6.766e-01	0.629	0.53129
Recharge [0-45]	-2.506e-01	6.089e-01	-0.412	0.68200
Recharge [45-123]	-1.187e+00	6.055e-01	-1.961	0.05407*
Recharge [123-224]	-1.112e+00	6.134e-01	-1.812	0.07440*
Recharge [224-355]	-8.856e-01	6.089e-01	-1.455	0.15047
Aquifer media [Crystalline rocks]	-9.851e-01	3.374e-01	-2.920	0.00477 **
Aquifer media [Siliciclastic sedimentary rocks]	1.893e-02	3.916e-01	0.048	0.96158
Aquifer media [Unconsolidated sediments rocks]	-7.632e-01	3.384e-01	-2.255	0.02740 **
Aquifer media [Volcanic rocks]	-5.245e-01	6.123e-01	-0.857	0.39469
Population density (people/km^2)	5.611e-04	6.887e-05	8.147	1.30e-11 ***
Residual standard error: 0.9116 on 67 degrees of freedom				
Multiple R-squared: 0.65				
F-statistic: 8.693 on 14 and 67 DF, p-value=2.422e-10 < 0.001				

Note: Statistical significance: ***p<0.001; **p<0.05; and *p<0.1.

The final multiple linear regression (MLR) model using the four variables yields an R^2 of 0.65, indicating that 65 % of the variation in observed log transformed mean nitrate concentration at the African scale is explained by the model. The result of the model is globally significant because the p-value =2.422e-10 at 95% of the significant level. The observed versus predicted log transformed mean nitrate concentration is shown in Figure 5-8 and indicates that the MLR fits the data well. The probability plot of model residuals indicates that they the distribution is close to normal (Figure 5-9). We performed the Shapiro-Wilk test as an additional check on the distribution of nitrate residuals. Because the probability associated with the test statistic is larger than 0.05, we accept the null hypothesis that the residuals follow a normal distribution. Despite the fact that a few points have higher Cook D value compared to the rest of the observation, they were kept in the MLR to represent the whole range of nitrate concentration data. In order to check the regressions assumptions of homoscedasticity, a plot of the residuals of log transformed mean nitrate versus the predicted log transformed mean values is illustrated in Figure 5-10. We observe that the majority of observations are in the range of -2 to 2 except for two outliers observed in the bottom left part of the graph. The residual standard error of the log transformed mean nitrate is 0.91116 (ln (mg/L)). We observe that the residuals decrease with increasing predicted nitrate concentrations. The Breusch-Pagan test was used to assess heteroscedasticity in the model residuals (BP=24.2773 and p-value= 0.042). With a p-value of 0.042, we reject the null hypothesis that the variance of the residuals is constant and infer that heteroscedasticity is indeed present. As a result, we may expect some bias in the MLR model.

Similarly to the log transformed mean nitrate concentration modelling, we developed another model corresponding to the log transformed maximum nitrate concentration. This model yielded only an R^2= 0.42 for the maximum values. The explanatory variables which influence the log transformed maximum nitrate concentration in groundwater are depth to groundwater, soil media, topography, rainfall, climate class and type of region. For the log transformed minimum concentration, the absence of normal distribution assumptions did not allow one to develop a MLR model.

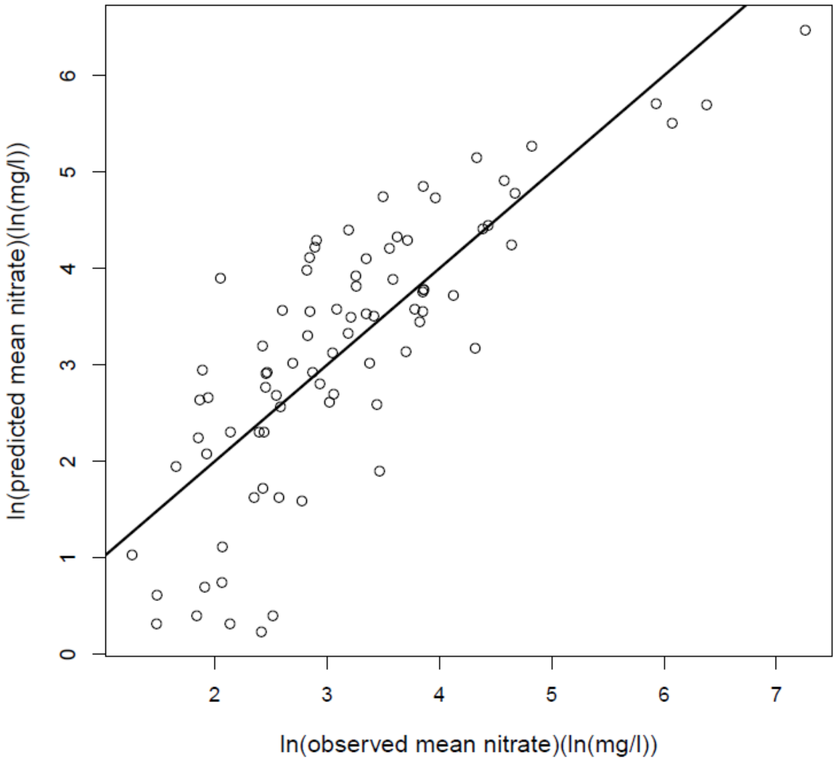


Figure 5-8: Predicted versus observed mean log transformed nitrate concentration (R^2=0.65)

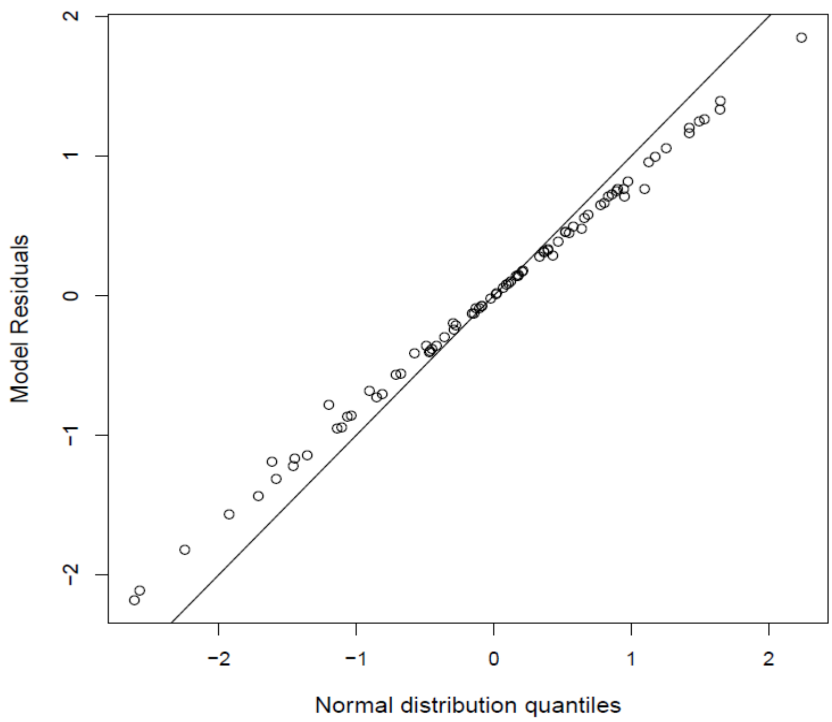


Figure 5-9: Normal probability distribution of model residuals for the predicted log transformed mean nitrate concentration

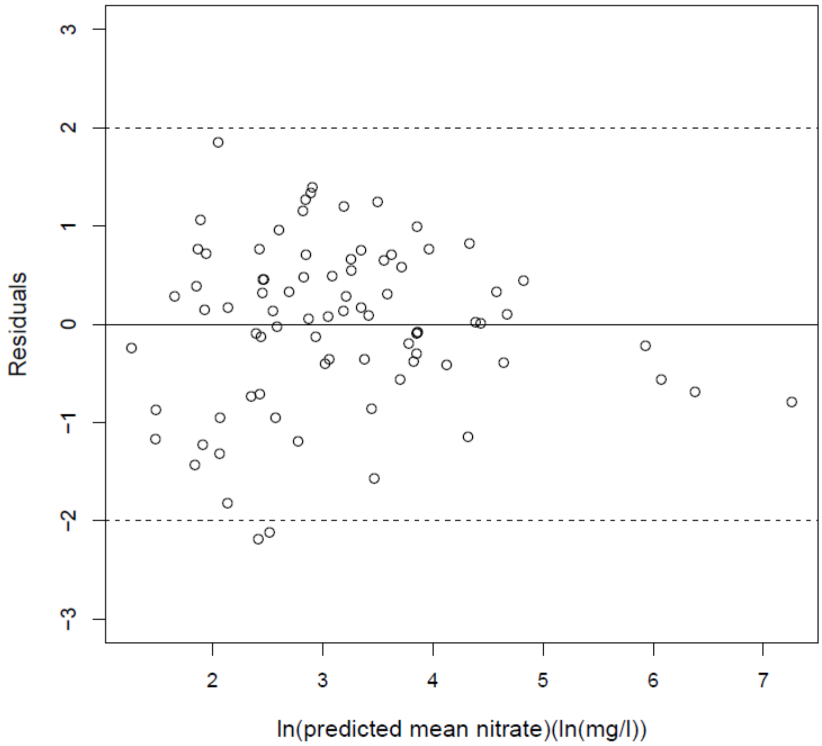


Figure 5-10: Relation between residuals and predicted log transformed mean nitrate concentration.

5.5 Discussion

We present in this study a database collected through the meta-analysis method to assess the vulnerability of groundwater systems for water quality degradation. We used the log transform of reported nitrate concentration as a proxy for groundwater vulnerability. We present a statistical model to explain this proxy in terms of generic data at the African scale. In a previous study, we evaluated the groundwater vulnerability for pollution at the African scale using the generic DRASTIC approach (Ouedraogo et al., 2016). However, the uncalibrated DRASTIC model predictions are subjected to quite some uncertainty, in particularly due to the subjectivity in assigning the generic DRASTIC model parameters. In contrast to this previous study, we focus in this chapter on nitrate pollution which is a parameter that is strongly related to vulnerability and that often is measured in on-going monitoring programmes. We integrate published nitrate in groundwater data explicitly in the assessment, thereby reducing the subjectivity of the DRASTIC approach.

We assessed in this study the quality of the data (Sect. 5.3.2). Yet notwithstanding this, some caution is needed in the interpretation of the results, in particular as bias may be present in the meta-analysis. For instance, there may be bias towards studies on aquifers which are productive and used for drinking water supply, irrigation or mining activities. Another possible bias is that some studies mainly focussed on nitrates originated from point sources (e.g.,sewage sanitation systems, unsewered urbanization,…) and diffuse pollution (e.g. organic and chemical fertilizers applied on arable lands to increase crop cultivation, on grassland to increase grass production and on pastures to support cattle breeding, …), while others are oriented to more general groundwater quality studies. Furthermore, the data were collected from different sources (peer-reviewed journal articles, book chapters or other grey literature). With such approach, sampling and analytical methods are not standardised, being an additional source of possible bias. Data availability is a major issue when developing a continental-scale groundwater nitrate statistical model. Unsurprisingly there are no consistent and standardised monitoring datasets at the continental scale. The available data sets are also patchy, both spatially and temporally. A meta-analysis of literature data is so far the only method for getting the picture at the continental scale. Results from this meta-analysis should not be over-interpreted. Whilst the data provide a useful preliminary assessment into the nitrate contamination in groundwater at the African scale, there are clear limitations.

In this study, we used multiple linear regression (MLR) for explaining nitrate pollution groundwater in terms of other generic spatially distributed environmental variables. MLR is an approach to model the relationship between a response variable and multiple sets of explanatory variables (Rawlings et al., 1998). MLR analysis is capable of both predicting and explaining a response variable using explanatory variables without compromise (Kleinbaum et al., 1988). Previous studies of MLR using spatial variables for nitrate concentration in groundwater showed R^2 values of 0.52 and 0.64 in shallow alluvial aquifers (Gardner and Vogel, 2005; Kaown et al., 2007) and R^2 of 0.82 in deep sandy tertiary aquifers (Mattern et al., 2009). For the application in this study, we selected the parameters using stepwise MLR regression, allowing to select only those variables which have a significant impact on the log transformed concentration values of nitrate.

The explanatory variables with the strongest influence on the mean log transformed nitrate concentration at the African scale are the population density and groundwater depth, which is in agreement with results from other studies such as Nolan, (2001), Nolan et al., (2002), Nolan and Hitt (2006), Liu et al., (2013), Bonsor et al., (2011) and Sorichetta et al. (2013). Both explanatory variables are directly related to the probability of having high nitrate concentrations in groundwater. The strong influence of the population density variable can be explained by the serious problem of sanitation in Africa townships. This is consistent with the conclusions of the UNEP/UNESCO project 'Assessment of Pollution Status and Vulnerability of Water Supply Aquifers Cities', stating that the major pollution pressure on African water bodies are related to poor on-site sanitation, solid waste dumpsites including household waste pits and surface water influences (Xu and Usher, 2006). This is also consistent with other studies stating that that leaking septic tanks and sewer systems are considerably causing nitrate contamination of groundwater in urban areas (Bohlke, 2002; Showers et al., 2008). The magnitude of contamination is not only affected by the population density but also by the socio-economic setting (UNEP/DEWA, 2014). A high population density is therefore often associated with the lack of adequate sanitation in many slums/shanty towns in Africa. The strong influence of population density in our model suggests that high concentrations in groundwater are mainly from subsurface leakage of municipal sewage systems, petrol service station (underground storage tanks), and agricultural chemicals in small scale farming. Lapworth et al. (2017) affirm that groundwater contamination does occur when waste from households, municipalities, livestock, agriculture, hospitals, and industries (including mining) is able to make its way inadequate management of household and industrial waste is leading to the pollution of groundwater resources in urban centres in sub-Saharan Africa. These authors add that: faecal waste is the largest source of contamination in urban (and rural) groundwater, in particular where there is high-density housing with poor and/or inadequate sanitation facilities and treatment of faecal waste and this situation is common in low-income areas of most major and growing urban centres in Africa. In this recent study, based on DRASTIC risk score for underlying aquifer vulnerability (from Ouedraogo et al.2016), Lapworth et al. (2017) demonstrated that the greatest nitrate contamination was in groundwater sources in settlements with extremely high population densities (over 40,000 people per km^2), there was wide variation in study findings from aquifers with similar risk levels. Hence, sanitation programmes in Africa must not be delinked from groundwater protection and controlling the use of fertilizer products in agriculture. Hence, sanitation programmes in Africa must not be delinked from groundwater protection and controlling the use of fertilizer products in agriculture. Because, by listing the major sources of urban groundwater contamination in SSA, the authors Lapworth et al. (2017) cited urban agriculture and gave for example leached salts, fertilisers, pesticides and animal/human waste.

The others elements of this list are: Municipal/domestic waste: for example pit latrines, septic tanks, sewer leakage, sewage effluent, sewage sludge, urban road runoff, landfill/waste dumps and health care facilities; Industrial sources and waste: for example process waters, plant effluent, stored hydrocarbons, tank and pipeline leakage; mining activities: including both current and historical solid and liquid waste.

Although the strong influence of population density factor on groundwater pollution by nitrate, particularly in extremely high population zones was highlighted; we think also that agricultural activities of small settlements in rural areas can made more damages on groundwater resources, than small cities with higher density of population to due to excessive use of fertilisers for example.

Nitrate concentrations were generally higher for shallower wells than for deeper groundwater systems. For deep groundwater, predicted nitrate concentration was lower as compared to shallow groundwater (Nolan et al., 2014). Alluvial and shallow aquifers are thus particularly vulnerable to nitrate pollution while deep confined aquifers are generally better protected. The inverse relation between depth and nitrate is consistent with previous groundwater studies that considered well depth or depth of the screened interval as explanatory variables (Nolan and Hitt, 2006; Nolan et al., 2014; Wheeler et al., 2015; Ouedraogo and Vanclooster, 2016b). Nitrate generally moves relatively slowly in soil and groundwater, and therefore there is a significant time lag between the polluting activity and detection of the pollutant in groundwater (typically between 1 and 20 years, depending on the situation) (Boy-Roura, 2013; Mattern and Vanclooster, 2009). Deeper groundwater may, therefore, predate periods of intensive fertilizer application (1950–present).

The rate at which nitrate moves through the subsurface depends on the permeability and extent of fissuring of soil and aquifer, which controls flow, diffusion and dispersion processes. According to Close (2010), nitrate is negatively charged and thus electrostatically repelled by media in unsaturated zone that usually have a negative charge, such as clay minerals. This means that nitrate sorption within the unsaturated zone is unlikely and that the large residence times are related to the slow physical transport process. Foster and Crease, (1974), and Young et al., (1976) were the first authors to mention a "storage of nitrate" in porewater and consequent slow vertical migration through the unsaturated zone towards groundwater systems. More recently, others investigators showed the process of nitrate accumulation in the unsaturated zone (Ascott et al., 2017; Ascott et al., 2016; Wang et al., 2016; Worall et al., 2015). The long travel distances towards deep aquifer systems increase the probability that nutrients will react for instance through denitrification (Stevenson and Cole, 1999; Thayalakumaran et al., 2004; Aljazzar, 2010; Wheeler et al., 2015). Denitrification is facilitated by the absence of oxygen. Denitrification was found to be relatively limited in unsaturated zone (Kinniburgh et al., 1994; Rivett et al., 2008), while it is the principle process responsible for reduction of nitrate in groundwater (Aljazzar, 2010, Stevenson and Cole, 1999; Thayalakumaran et al., 2004), in particular in reduced groundwater (Burow et al.,2013). Boy-Roura et al., (2013), for instance, found low nitrate concentrations (below 50 mg/L) in those areas where denitrification processes have been identified. An indicator of the presence of denitrification processes contributed as such to explain nitrate contamination in the Osona region (NE Spain) (Boy-Roura et al., 2013). In our study, an indicator of the presence of denitrification processes in the groundwater system was not available and could not be included in the model.

Another remark concerns the presence of nitrate in some specific geological formations. According to Tredoux and Talma (cited in Xu and Usher, 2006), an apparent correlation may exist between the occurrence of high nitrate levels and certain geological formations. The apparent correlation however between the occurrence of high nitrate levels and certain geological formations is mainly due to secondary effects. Only in exceptional cases, geological formations can serve as a primary source of nitrogen. This happens when contamination ions are incorporated in rock minerals to be released by weathering and oxidized to nitrate. These authors further concluded that in most cases, the occurrence of high levels of nitrate is due to contamination related to anthropogenic activities.

The strong relation between nitrate contamination and both, groundwater depth and population density is a particular point of concern given the fact that the majority (85 %) of Africa's population lives in regions where depth to groundwater is shallow (0-50 m bgl) and where hand pumps may be used to abstract water. Eight percent of these people (i.e. nearly 66 million people) are likely to live in areas where depth to groundwater is 0-7 m bgl. A significant minority (8 %) of Africa's population lives in regions where the depth to groundwater is between 50 and 100 m bgl and common hand pump technologies (e.g. India Mark) are inoperable in these cases. These areas are mainly within southern Africa and to a lesser extent situated in the Sahel.

A third important explanatory variable that was included in the model was the groundwater recharge rate. The recharge rate of an aquifer is indeed another factor that controls groundwater flow regime and hence the movement of nitrate. Nitrate can easily be transported to shallow groundwater in well-drained areas with rapid infiltration and highly permeable subsurface materials. However, according to a recent study in the shallow unconfined aquifer of the Piemonte plain, dilution can be considered as the main cause for nitrate attenuation in groundwater (Debernardi et al., 2007). The variable recharge in our model is consistent with studies like Hanson (2002) and Saffigna and Keeney (1997). According to UNEP/DEWA (2014), recharge from multiple sources influences groundwater microbial and chemical water quality. Groundwater recharge rate is interlinked with many other environmental variables including, but not limiting, soil type, aquifer type, antecedent soil water content, land use/land cover type and rainfall (Sophocleous, 2004; Ladekarl et al., 2005; Anuraga et al., 2006). Hence, to avoid multi-collinearity, variables like land use/land cover type, rainfall, and soil type were not considered in the final model.

Despite land cover/land use type is not explicitly included in the final model, the exploratory analysis clearly shows a strong relationship between nitrate concentration and land use/land cover type. Indeed, nitrate concentrations are generally higher in urban areas. This is consistent with many other studies such as Showers et al., (2008). The high contamination in urban areas jeopardises groundwater exploitation in urban areas. Urbanization is a pervasive phenomenon around the world, and groundwater demands in urban areas are increasingly growing. The degradation of groundwater bodies in urban areas is, therefore, a particular point of concern. Also, agricultural land exhibit an impact on groundwater nitrate concentrations compared to the grassland/shrubland, water bodies, and forest/bare area, but this effect is less important as compared to agricultural land effects in other parts of the world (e.g. Europe).

The influence of aquifer type to the nitrate contamination was demonstrated by Boy-Roura et al., (2013) and the influence of soil type by Liu et al., (2013). As with land cover/ land use type, these variables were not retained in the final model to avoid collinearity with recharge.

The advantage of the MLR technique is that it can be easily implemented and that model parameters can be easily interpreted if the possible interaction between variables is ignored. However, MLR cannot represent well the many non-linear dynamics that are associated with the contamination of groundwater systems. The violation of the homoscedasticity hypothesis, for instance, indicates that some bias will be present in our MLR model. Standard statistical models employed in distribution modelling, such as MLR, work under the assumption of independence in the residuals and homoscedasticity. When heteroscedasticity is present, residuals may be autocorrelated. This will lead to inflated estimates in degrees of freedom, an underestimation of the residual variances and an overestimation of the significance of effects (Legendre and Fortin, 1989; Legendre, 1993; Dale and Fortin, 2002; Keitt et al., 2002). This may show that others variables should be included in the model or that the system may be highly non-linear.

We could avoid heteroscedasticity and improve the modelling performance by introducing non-linear regression techniques (Prasad et al., 2006) or by introducing additional variables in the model. Indeed, many studies showed that non-linear statistical models of groundwater contamination outperform as compared to linear models (e.g. Pineros-Garcet et al., 2006; Mattern et al., 2009; Oliveira et al., 2012 and Wheeler et al., 2015). To uncover non-linear relationships, non-parametric data mining approaches provide obvious advantages (Olden et al., 2008; Wiens, 1989; Dungan et al., 2002). Machine learning provides a framework for identifying other explanatory variables, building accurate predictions, and exploring other non-linear mechanistic relationships in the system. We may, therefore, expect that non-linear statistical models will improve the explanatory capacity of the model and remove heteroscedasticity from the model.

However, we believe that this theoretical constraint of heteroscedasticity does not undermine the overall results. The observed heteroscedasticity can be considered modest in view of the large extent of the study, and the violation of statistical design criteria when collecting data through a meta-analysis. Also, the interpretation of the factors and coefficients associated with non-linear regression techniques become more complicated. We, therefore, prefer to maintain in this study the MLR techniques as a first approach to screen the factors that contribute to log transformed mean nitrate concentration risk. We suggest however that future studies should address the added value that can be generated with non-linear modelling techniques. Such non-linear modelling techniques are particularly needed for the maximum concentration for which the R^2 of simple MLR remains currently too poor and also for the minimum concentration who shows the absence of normal distribution assumptions.

Also, in this study, we only identified a MLR model based on a meta-analysis spanning the African continent. Since, the data collected through the meta-analysis are very heterogeneous, the quality of the data set remains rather poor. Therefore, future studies should critically address the validity of the identified model and explore how the model can be improved and be used in a predictive model. It is however suggested that such model improvement and validation step should be based on a more homogeneous data set. We, therefore, suggest to perform this future model validation and model improvement step using data collected at the regional scale using more homogeneous data collection protocols.

5.6 Conclusion

Contamination of groundwater by nitrate is an indicator of groundwater quality degradation and remains a point of concern for groundwater development programmes all over the world. It is also a good proxy of overall groundwater vulnerability for water quality degradation. We address in this chapter the issue of nitrate contamination of groundwater at the African scale. We inferred the spatial distribution of nitrate contamination of groundwater from a

meta-analysis of published field studies of groundwater contamination. We analysed the literature for reported mean, minimum and maximum concentration of nitrate contamination. We subsequently analysed, using box-plots, the reported contamination in terms of spatially distributed environmental attributes related to pollution pressure and attenuation capacity. We extracted the explanatory variables from a geographic information system with the ArcGIS 10.3™ tool.
We finally developed a MLR statistical model allowing to explain quantitatively the log transformed observed contamination that is a proxy of vulnerability, in terms of spatially distributed attributes. We selected the explanatory variables using a stepwise regression method.

Groundwater contamination by nitrates is reported throughout the African continent, except for a large part of the Sahara desert. The observed nitrate concentrations range from 0 mg/L to 4625 mg/L. The mean nitrate concentration varies between 1.26 to 648 mg/L. The sample mean of this mean nitrate concentration is 54.85 mg/L, its standard deviation was 89.91 mg/L and its median was 27.58 mg/L. The minimum nitrate concentration varies between 0 to 185 mg/L while the maximum concentration varies 0.08 to 4625 mg/L. The sample mean of the minimum and maximum concentrations is 8.91 mg/l and 190.05 mg/L; the sample standard deviations is 23.17 mg/L and 428.69 mg/L; and the sample median is 0.55 mg/L and 73.64 mg/L, respectively. The distribution of the reported nitrate contamination data is strongly skewed. We, therefore, build statistical models for the log transformed mean and maximum concentrations.

The graphical box plot analysis shows that nitrate contamination is important in shallow groundwater systems and strongly influenced by population density and recharge rate. Nitrate contamination is, therefore, a particular point of concern for groundwater systems in urban sectors.

The MLR model for the log transformed mean nitrate concentration uses ‘the depth to groundwater’, ‘groundwater recharge rate’, ‘aquifer type’ and ‘population density’ as an explanatory variable. The total variability explained by the model is 65 %. This suggests that other variables may be needed to explain the reported nitrate concentrations. These findings highlight the challenges in developing appropriate regional databases to predict groundwater degradation. The MLR shows that the population density parameter is the most statistically significant variable. This authenticates that leaking cesspits and sewer systems are considerably causing nitrate contamination of groundwater predominantly in urban areas. We identified similar MLR models for the log transformed maximum nitrate concentrations. Yet, for this latter attribute, the explained variation using the simple MLR techniques (i.e. 42 %) remains small.

One of the main strengths of our study is that it is based on a large database of groundwater contamination reports from different countries, spanning the African continent and linked to environmental attributes that are available in a spatially distributed high-resolution format. In addition, the development of a continental-scale model of nitrate contamination in groundwater of Africa allowed determining which explanatory variables mainly influence the presence of nitrate. This represents an important step in managing and protecting both water resources and human health at the African scale. The main weakness of the modelling approach lies in the lack of detailed information available at the African scale, particularly the lack and uneven distribution of measured nitrate points. In spite of weaknesses and uncertainties caused by a moderate heteroscedasticity from residuals in the model, the modelling approach presented here has great potential. Although the meta-analysis should not replace systematic nitrate monitoring, it gives a first indication of possible contamination. It can be also applied to the preliminary assessment of nitrate using spatial variables. This may support the water resources development program for transboundary aquifers managers and regional basin organizations. This is particularly important as the demand for drinking water is increasing rapidly at the African scale.

We suggest that further development include the use of non-linear modelling techniques such as Random Forest techniques. Such techniques have the potential to improve the quality of explanation and eventually prediction by incorporating spatial autocorrelation. We also suggest that the models should be further validated using more homogeneous data sets. In a predictive mode, statistical models like those developed in the present chapter can be used for exposure estimate in epidemiological studies on the effect of polluted groundwater on human health. Similar models can also be developed for others contaminants could be explored.

Chapter 6 Modelling groundwater nitrate concentrations at the African scale using Random Forest Regression Techniques[3]

[3] *Based on:* ***Ouedraogo, I.,*** *Defourny, P., and Vanclooster, M. (2017). Modelling groundwater nitrate concentrations at the African scale using Random Forest Regression Techniques. Accepted April 24th to review for the special issue on Groundwater in Sub-Saharan Africa for Hydrogeological Journal (HJ) (in progress, book expected in December 2017).*

6.1 Abstract

We use in this study the Random Forest Regression (RFR) method for modelling groundwater nitrate contamination at the pan-African scale. When compared to more conventional techniques, key advantages of RFR include its non-parametric nature, its high predictive accuracy, and its capability to determine variable importance. This last characteristic can be used to better understand the individual role and the combined effect of explanatory variables in a predictive model.

In the absence of a systematic monitoring program for groundwater at the pan-African scale, we used the pan-African groundwater nitrate contamination database obtained from a meta-analysis (Ouedraogo and Vanclooster, 2016a) to test the modelling approach. In this dataset, 250 groundwater nitrate pollution studies from the African continent were compiled. The literature data were filtered using the following criteria: (i) the publication should explicitly report on nitrate concentrations in groundwater; (ii) the publication should be published after 1999. As predictors, we collected a comprehensive GIS database of thirteen spatial attributes related to land use, soil type, hydrogeology, topography, climatology, regions types and nitrogen fertilizer application rate.

The performance of the RFR is evaluated in comparison to the Multiple Linear Regression (MLR) methods. Both techniques identified the population density as the most important variable explaining reported nitrate contamination. However, RFR has a much higher predictive power than a traditional linear regression model. RFR is therefore considered a very promising technique for large-scale modelling of groundwater pollution by nitrates.

6.2 Introduction

Across the World, groundwater is one of the most valuable natural resources serving as a major source of water for communities, agriculture and industrial purposes. In Africa, groundwater is a crucial natural resource supporting the development, but it is subject to many pressures. According to Xu and Usher, (2006), degradation of groundwater is the most serious water resources problem in Africa. The two main threats are overexploitation and contamination (MacDonald et al., 2013). Nitrate is a common chemical contaminant of groundwater and the level of contamination also increases in many African aquifers (Spalding and Exner, 1993; Puckett et al., 2011). Nitrate ingestion has been linked to methemoglobinemia, adverse reproductive outcomes, and specific cancers (Ward et al., 2005). In addition, nitrate is often a proxy of other possible pollutants of groundwater. Nitrate contamination is therefore very informative for overall groundwater quality. However, it is a space-time variable and the level of contamination depend on many other space-times environmental and anthropogenic attributes. The regional modelling of nitrate contamination of groundwater remains, therefore, a technical and scientific challenge.

Statistical models are often deployed to explain the spatial distribution of observed nitrate concentration in terms of available environmental and anthropogenic attributes, or to discriminate sources of contamination (Nolan and Hitt, 2006). Most statistical models used in such a context uses Multiple Linear Regression (MLR), nonlinear regression, logistic regression, Bayesian approaches, Artificial Neural Networks (ANN), or classification and regression trees in order to extract the variables that explain nitrate contamination (Rwalings et al., 1998; Burow et al., 2010; Mair and El-kadi, 2013; Gurdak and Qi, 2012; Mattern et al., 2012). For example, Bauder et al., (1993) investigated the major controlling factors for nitrate contamination of groundwater in agricultural areas using land use, climate, soil characteristics, and cultivation types as explanatory variables. However, these different techniques show a variety of problems such as the lack of sensitivity towards outlier values of logistic regression, and the opacity of neural networks (Abrahart et al., 2008).

The use of modern data mining or machine learning approaches avoids many of these limitations. The emerging type of techniques which utilizes ensembles of regressions is receiving highlighted interest in other fields of knowledge (Hansen and Salamon, 1990; Steele, 2000; Khalil et al., 2005; Sesnie et al., 2008). Ensemble learning algorithms use the same base algorithm to produce repeated multiple predictions, which are averaged in order to produce a unique model (Breiman, 2001a; Friedl et al., 1999). They may reduce bias and improve prediction efficiency (Breiman, 2001a; Cutler et al., 2007; Peters et al., 2007; Fernández-Delgado et al., 2014).

Random Forests Regression (RFR) is an example of such an ensemble regression method. RFR is non-parametric and thus data do not need to come from a specific distribution (e.g. Gaussian) and can contain collinear variables (Cutler et al., 2007). Furthermore, RFR work well with very large numbers of predictors (Cutler et al., 2007). These methods can deal with model selection uncertainty as predictions are based upon a consensus of many models and not just on a single model selected with some measure of goodness of fit. RFR is appropriate for illustrating the nonlinear effect of variables; it can handle complex interactions among variables and is not affected by multicollinearity (Breiman, 2001b). Major applications of RFR are found in environmental and ecological modeling (e.g. Yost et al., 2008; Moreno et al., 2011; Oliveira et al., 2012; Oppel et al., 2011; Hoyos et al.,2015), in eco-hydrological distribution modeling (e.g. Peters et al., 2007), in landslide susceptibility mapping (Park, 2014; Youssef et al., 2015) and in remote sensing (e.g. Gislason et al., 2006; Pal, 2005; Rodriguez-

Galiano et al., 2012a, 2012b). In groundwater research, RFs have been applied to model nitrate and arsenic in aquifers of the southwestern U.S. (Anning et al., 2012), nitrate in an unconsolidated aquifer in southern Spain (Rodriguez-Galiano et al., 2014), nitrate in private wells in Iowa (Wheeler et al., 2015) and nitrate in shallow and deep wells of the Central Valley (Nolan et al., 2014). A perceived disadvantage of another machine learning methods such as ANN is their ''black box'' nature; without estimated coefficients, it is difficult to show significant relations between the response and predictor variables (Nolan et al., 2015). According to Rodriguez-Galiano et al. (2014), RFR is relatively robust to outliers and it can overcome the "black-box" limitations of ANNs by assessing the relative importance of the explanatory variables, by selecting the most important ones (features) and, hence, reduce the dimensionality.

RFR is based on bootstrap aggregated of regression trees, which typically outperforms compared to the traditional models such as logistic regression (Breiman, 2001a; Breiman et al., 1984). Moreover, the parameterization of RFR is very simple and it is computationally less demanding (Rodriguez-Galiano and Chica-Rivas, 2012). RFR provides very good results compared to other machine learning techniques such as support vector machines (SVM) and ANNs or to other decision tree algorithms (Breiman, 2001a; Liaw and Wiener, 2002). Furthermore, Loosvelt et al. (2012) demonstrated that uncertainty estimates can be easily assessed when RFR is applied.

In this study, we use RFR to explain and predict groundwater nitrate contamination at the continental scale and compare the performance of RFR with MLR techniques. Use is made of the nitrate contamination data set as compiled through a meta-analysis (Ouedraogo and Vanclooster, 2016a). The modelling of nitrate contamination at this scale can provide guidance for the planning and implementation of groundwater monitoring programs; in particular, the design of transboundary groundwater management strategies adjusted to the conditions of different regions of Africa.

6.3 Materials and methods

6.3.1 The pan-African groundwater nitrate contamination dataset

In the major part of Africa, there is very little, or no systematic monitoring of groundwater. In the absence of data, we used compiled nitrate pollution data at the pan-African scale from a meta-analysis (Ouedraogo and Vanclooster, 2016a). We collected 250 groundwater pollution studies in literature from available books and the internet web of sciences (Scopus™, Sciences Direct™, Google™, and Google Scholar™). We filtered the literature data using the following criteria: (i) the publication should explicitly report on nitrate concentrations in groundwater; (ii) the publication should be published after 1999. We derived various aggregated measures of nitrate concentration from the different studies. So, we were able to retain 206 points where the maximum concentration of nitrate was reported, 187 points where the minimum concentration was reported and 94 studies on the mean concentration of nitrate. Out of the 94 datasets for which mean values were reported, 12 field sites have nitrate concentration smaller than 1 mg/L. Therefore, we have kept only 82 values for the mean nitrate concentration in this study. Figure 6-1 gives an example of the distribution of mean nitrate concentrations collected and overlaid on a groundwater pollution risk map (Ouedraogo et al., 2016). This figure shows that nitrate concentration in groundwater is irregularly distributed in Africa. However, this distribution shows a coherent distribution according to groundwater vulnerability map i.e. where the groundwater is subjected to a pollution risk (Ouedraogo et al., 2016). We study only in this chapter the reported mean nitrate concentrations. This choice is guided by the fact that this category of data is less sensitive to outliers and more robust as compared to a minimum or maximum concentration data. Groundwater nitrate concentration data are summarized in Table 6-1. In the present study, the modelled response variable is the natural log of sampled groundwater nitrate concentration. The average mean nitrate concentration is 54.85 mg/L, the standard deviation is 89.91 mg/L, and the median concentration is 27.58 mg /L. The log transform reduces the influence of very high nitrate values (up to 648 mg/l) on models predictions. The nitrate studies were separated into two groups: 80 % of the dataset for building the model (training dataset) and 20 % of the data set for the validation of the model (tested dataset).

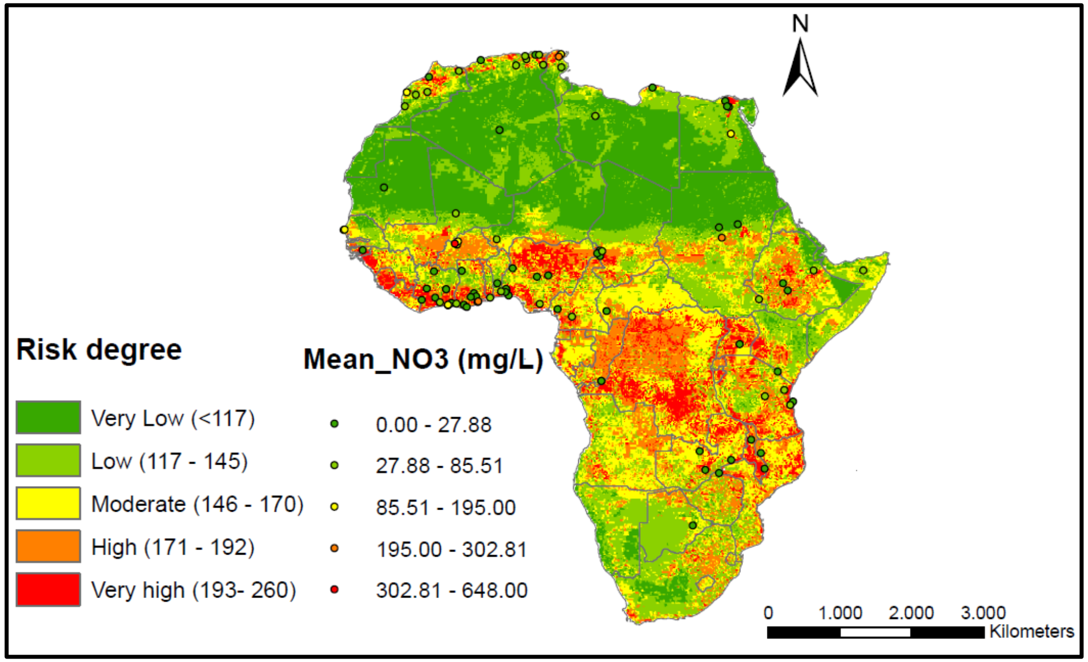


Figure 6-1: Spatial distribution of mean nitrate concentration in groundwater (Ouedraogo et al. 2016)

Table 6-1: Summary statistics of original and ln-transformed nitrate data (from Ouedraogo and Vanclooster, 2016a)

Variable	**Mean NO_3^- concentration**	**Mean $\ln(NO_3^-)$ concentration**
Minimum (mg/l or ln (mg/l))	1.26	0.231
Maximum (mg/l or ln(mg/l))	648	6.473
Mean (mg/l or ln(mg/l))	54.85	3.169
CV(-)	8085.08	1.935
Standard Deviation (mg/l or ln(mg/l))	89.91	1.391
Median (mg/l or ln(mg/l))	27.58	3.317
Variance $(mg/l)^2$ or $\ln(mg/l)^2$)	163.92	43.901
Kurtosis (mg/l or ln(mg/l))	23.99	-0.167
Skewness (mg/l or ln(mg/l))	4.31	-0.294
Number of observations (-)	82	82

6.3.2 The dataset of explaining factors

We collected data from a total of 13 possible explaining factors, extracted from several high-resolution databases covering physical and anthropogenic attributes. These attributes are related to land use, soil type, hydrogeology, topography, climatology, etc. Table 6-2 presents the 13 explanatory factors, their spatial resolution, and their data sources. We integrated all explanatory factors into a Geographical Information System (GIS) and processed in ArcGIS10.3™ in a raster format of 15 km x 15 km spatial resolution. This resolution is the best compromise considering the resolution of the different available datasets and the large extent of the study area.

6.3.2.1 Climate

Climate conditions have an effect on the probability of nitrate occurrence pollution in groundwater. The climate class data used is the "Derived Climate classes for the African continent" raster format with the resolution of 0.5 degrees and classified into five classes (Trambauer et al., 2014). We obtained the regions type data in raster format and classified into six classes according to the UNEP classification (1997) directly from P.Trambauer from UNESCO-IHE (Delft/ The Netherlands). We generated the rainfall map from the UNEP/FAO World and Africa GIS Data Base.

6.3.2.2 Topography

Land surface slope indicates whether the runoff will remain on the surface to allow contamination percolation to the saturated zone. We inferred the slope from the 90-meter Shuttle Radar Topography Mission (SRTM90) topographic map, using the Spatial Analyst software of ArcGIS10.3™. Elevation values at 90 m resolution were aggregated at 15 km.

6.3.2.3 Soil type and land use

Soil texture influences the nitrogen loss. Nitrate leaching is generally greater from poorly structured sandy soils than from clay soils because of the slower water movement and the greater potential for denitrification to occur in the clay soils (Cameron et al., 2013). We derived the soil texture in this study from soil grids at a 1 km resolution produced by Hengl et al., (2014). There are 9 classes of soil texture: sandy, sandy loam, loamy sandy, loam, clay loam, sandy clay, sandy clay loam, silty clay loam, and clay.

We produced land cover and land use from the high-resolution CCI LC dataset (Defourny et al., 2014). To create a consistent measurement of land cover, we aggregated the original 22 classes that represent the African's area into 6 dominant classes (water bodies, bare area, grassland/shrubland, forest, urban, croplands).

6.3.2.4 Geology and hydrogeology

The groundwater table and vadose zone thickness determine the N transfer time and dilution potential from the surface to the groundwater. The aquifer medium is a hydrogeological factor that describes the ability of pollutants to move within this aquifer according to its type. In this study, we inferred the depth to groundwater map from data presented by Bonsor et al., (2011). We derived the aquifer and vadose zone type from the high resolution global lithological database (GliM) of Hartmann and Moosdorf (2012). We determined aquifer type and unsaturated lithological zone for each of the five hydrolithological and lithological categories as defined by Gleeson et al., (2014). These categories are unconsolidated sediments, siliciclastic sediments, carbonate rocks, crystalline rocks, and volcanic rocks.

Recharge to the groundwater as a portion from rainfall amounts depends on rainfall data, soil permeability, and topographic setting. Groundwater recharge is a function of many parameters including, but not limited to soil type, antecedent soil water content, land cover, and rainfall (Anuraga et al.,2006; Sophocleous, 2004). In our study, we inferred the recharge from the global-scale modelling of groundwater recharge presented by Döll and Fiedler (2008).

Hydraulic conductivity and transmissivity are important for the assessment of the aquifer's ability to transmit water, determine the rate of flow of a contaminant material within the groundwater. We determined the hydraulic conductivity of aquifers using the Global Hydrogeology MaPS (GHYMPS) of permeability and porosity data (Gleeson et al., 2014).

6.3.2.5 Nitrogen fertilizer application

We generated the mean nitrogen fertilizer application map (kilogram per square kilometer) from the Potter and al., (2010) dataset. The values shown on this map represent an average application rate for all crops over 0.5° resolution grid cell. Following this study, the highest rate of N fertilizer application (i.e. 220 kg/ha) is found in Egypt’s Nile Delta.

6.3.2.6 Population density

The population density represents the distribution of potentially causative agents, considering that nitrates in Africa scale are mainly human-caused. Data on population density at the African scale was obtained from the UNEP website. The population density for the year 2000, considered in this study, was produced by Nelson (2004).

Table 6-2: Explanatory variables and nitrate concentrations used in the Random Forest model

	Name	Type of data	Units or Categories	Spatial resolution/Scale	Date	Data source(s)
Explanatory variables	Land Cover/Land Use	Categorical	-	300 m	2014	Personal contact: UCL/ELIe-Geomatics (Belgium)
	Population density	Continuous point	people/km^2	2.5 km	2004	ESRI : www.arcgis.com/home
	Nitrogen application	Continuous point	kg/ha	0.5° x 0.5°	2009	SEDAC : www.sedac.ciesin.columbia.edu
	Climate class data	Categorical	-	0.5°	1997	Personal contact: P. Trambauer (UNESCO-IHE, Delft, The Netherlands)
	Type of regions	Categorical	-	0.5°	2014	Personal contact: P. Trambauer (UNESCO-IHE, Delft, The Netherlands)
	Rainfall class	Categorical	mm/year	3.7 km	1986	UNEP : http://www.grid.unep.ch
	Depth to groundwater	Categorical	m	0.05° x 0.05°	2012	British Geological Survey: www.bgs.ac.uk/
	Aquifer type	Categorical	-	1:3750 000	2012	Personal contact: N. Moosdorf (Hamburg University)
	Soil type	Categorical	-	1 km × 1 km	2014	ISRIC, World Soil Information: www.isric.org/content/soilgrids
	Unsaturated zone(impact of vadose zone)	Categorical	-	1:3750 000	2012	Personal contact: N. Moosdorf (Hamburg University)
	Topography/Slope	Continuous point	Percentage (%)	90 m	2000	Personal contact: UCL/ELIe-Geomatics (Belgium) and CGIAR/CSI (SRTM data)
	Recharge	Continuous point	mm/year	5 km	2008	Personal contact: P.Döll and F. Portman (University of Frankfurt)
	Hydraulic conductivity	Continuous point	m/day	Average size of polygon ~100km^2	2014	Personal contact: T.P. Gleeson (McGill University)
Response variable	Nitrates	Continuous point	mg/l	-	2000 to 2015	Ouedraogo and Vanclooster,(2016a)

6.3.3 Description of the models

The preliminary analysis of the mean nitrate data revealed a non-normal distribution. Different transformations were tested in order to obtain a normal distribution of the dependent variable, as required in Multiple Linear Regression (MLR) model. The original dataset was randomly divided into calibration (80 %) and validation (the remaining 20 %) samples. We identified and validated a MLR and a RFR model. All the models were implemented using the R Statistical Software (version 3.1.1; R Development Core Team, 2015). We evaluated the goodness of fit using the FITEVAL model (Ritter and Munoz-Carpena, 2015).

6.3.3.1 Multiple Linear Regression (MLR)

Regression techniques such as linear regression (Boy-Roura et al., 2013) or logistic regression (Nolan and Hitt, 2006), have been widely applied in nitrate modelling. Usually, these models aim to use the fewest predictors to explain the greatest variability in the response variable (Graham, 2003). Stepwise approaches are used to select the most relevant predictors in regression models, using different selection criteria such as Akaike's Information Criterion (AIC), Schwarz's Bayesian information criterion of F statistics, and others (Murtaugh, 2009). In our case, we performed a MLR and used the AIC criterion to select the predictors. The rational of this selection method is to combine the measure of fit with a penalty term based on the number of parameters used in the model. If more parameters (i.e., the number of trends or explanatory variables) are used, the model fit can be better, but the penalty for the extra parameters is higher as well. The smallest AIC indicates the most appropriate model.

6.3.3.2 Random Forest Regression (RFR)

We identified also a Random Forest Regression (RFR) model on the same data set. RFR modelling is an ensemble machine learning method for classification and regression that operates by constructing a multitude of decision trees (Breiman, 2001a). The philosophy behind ensemble learning techniques is based on the premise that its accuracy is higher than other machine learning algorithms because the combination of predictions performs more accurately than any single constituent model does. The individual decision trees in RFR tend to learn highly irregular patterns, i.e. they overfit their training datasets. RFR is a way of averaging multiple decision trees, trained on different parts of the same training dataset, with the goal of reducing the prediction variance (Hastie et al., 2008). RFR modelling is appropriate for modelling the nonlinear effect of variables. It can handle complex interactions among variables, and is not affected by multicollinearity (Breiman, 2001b). RFR can assess the effects of all explanatory variables simultaneously and automatically rank the importance of these variables in descending order (Rodriguez-Galiano et al., 2014).

A detailed description of the mathematical formulation of the RFR model is found in Breiman (2001a); Liaw and Wiener, (2002). The algorithm for RFR consists of building a forest of uncorrelated trees. Each individual tree is grown using a randomized subset of predictor variables. The trees are grown to the largest extent possible without pruning, and they are aggregated by averaging them. Out-of-bag (OOB) samples are used to calculate variable importance and to get an unbiased estimate of the test set error which is one of the advantages of RFR because there is no need for cross-validation. The method behaves essentially as a ''black box'' since the individual trees cannot be examined separately (Prasad et al., 2006) and it does not calculate regression coefficients nor confidence intervals (Cutler et al., 2007). Nevertheless, it allows the computation of variable importance measures that can be compared to other regression techniques (Grömping, 2009). In this study, the "randomForest" package of R 3.1.1 of open source statistical software(R Development Core Team, 2015) was used for all modeling.

In this study, we used 13 explanatory variables (Table 6-2). In order to maintain a similar procedure between MLR and RFR, we applied RFR on the training and the validation dataset. Even though independent validation samples are not required in RFR, they provide the opportunity to assess the generalization capability of this method (Cutler et al., 2007). To run the RFR model, it was necessary to define a priori two parameters: the number of variables or factors to be used in each tree-building process (mtry) and the number of trees to be built in the forest to run (ntree). Concerning the number of trees, Breiman (1996) demonstrated that by increasing the number of trees, the generalization error always converges; hence, overtraining is not a problem and the number of trees can be fixed once the error has converged. Rodriguez-Galiano et al., (2014) demonstrated that the error was minimum and stable when considering 1000 trees. Random forest never suffers the problem of overfitting Geng (2006). Breiman states that the test set error rates are monotonically decreasing and converge to a limit as the number of trees increases approaching ∞ (The Law of Large Numbers insures convergence as ∞). Geng (2006) argues that because each tree is constructed using 63 % of the dataset selected at random with replacement and each node is split using the best split in a small random sample of available variables (usually a square root of the number of available variables are selected at random as a potential splitter), every tree is constructed at random and is independent of other trees. Therefore, adding trees to the forest does not cause a problem of overfitting (cited in RandomForests™ version 1.0 Manual, Salford Institute).

We determined the parameter mtry via the internal Random Forest function TuneRF, that recognizes the optimal number of factors (the default value of mtry is a total number of variables/3 for regression) and it looks below and above this threshold for the value of the minimum OBB error rate. Breiman, (2001a) and Liaw and Wiener, (2002) stated that even a variable or factor (mtry = 1) can generate good accuracy, while Grömping (2009) proves the need to include at least two variables/factors (i.e. mtry = 2, 3, 4,…, m) in order to avoid using the weaker regressors as splitters.

6.3.3.3 Variable importance in random forest

The RFR used to predict nitrate concentration in groundwater, allows to estimate the variable importance of environmental attributes in the explaining model. The advantage of the RFR algorithm is that it allows explicitly to measure variable importance with two metrics: mean decrease in GINI Index and the other being the mean decrease in accuracy (%IncMSE). The mean decrease in GINI Index is used to measure the quality of a split for each variable in a tree; while the mean decrease in accuracy, based in Mean Squared Error (MSE) measured the mean decrease in prediction accuracy. In others words, the former measures the node impurity of the explaining factors, while the latter measures the contribution of the factor towards the overall fit. Each of these metrics measures the impact of the explanatory factor on the overall prediction (Breiman, 2001a). Yet, the GINI Index has been shown to have a bias (Strobl et al., 2007). Also, Genuer et al., (2010) considered that the percentage in explained mean square error is a more reliable measure than the decrease in node impurity. We therefore majorly use percentage in explained mean square error to assess variable importance.

6.3.4 Model validation

We evaluated the quality of the statistical models by means of the FITEVAL code (Ritter and Munoz-Carpena, 2013). This code uses the most general formulation of the coefficient of efficiency. For a complete model goodness-of-fit evaluation, the graphical results of FITEVAL contain the following elements (Ritter and Munoz-Carpena, 2013): (1) a plot of observed vs. estimated values illustrating the match of the 1:1 line; (2) the evaluation of NSE (Nash-Sutcliffe coefficient of efficiency) and the root mean square error (RMSE) and their correspondence 95 % interval; (3) the qualitative goodness-of-fit interpretation based on established classes (unsatisfactory, acceptable, good, very good); (4) a verification of the presence of bias or the possibility presence of outliers; (5) the plot of the NSE cumulative probability function superimposed on the NSE class region; and (6) a plot illustrating the evolution of observed and estimated values.

6.4 Results

6.4.1 Modelling results

6.4.1.1 Multiple Linear Regression (MLR)

The final MLR model built includes four variables which are: (i) depth to groundwater, (ii) recharge, (iii) aquifer type, and (iv) population density. Table 6-3 summarizes the results of this MLR model. The percentage of variance explained by the model was 64 % and the residual standard error is 0.95 (ln (mg/l)). The sign of the parameter coefficient indicates the direction of the relationship between independent and dependent variables (Boy-Roura et al., 2013). The lower the p-value, the more significant the model parameter. We retain only explanatory variables with p values ≤ 0.1.

The MLR results show that the population density has a strong positive relationship with ln-transformed mean nitrate concentration. As the p-value < 0.0001, this variable strongly affects the nitrate occurrence in groundwater at the pan-African scale.

The second variable included in the model is the depth to groundwater. The three classes (0-7; 25-50; 50-100 m b.g.l) of this variable are all statistically significant. We observe among these three classes that the 0-7 m class has the strongest statistical significance and a positive coefficient, indicating a large contamination for shallows groundwater. Regarding the largest groundwater depth class (100-250 m b.g.l), this class is not statistically significant (p-value >0.05). Therefore, we can affirm that the shallow groundwaters are most vulnerable to nitrate pollution in Africa compared to deep aquifers.

The third variable retained in the model is recharge. The two class of recharge rates (45-123; 123-224, in mm/year) are statistically significant and correspond in general to semi-arid and dry sub-humid climate. The high nitrate in these climate conditions can be explained by the intensive agriculture developed in these regions that strongly rely on irrigation.

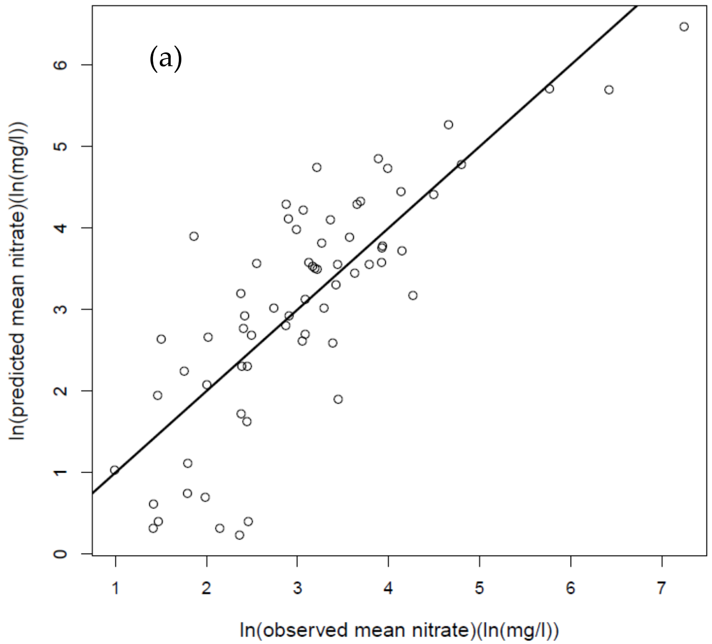
The last variable included in the final model is aquifer media. We observe that two categories of aquifer media are significantly in the model. These are: crystalline rocks and unconsolidated sediment rocks. Indeed, the analysis of their negative regression coefficients estimates shows that the likelihood of nitrate contamination decreases with the presence of unconsolidated sediments and crystalline rocks. The other categories of aquifer type namely siliciclastic sedimentary rocks and volcanic rocks are found statistically insignificant in the model. However, the variable of aquifer type is an important parameter to assess groundwater vulnerability and provides information about the hydrogeological setting.

A plot of predicted versus the observed log nitrate (ln NO_3) concentration in Figure 6-2a for the training data, indicates the MLR model shows an acceptable fits the observed data.

Table 6-3: Optimal MLR model for explaining the ln-transformed mean nitrate concentration.

Variables	Estimate	Std. Error	t value	Pr (>|t|)
(Intercept)	3.427e+00	7.306e-01	4.690	2.08e-05 ***
Depth [0-7]	1.384e+00	5.003e-01	2.766	0.00789 **
Depth [7-25]	7.322e-01	4.603e-01	1.591	0.11788
Depth [25-50]	1.408e+00	5.645e-01	2.493	0.01594 **
Depth [50-100]	1.000e+00	5.185e-01	1.929	0.05928*
Depth [100-250]	1.332e+00	8.694e-01	1.532	0.13175
Recharge [0-45]	-6.094e-01	6.903e-01	-0.883	0.38154
Recharge [45-123]	-1.580e+00	6.775e-01	-2.333	0.02365 **
Recharge [123-224]	-1.334e+00	6.638e-01	-2.010	0.04974 **
Recharge [224-355]	-9.021e-01	6.535e-01	-1.380	0.17350
Aquifer media [Crystalline rocks]	-1.116e+00	4.010e-01	-2.783	0.00753 **
Aquifer media [Siliciclastic sedimentary rocks]	-1.196e-01	4.770e-01	-0.251	0.80306
Aquifer media [Unconsolidated sediments rocks]	-8.010e-01	3.954e-01	-2.026	0.04802 **
Aquifer media [Volcanic rocks]	-4.044e-01	6.658e-01	-0.607	0.54631
Population density (people/km^2)	5.982e-04	8.536e-05	7.008	5.29e-09 ***
Residual standard error: 0.95 on 51 degrees of freedom Multiple R-squared: 0.64				
F-statistic: 6.75 on 14 and 51 DF, p-value=1.688e-07 < 0.001				

Note: Statistical significance: ***p<0.001; **p<0.05; and *p<0.1.



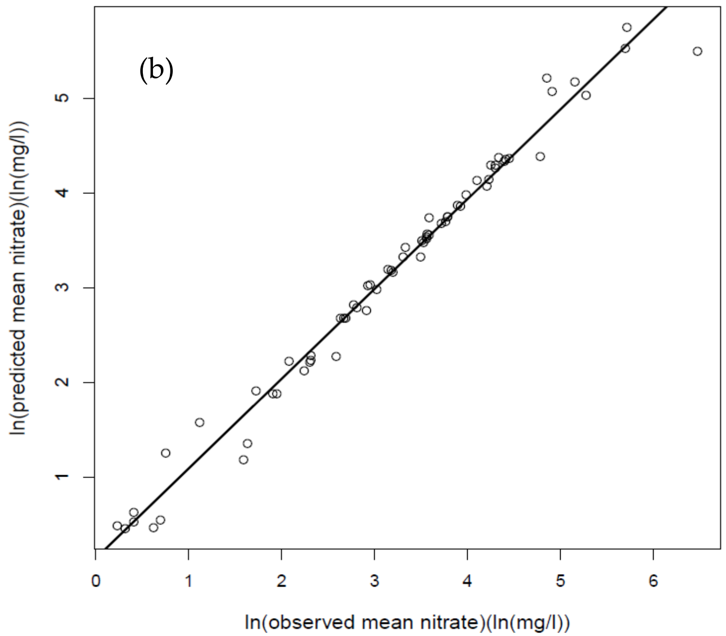


Figure 6-2: Comparison of observed and predicted log (ln) nitrate concentration on training dataset: (a) Linear regression and (b) RF regression

6.4.1.2 Estimating independent variables importance

The variable importance plot is a critical output of the random forest algorithm. Figure 6-3 shows the ranking of the relative importance of environmental attributes on groundwater nitrate occurrence. Higher values of percent increase in mean squared error (MSE) indicate higher importance. Population density is the most important predictor of nitrate concentration. This can be considered a relevant finding because the population has a direct effect on nitrates pollution in groundwater. If this variable was omitted, the quality of the model could be reduced drastically. Rainfall was also found to a relevant predictor of nitrate contamination, followed by recharge and aquifer type. The most important intermediate variables are nitrogen fertilizer application, climate classes, and hydraulic conductivity; while land use, depth to water, slope, soil media and region type are in the bottom of the ranking, thus has the smallest influence on the quality of the RF model.

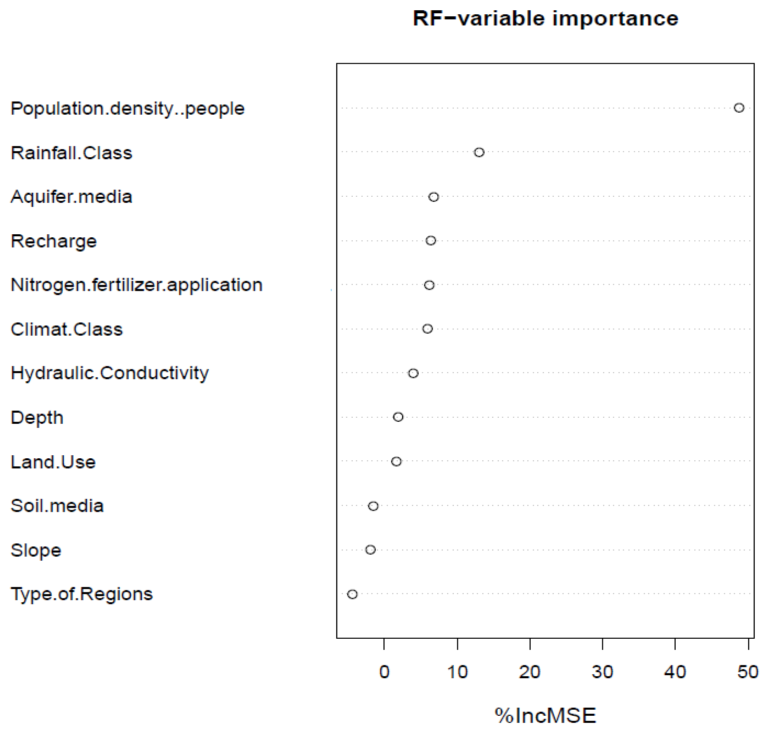


Figure 6-3: Variable importance according to the percent increase in mean squared error (%IncMSE)

6.4.1.3 Application of Random Forest Regression

The mtry parameter is the number of predictors used at each split. The tuneRF function suggests an optimal value for mtry=4. This value is equivalent to the default value for mtry. We also specify ntree=1000. We built the final model with the 4 first variables shown in Table 6-4. The percentage of variance explained with this model is 97.9 % (mean of squared residuals = 0.0407 ln (mg/l)). In this model, the fourth most important variable are population density, rainfall class, recharge, and aquifer type. Figure 6-2b shows a plot of the predicted versus the observed ln-transformed nitrate concentration values for the training data, based on only 80 % of observations. The RFR shows a better fit. Figure 6-4b shows the predicted versus the observed values for the test data, based on 20 % observations.

Table 6-4: Variables includes in the final RFR model, in descending order of importance based on percentage of mean decrease in accuracy (% IncMSE)

Variables	**% IncMSE**
Population.density.people.km^2.	50.3
Rainfall. Class	10.2
Aquifer. Media	5.3
Recharge	5.2

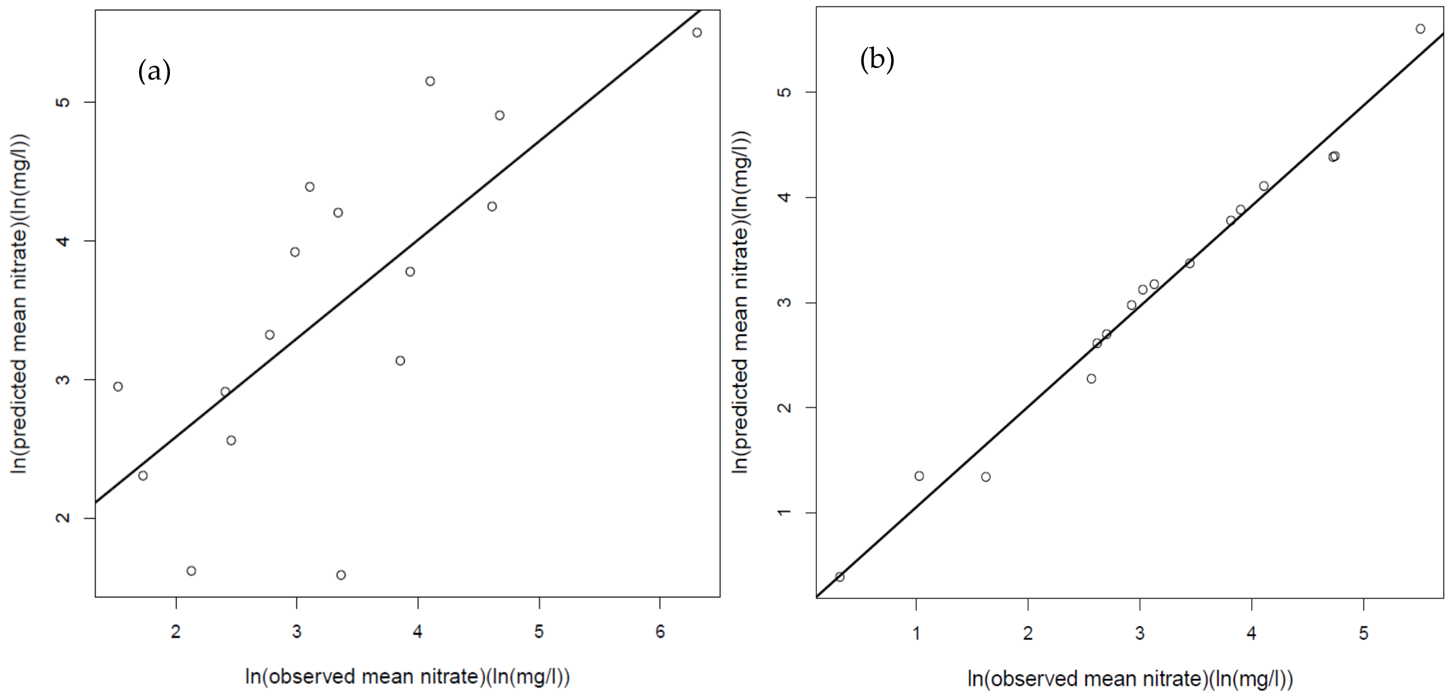


Figure 6-4: comparison of validation results on tested dataset: (a) Linear model and (b) RF regression

6.4.2 Evaluation of model performance

The results of MLR and RFR models explain respectively 64 and 97 percent of ln-transformed mean nitrate concentration. To validate the predictive ability of these two models, we used FITEVAL for evaluating first the training, and second the performance of the validation. Figure 6-5 to Figure 6-8 illustrates the results of the FITEVAL evaluation for the 2 models. Figure 6-5 suggests that MLR yields unsatisfactory to acceptable (NSE=0.554 [0.129-0.743]). In this figure, scatters follow the 1:1 line, but calculated values deviate from the observations positively and negatively along the prediction range. Figure 6-6 suggests that RFR exhibits a very good (NSE=0.998 [0.996-0.999]) prediction. This model shows a very good performance since they clearly show that computed values are very similar to the observations.

As regards to the testing dataset, the results of the MLR model Figure 6-7) varies from an unsatisfactory to acceptable prediction (NSE=0.289 [-0.462 to 0.7]). The scattered data follow the 1:1 line, but the plot scale of observed vs. predicted values is substantially reduced. On the basis of the qualitative goodness-of-fit, the model performance is considered unsatisfactory. Figure 6-8 illustrates the results of the RFR model. The fit shows very good prediction of groundwater nitrate pollution (NSE= 0.981 [0.959 - 0.991]). The model performance is significant even though there is a probability of obtaining an NSE<0.65 (28.1%). The performance is considered to be good on the basis of the qualitative good-of-fit.

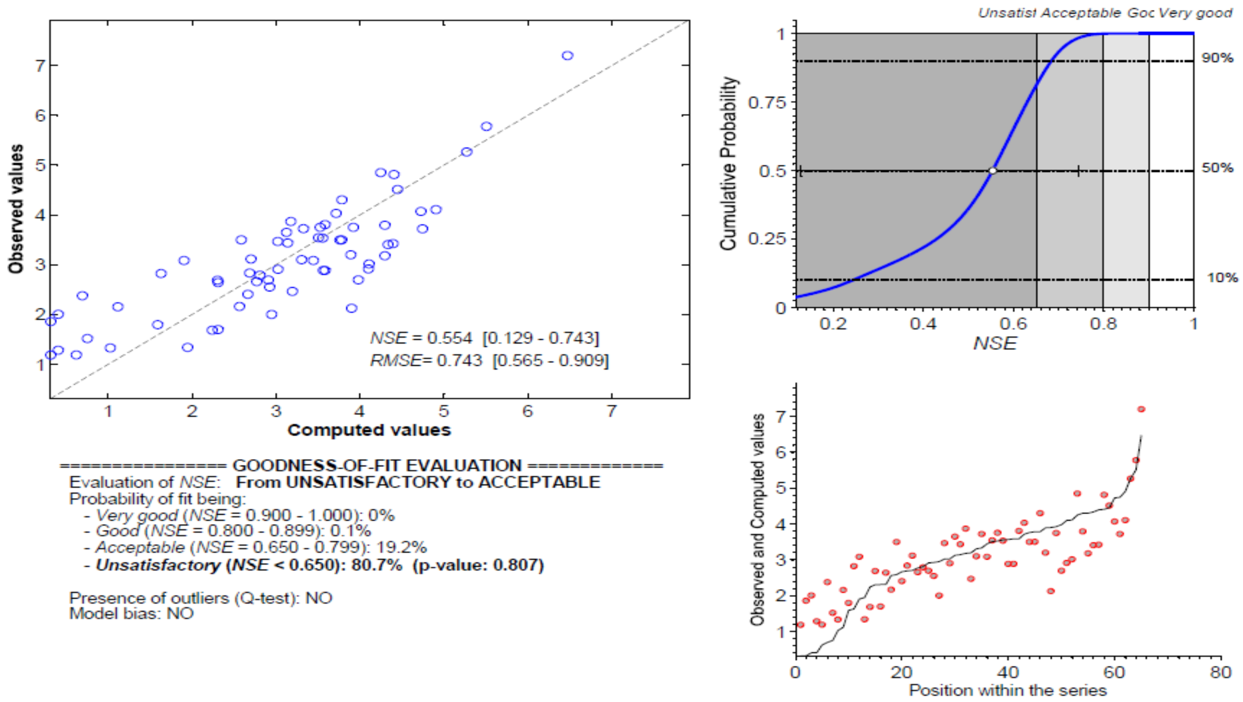


Figure 6-5: Goodness-of-fit evaluation for training dataset in the MLR

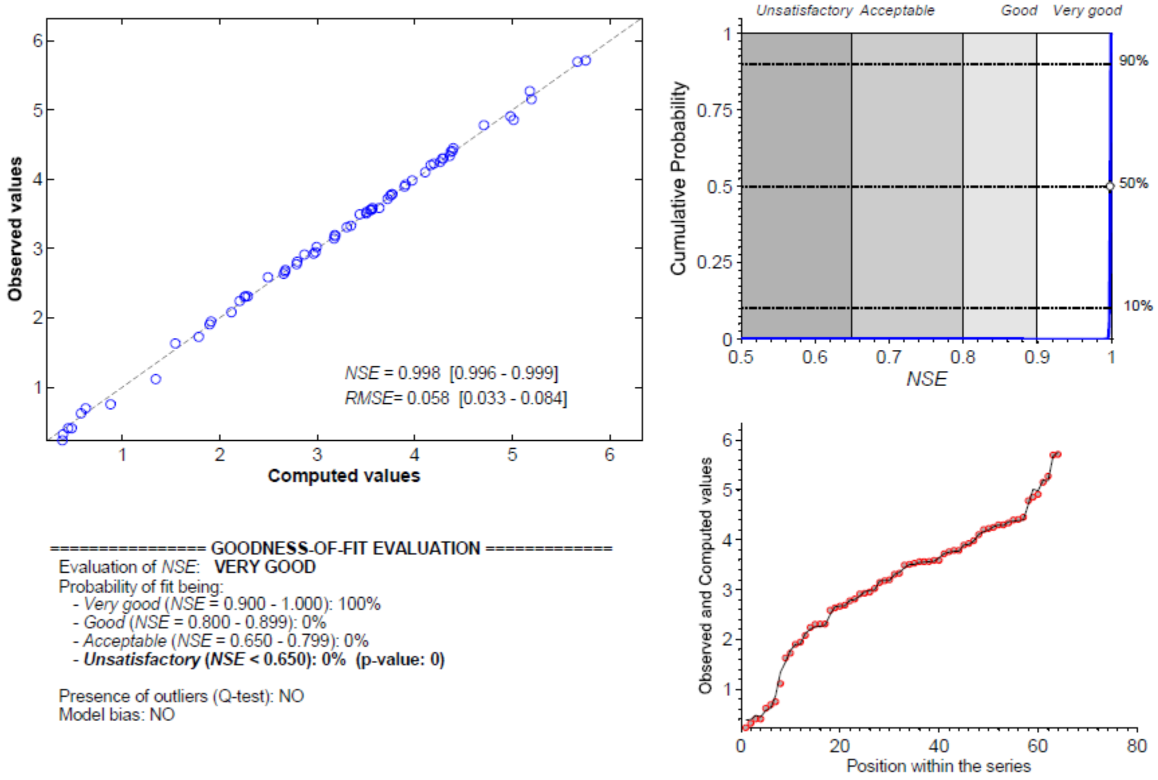


Figure 6-6: Goodness-of-fit evaluation for training dataset in the RFR

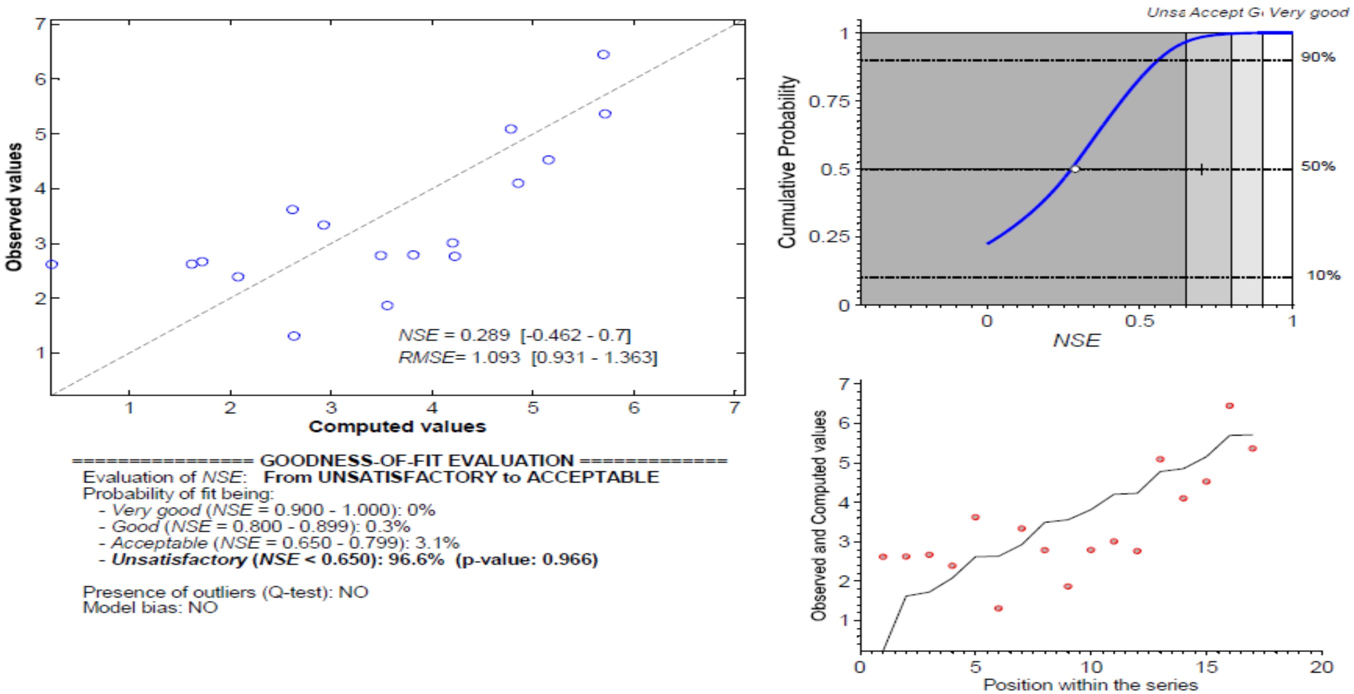


Figure 6-7: Goodness-of-fit evaluation for validation dataset in the MLR

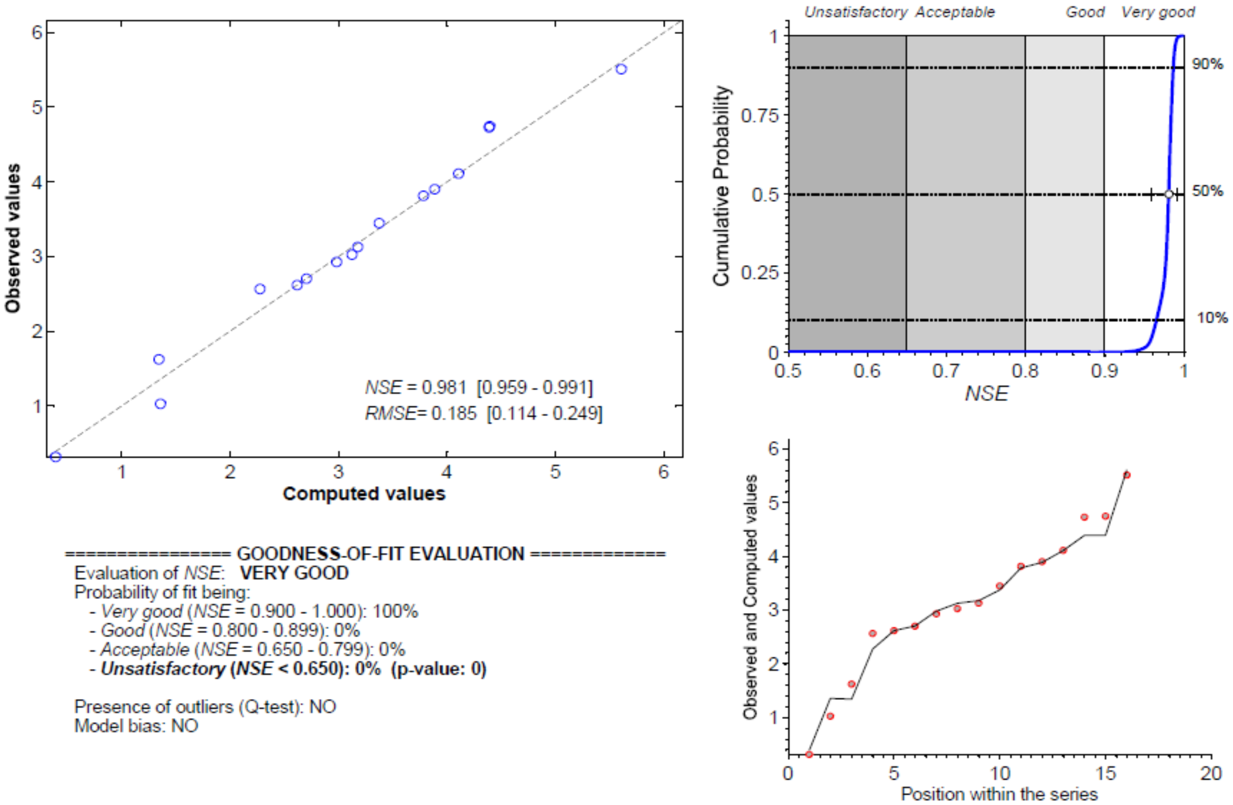


Figure 6-8: Goodness-of-fit evaluation for validation dataset in the RFR

6.5 Discussion

Nitrate contamination of groundwater at the pan-African scale is spatially variable. The results of this study show that the contamination of nitrate is influenced by both physical and anthropogenic factors. Previous studies suggest that nonlinear relationships exist between nitrate concentration pollution and the independent variables (Rodriguez-Galiano et al., 2014; Kihumba et al., 2015; Wheeler et al., 2015). In these studies, the superiority of nonlinear techniques for predicting groundwater nitrate concentrations as compared to linear multiple regression models has been demonstrated. A non-parametric non-linear statistical model is therefore considered suitable for modeling observed nitrate concentrations at the pan-African scale.

The comparison between the results shows that RFR has a much higher predictive ability compared to MLR. Yet, MLR shows an acceptable but weak relationship between the dependent variable and the predictors. The RFR has a better performance than MLR in both the training and validation dataset and explained respectively 97.9 % and 98 % of the variation in ln-transformed nitrate concentrations. (See Figure 6-2b and Figure 6-4b). By comparison, the MLR explained only 64 % of the variation in ln-transformed nitrate concentration for the training dataset. The better performance of RFR is due to the ability to handle nonlinear relationships between the nitrate pollution and explaining factors.

The most important variable identified in both models was the population density. This is most likely related to the lack of sanitation in major parts of African continent. According to Warah (2003), Sub-Saharan Africa hosts the largest proportion of the urban population residing in slums/informal settlements (71.9 per cent). These settlements often contain the majority of the city's population, for example, more than 70 per cent in Dar es Salaam (Kombe, 2005), 80 per cent in Luanda (Palamuleni, 2002), and over 50 per cent in Nairobi (Wegelin-Schuringa and Kodo, 1997). Such settlements are mainly characterized, among other things, by high population densities, deplorable housing, inadequate basic service infrastructure (safe water supply, sanitation, roads, etc.), location in flood plains and lack of legal status as residential dwellings (Parkinson and Tayler, 2003). As stated previously, urban sanitation provision and waste management systems across SSA are inadequate, with an estimated average of 40 per cent coverage for improved sanitation facilities (World Bank, 2012). In-situ sanitation, largely in the form of pit latrines and septic tanks is considered the dominant cause of microbiological contamination and a major cause of nutrient loading to water sources in SSA (Lapworth et al. 2017). These authors add that: water treatment options are often very limited and in many cases, municipal facilities for waste and water treatment are overloaded or experiencing reduced functionality partly due to limited funding and poor governance. The strong influence of the population density on groundwater nitrate contamination is consistent with a previous UNEP study (UNEP/DEWA, 2014). In addition, others studies such as Zingoni et al. (2005) demonstrated that the highest nitrate concentrations were associated with the highest population and pit latrine density in an informal settlement in Zimbabwe. Similar patterns have been observed in Senegal and South Africa (Tandia et al. 1999; Vinger et al. 2012).

Rainfall is identified in the RFR as the second most important variable, while this variable is not among the 04 variables in the final model of MLR. This may indicate that a nonlinear association between rainfall and nitrate concentration exists, and, as such, it was better identified by the RFR procedure. According to Pearson (2015), rainfall is indeed a major factor explaining nitrate occurrence in groundwater environments. Following Kulabako et al. (2007, rainfall is the primary climatological control factor that aids the washing of contaminants to the shallow groundwater aquifer. These authors add that the increase in nitrate in the shallow groundwater after rain suggests that the system receives high loads of organic nitrogen through leaching (from pit latrines, drains, solid waste dumps, animal waste dumps, and others). Several other studies found that increasing precipitation may positively affect nitrate concentration in groundwater (Davis and Sylvester-Bradley, 1995; Rankinen et al., 2007). Conversely, other studies suggest that higher average precipitation could foster the uptake of nitrogen by crops (Schweigert et al., 2004; Sieling and Kage, 2006) or support the dilution of nitrates (Hofreither and Pardeller, 1996 cited in Wikck et al., 2012) and hence decrease potential nitrate leaching. These opposing effects suggest that the coefficient of precipitation could have either a negative or a positive sign. In our MLR analysis, the sign is unknown, because the precipitation parameter is not explicitly in the final model; which shows that the linear model is not well adapted for the interpretation of this data set of nitrate at the African scale.

Recharge and Aquifer type comes in 3rd and 4th position in RFR model, and they occupy the 3rd and 2nd position respectively in the MLR model. The influence of the groundwater recharge rate to nitrate contamination is consistent with studies like Saffigna and Keeney (1997) and Hanson (2002). Furthermore, according to UNEP/DEWA, (2014), recharge from multiple sources influences groundwater microbial and chemical water quality. Groundwater recharge rate is interlinked with many other environmental variables including, but not limiting, soil type, aquifer type, antecedent soil water content, land use/land cover type and rainfall (Sophocleous, 2004; Anuraga et al.,2006). According to a recent study in the shallow unconfined aquifer of the Piemonte plain, dilution can be considered as the main cause for nitrate attenuation in groundwater (Debernardi et al., 2007). Furthermore, Andrade and Stiger, (2009); Nolan and Hitt, (2006) found also that dilution by surface water irrigation was an important attenuation process. The negative sign on the recharge factor in the

MLR is consistent with these studies, but also for this factor, caution should be taken with the interpretation of the sign in the MLR as the MLR does not handle the non-linearity of possible relationships. The influence of aquifer type to the nitrate contamination was demonstrated by Boy-Roura et al. (2013). Also, Stiger et al., (2008) showed that nitrate concentration was correlated with aquifer media and land use.

Nitrogen fertilizer is the 5th important variable in the RFR model. Previous studies have already observed groundwater nitrate pollution associated with nitrogen fertilizer loading and manure application (Greene et al., 2005; Nolan et al., 2002). Nolan et al., (2014) showed that N fertilizer was the most important in their RFR model. Furthermore, Boy-Roura et al., (2013) found that net nitrogen load (kg/ha) provide a better performance for their MLR. These latter authors concluded that nitrate concentration in groundwater is higher with increasing net loading.

Climate classes come in 6th position in RFR. This is consistent with other previous studies showing the importance of the climatic conditions in groundwater degradation (Wick et al., 2012; Ramasamy et al., 2013). For instance, Fram and Belitz, (2011), used the aridity index data to develop a logistic regression model for predicting probabilities of detecting perchlorate at concentrations in California and the Southwestern United States. They demonstrated that the predicted probability of perchlorate occurrence is a function of climate, expressed in terms of the aridity index. This latter index incorporates precipitation and evapotranspiration.

As regards to the depth factor of groundwater, the absence of this important factor among the top 6 most important variables in the RFR model could be due by the use of interval depth as a proxy. This surprising result is in contrast with some other studies showing that the nitrate concentration in groundwater decreases with increasing sampling depth (Tesoriero and Voss, 1997; Nolan and Hitt, 2006; Nolan et al., 2014; Wheeler et al., 2015; Ouedraogo and Vanclooster, 2016b). Groundwater age is a fundamental characteristic of groundwater that impacts diverse geologic processes (Gassiat et al., 2013). It is defined as the time that has passed since the water entered the groundwater system (Alley et al., 2002; Kazemi et al., 2006). The distribution of groundwater age depends on many factors including permeability, recharge rate, aquifer geometry, and topography (Gassiat et al., 2013). Deeper groundwater typically is older and may predate periods of intensive fertilizer application (1950-present), and there is enhanced the opportunity for denitrification because groundwater requires more time to travel to deeper aquifers. Additionally, according to Dubrovsky et al., (2010), the deeper the well, the more likely that the sampled groundwater is a mixture of different ages and land uses. Furthermore, it was indicated by Luo et al., (2003), that there is a significant downward movement of nitrate, and hence nitrate concentration at certain depth will decrease with time. Age is among the most important variables controlling groundwater nitrate concentration, but it remains a variable that is difficult to estimate (Nolan et al., 2015). Numerical groundwater flow models may allow estimating the groundwater travel time. Such models demonstrated that travel time increases with increasing distance up-gradient of a well (Masterson et al., 2002). According to Dubrovsky et al., (2010), a 10-years travels time is reasonable for areas with well-drained soils and flat topography. Similar studies of large recharge times for deep sandy aquifers were also identified by Mattern and Vanclooster, (2009). As a correlary to age and travel time, denitrification is significantly recognized for its role in reducing nitrate in soil and groundwater (Stevenson and Cole, 1999; Thayalakumaran et al., 2004; Aljazzar, 2010).

Other variables like the hydraulic conductivity, land cover/land use, slope, soil media and type of region were not included in both final models. This is in contrast to other studies where these factors were considered as being important to explain groundwater degradation

(Gemitzi et al., 2009; Wick et al., 2012; Liu et al., 2013; Jung et al.,2015; Kihumba et al., 2015).

Validating predictions for the entire continent of Africa is certainly not trivial. Figure 6-1, clearly demonstrates that the study efforts of the nitrate groundwater contamination problem is not equally distributed between the different African countries. For many countries, such as Liberia, Guinea, Equatorial Guinea, and Sierra Leone, but also large land areas such as Democratic Republic of Congo, Chad, Namibia, Angola and South Sudan, few studies on the nitrate pollution problem are available. In many countries in Africa, there are considerable concerns with systematic groundwater monitoring. The major constraint in the validation of the pan-African modelling study lies therefore in the unavailability of a homogeneous data set on nitrate contamination of groundwater. Results from this analysis should therefore not be over-interpreted. Whilst the available data inferred from a meta-analysis provide a useful preliminary assessment of the nitrate contamination in groundwater at the pan-African scale, there are clear limitations. First, the data come from different sources and the methods used to collected and produce the results of each study are not the same. Second, bias can be introduced due to the set-up of the different reported studies. Certain studies address groundwater nitrate contamination as a support for a drinking water supply project; others studies address groundwater nitrate contamination for an irrigation project, and still others address the issue within a mining context. The different set-ups of these studies may, therefore, introduce a possible bias such as approach, sampling and analytical methods which are not standardised. The data considered to calibrate and validate the models should therefore not be treated as nitrate measurements as collected in standardised groundwater monitoring programs. Further studies based on less biased data sets should be performed to demonstrate the robustness of the developed models.

It may therefore be expected that a revised robust model can be identified if new homogeneous data sets will become available. It may also be expected that such new data sets will be produced and improved continuously in time. As time progresses, better and more homogeneous data sets will become available. We, therefore, suggest that the statistical models that were identified in our study would be integrated into a time-related dynamic data assimilation framework. The RFR model structure that outperforms in our study, as demonstrated by the objective goodness-of-fit analysis, would be an excellent modelling structure to be integrated in such a data assimilation framework. With the high performance of predictive ability observed with RF, it is important to note that Random Forests could be prone to overfitting for some datasets. To this regard, Radenkovic. (n.d), affirms that the main disadvantage of RF is a tendency to overfit for some noisy datasets in classification/regression tasks. In contrast, Geng (2006) found by comparing Logistic Regression with Random Forests classification that adding trees to the forest does not cause a problem of overfitting. Steinberg et al. (2004) affirms that Random Forests are resistant to overtraining (overfitting).

Despite all these limitations, the results in our study provide already valuable insights into the potential causes of nitrate occurrence in groundwater across the African scale that may be considered in groundwater management and protection programs. The analysis confirmed the importance of the population density as controlling factor, in addition to a set of other physical environmental attributes particularly those related to aquifers properties (rocks materials), and climatic conditions. Groundwater management and protection programs should therefore firstly focus on the densely populated areas and consider the remediation of anthropogenic pollution sources such as leaking water sanitation systems, poorly controlled livestock systems, and urban agriculture. To support this idea, UN (2015); UNEP (2008) argues also that priority regions for research are areas which are experiencing the fastest urban population growth and expansion, and include regions such as the Lake Victoria Basin and parts of West Africa. Recently, in his study entitled:" *Urban groundwater quality in sub-Saharan Africa: current status and implications for water security and public health*", Lapworth et al. (2017), proposed targeted investments in priority research areas, who are needed in SSA to provide evidence to inform the provision of climate ready urban water and sanitation infrastructure. This is required in order to enhance safe drinking water and sanitation delivery to the rapidly expanding urban and peri-urban populace and work towards the sustainable development goals in SSA. The same author adds that "moreover, with ongoing health epidemics in urban areas, including viral/ bacterial diseases, many of which are from faecal sources, both the national governments and the international community should consider investments in improved waste management and clean and safe water supplies as a matter of priority."

6.6 Conclusion

We explored in this study the potential of Random Forests Regression (RFR) techniques, to model nitrate in groundwater at the continental scale of Africa. The pollution of groundwater by the nitrate at the pan-African scale depends on the interaction between the physical and anthropogenic variables that affect groundwater vulnerability to nitrate contamination. Both categorical and continuous explanatory variables have been used by RFR allowing: (i) to establish the relation between explaining attributes and the mean ln transformed nitrate concentration; (ii) to measure and assess the importance and role of the explanatory variables in the groundwater pollution; (iii) to build a robust model based on environmental data and anthropogenic attributes; (iv) to provide guidelines for evaluating their role in influencing groundwater vulnerability to pollution. Determining which explanatory variables mainly influence the presence of contaminants in groundwater represents an important step in managing and protecting both water resources and human health. In this study, we also compared the performance of the RFR with a Multiple Linear Regression (MLR) model.

The results of this study illustrate that the RFR outperforms in modelling pan-African nitrate concentration. The good performance of the RFR is attributed to its non-parametric nature, i.e., it does not need to follow a normal distribution. Moreover, its robustness against outlier values is bigger than that of other methods, as each tree in the RFR is generated from different data subsets. A perceived disadvantage of this machine learning method is their "black box" nature. The RFR does not allow estimating directly coefficients related to explanatory variables. But, the RFR allowed ranking the variables according to their relative contribution to the model using a non-parametric approach.

The validation of the MLR and RFR models based on an objective goodness-of-fit confirmed the good performance of the RFR as compared to MLR. The RFR is, therefore, a promising technique for modeling groundwater degradation because of its ability to provide meaningful analysis of nonlinear and complex relationships such as the ones found in hydrogeological studies.

However, model performance could be influenced by the size of sample and bias of nitrate concentrations collected. Furthermore, groundwater nitrate pollution is not only a spatial but also a temporal variable process. Nitrate is not a conservative tracer since its concentration can be affected by the complex biogeochemical process, in particular, redox chemistry. This temporal dimension has not been included in the current study yet. The lack and bias of groundwater quality data have been pointed out as a major limitation for the systematic investigation of nitrate in groundwater at the continental scale. This prompts for consolidating and further developing groundwater monitoring programs at the continental scale. For example, we recommend on establishment of country monitoring networks, unification of sampling methods and frequency, minimal extent of chemical analysis to others parameters, expand national and international funding sources for monitoring networks operation. Nevertheless, the data scarcity and bias issue, some overall conclusions could be drawn related to important groundwater pollution sources. Results have demonstrated that groundwater nitrate contamination is strongly linked to population density.

The current study is a novel application of machine learning techniques for groundwater nitrate contamination modelling at the African scale. Further studies are needed to reduce their uncertainty and incorporate homogenous data to test the model and increase the accuracy of this model. The analysis presented here represents an important step toward developing tools that will allow us to accurately predict the distribution of nitrate contamination in groundwater in the climate change context. Such conclusion could prompt national or international authorities to foster targeted local investigations. It yields also important baseline information for monitoring progress in the implementation of the United Nations Sustainable Development Goals (UN SDGs) for water.

Chapter 7 Validating a continental-scale groundwater diffuse pollution model using regional datasets[4]

[4] ***Ouedraogo, I.,*** *Defourny, P., and Vanclooster, M. (2017). Validating a continental scale groundwater diffuse pollution model using regional datasets. In Environmental Science and Pollution Research (ESPR) journal. Submitted, June 23rd 2017 (under review).*

7.1 Abstract

In this study, we assess the validity of an African scale groundwater pollution model for nitrate. In a previous study, we identified a statistical continental scale groundwater pollution model for nitrate (Ouedraogo et al., 2017; *accepted to review*). The model was identified using a pan-African meta-analysis of available nitrate groundwater pollution studies. The model was implemented in both RF (Random Forest) and Multiple Regression formats. For both approaches, we collected as predictors a comprehensive GIS database of thirteen spatial attributes, related to land use, soil type, hydrogeology, topography, climatology, region typology, nitrogen fertilizer application rate, and population density. In this paper, we validate the continental scale model of groundwater contamination by using a nitrate measurement dataset from three African countries. We discuss the issue of data availability, and quality and scale issues, as a challenge in validation. Notwithstanding the modelling procedure exhibited very good success using a continental scale dataset (e.g. R^2=0.97 in the RF format using a cross-validation approach), the continental scale model could not be used without recalibration to predict nitrate pollution at the country scale using regional data. In addition, when recalibrating the model using country scale datasets, the order of model exploratory factors changes. This suggests that the structure and the parameters of a statistical spatially distributed groundwater degradation model for the African continent are strongly scale dependent.

7.2 Introduction

Throughout the world, groundwater is an important source of freshwater, used by industry, agriculture, and domestic users. However, worldwide groundwater systems are experiencing increasing threat from and risk of pollution from agricultural activities, urbanization, and industrial development (Foster et al. 2003; Aljazzar, 2010; Charrière and Aumond, 2016; Constant et al.2016). According to Gurdak (2014), all groundwater resources are vulnerable to nonpoint source (NPS) contamination. Diffuse NPS pollution from farming activities and point source pollution from sewage treatment and industrial discharge are the principal contaminant sources (Boy-Roura, 2013). One of the most common and persistent problems of groundwater pollution is associated with diffuse pollution generated through the intensification of agricultural activities over the last decades, with increased use of chemical fertilisers and higher concentrations of animal excrement in smaller areas (Boy-Roura, 2013). Agricultural land use leads to elevated concentrations of nutrients. According to Haller et al. (2013), on a global scale agricultural land use represents the largest diffuse pollution threat to groundwater quality. Elevated concentrations of nutrients (especially nitrogen and phosphorus) can cause a variety of problems, including degradation of ecosystems (for example, eutrophication of water bodies), and human health issues. Nitrate is the most ubiquitous nonpoint (NPS) contaminant of groundwater resources worldwide (Spalding and Exner, 1993). Nitrate ingestion has been linked to methemoglobinemia, adverse reproductive outcomes, and specific cancers (Ward et al., 2005).

In Africa, groundwater is a crucial natural resource supporting the development of the continent, but it is also subject to many pressures. Two main threats are overexploitation and contamination (MacDonald et al., 2013). The pressures exerted by the agricultural sector on groundwater are of primary concern (Xu and Usher, 2006; Sharaky, 2016). In particular, we found also in our previous studies, like as Kulabako et al. (2007) that African shallow groundwater systems are vulnerable to pollution (Ouedraogo et al., 2016; Ouedraogo and Vanclooster, 2016b).

In the overwhelming majority of African water bodies, nitrate remains one of the most critical pollutants, and the level of contamination is increasing (Spalding and Exner, 1993; Puckett et al., 2011). Nitrate in groundwater is derived from various point and diffuse sources but mainly originates in the extensive use and release of anthropogenic nitrogen compounds in agricultural and urban environments (Strebel et al., 1989; Spalding and Exner, 1993; Foster, 2000; Böhlke, 2002; Wakida and Lerner, 2005). The presence of nitrates also depends on environmental attributes, such as soil type, climatology, hydrogeology, and others (Davis and Sylvester-Bradley, 1995; Nolan and Hitt, 2006; Kulabako et al. 2007; Boy-Roura et al. 2013; UNEP/DEWA, 2014; Nolan et al. 2014; Pearson, 2015; Wheeler et al. 2015; Ouedraogo and Vanclooster, 2016a). In this regard, reliable predictions of nitrate concentrations in groundwater, in terms of land use or agricultural practices, are essential for groundwater development programs. Indeed, the ability to predict groundwater quality is key to designing sustainable land and water management programs. Yet, at present, there are few regional or continental scale nitrate groundwater pollution studies for Africa.

Statistical data modelling can help to improve our understanding of the key processes involved in nitrate contamination of groundwater. Because statistical approaches differ in their ability to model relationships, an evaluation of different statistical approaches can provide insights into which approach is most appropriate for modelling groundwater quality. To this end, numerous studies have compared a suite of statistical approaches, including linear models (Bauder et al.1993; Rawlings et al.1998; Boy-Roura et al. 2013; Jung et al.2016), generalised linear models (Shamsudduha et al.2015), generalised additive models (Yee and Mitchell, 1991; Barrio et al.2013), artificial neural networks (Gemitzi et al.2009), classification and regression trees, multivariate regression trees, and other highly computational statistical methods, such as Random Forest (RF) methods (Breiman et al., 1984; De'ath and Fabricius, 2000; De'ath, 2002; Breiman 2001; Evans et al., 2011). Generally, classification tree-based approaches behave better, because they allow for incorporating complex nonlinear processes into the statistical model. Among these tree-based approaches, RFs are often well performing (e.g. Lawler et al., 2006; Prasad et al., 2006; Knudby et al., 2010). RF is an ensemble learning method which combines multiple models that are built using bootstrap samples (Breiman, 2001). Ensemble learning techniques generate many classifiers and aggregate their results (Liaw and Wiener, 2002). RF consists of a compilation of regression trees (e.g. 1000 trees in a single RF) and is empirically proven to be better than its individual members (Hamza and Larocque, 2005).

We developed in a previous study a statistical model based on a meta-database of nitrate obtained at the African scale (Ouedraogo et al., 2017; *under review*). Using a cross-validation approach, this model allowed predicting the spatial patterns of the continental scale groundwater degradation as observed in the metadata base (R^2=0.97). In the present study, we attempt to evaluate the predictive ability of the continental scale RF model to the regional scale by using independently collected regional datasets. To this end, we used groundwater nitrate measurement datasets for three African countries: Senegal, South-Africa and Burkina Faso.

7.3 Data and methods

7.3.1 Measurement of nitrate data in groundwater

Nitrate measurements in groundwater were compiled for South-Africa, Senegal, and Burkina Faso. A summary of the basic statistics and sources of nitrate collected is given in Table 7-1. The nitrates in groundwater were determined from several stations (wells, boreholes, and springs) that are very often used for drinking-water supply. Comparability of water quality data from different laboratories can only be ensured if it is identical, or at least if similar methods are used (Chapman, 1996). There are many comprehensive standard manuals and guidebooks describing laboratory methods in detail, such as the GEMS/WATER Operational Guide (WHO, 1992) and the practical guide to the methods discussed in this volume (Bartram and Ballance, 1996). In our case, no standard guidance was followed on methods for the collection and interpretation of the data, although such guidance would clearly be beneficial and help to eliminate much of the subjectivity introduced in the dataset.

Data quality control is a complex and time-consuming activity which must be undertaken continuously to ensure meaningful water quality assessments (Chapman, 1996). Every stage of data handling increases the risk to introduce errors. Most risks are associated with a human error during written transcription or 'keying-in' via a computer keyboard. Possible sources of errors in the collected samples could be: (i) lack of trained and experienced data collectors, i.e. the laboratory personnel should be sufficiently trained and qualified to carry out the necessary analytical operations properly; (ii) lack of good quality supervision, for example not enough time allocated to supervision, high ratio of data collectors to supervisors; or (iii) errors in data handling operations, such as data entry/omission in data reports, or when checking and validating measurement data. Therefore, in order to control the quality of the data, all datasets were analyzed and filtered to eliminate at least some bias. For example, we eliminated all negative and zero values of nitrate recorded in the datasets. Nitrate data are principally collected at given geographical locations in the groundwater. Thus, the longitude and latitude of the sampling or measurement sites (x and y coordinates) which did not have a nitrate value reported were deleted. Out of a total of 37,382 samples for Burkina Faso, we retained 9049 samples after evaluation. As another example, in the Burkina Faso dataset we observed a maximum value concentration of 55 550 mg/L and decided to delete this value. In this case, we assumed there exists an error for this reported value or measurement, because of the large difference between this value and the second maximum value in the dataset (in this case 1 282 mg/L). Hence, concentrations of NO_3^- in the Burkina Faso dataset ranged from 11 to 1 282 mg/L, with a mean concentration of 55.10 mg/L. Out of a total of 2 913; 2 813 samples were used in the South Africa case, where NO_3^- concentrations ranged from 50.1 to 1 599 mg/L with a mean concentration of 126.79 mg/L. For Senegal, out of a total of 3 721 samples, we kept 1 332 samples after evaluation. For this country, NO_3^- concentrations ranged from 0.02 to 889.7 mg/L, with a mean concentration of 19.37 mg/L. We observed that the mean concentration of nitrate in groundwater for the Burkina Faso and South Africa datasets exceeds the WHO (World Health Organisation) drinking water standard of 50 mg/L. Furthermore, we observed that the maximum nitrate concentration for all these countries is very high. These high values of nitrate concentration demonstrate that the problem of nitrate pollution in African countries is very acute. The spatial distribution of the collected data is illustrated in Figure 7-1, Figure 7-2, and Figure 7-3. We decided to represent only the points of sampling with the level of nitrate above of 50 mg/L. From the distribution of the sampling points in Burkina Faso, it is evident that groundwater sampling was concentrated in certain areas, e.g. "Nord", Centre-Nord", "Centre-Est", Centre and Plateau-Central"; while in regions of "Boucle du Mouhoun", Haut-Bassins", Cascades", Sud-

Ouest", the sampling is not concentrated, but showed a high level of nitrate. We observe in the region of "Sahel" more high level of nitrate compared to others regions, like "Est". These zones cited in French correspond of names some administrative regions in Burkina Faso, because, the country is divided into thirteen regions. In South Africa, the spatial distribution, show that the groundwater sampling was more concentrated in Limpopo province. We observe less sampling of nitrate in Orange Free State. The high level of nitrate in observed almost everywhere in this country, but Limpopo province show more points of high values of nitrate.

From the spatial distribution of nitrate in Senegal, we observe on sampling point with the high level of nitrate in Dakar; while Tambacounda presents more sampling points with a high level of nitrate concentration. In this area, the nitrate level varies enormously. In Centre of Senegal, we haven't sampling points of nitrate.

Table 7-1: Summary statistics and sources of compiled nitrate measurements

Country	Number of samples	Min.	Mean	Max.	Period of collection	Sources/references
		mg/L				
Burkina Faso	9049	11	55.10	1282	2009	Zougrana Jacqueline, [1]DEIE/Burkina Faso. zougjac@yahoo.fr
Senegal	1332	0.02	19.37	889.7	1952–2009	Moussa Cissé/DGPRE[2], Senegal, scissemoussa@yahoo.fr
South Africa	2923	50.1	126.79	1599	1994–2009	https://ggis.un-igrac.org/ggis-viewer/viewer/groundwaterafrica/public/default

[1]DEIE: Direction des Etudes et de l'Information sur l'Eau;

[2]DGPRE: Direction de la Gestion et de la Planification des Ressources en Eau.

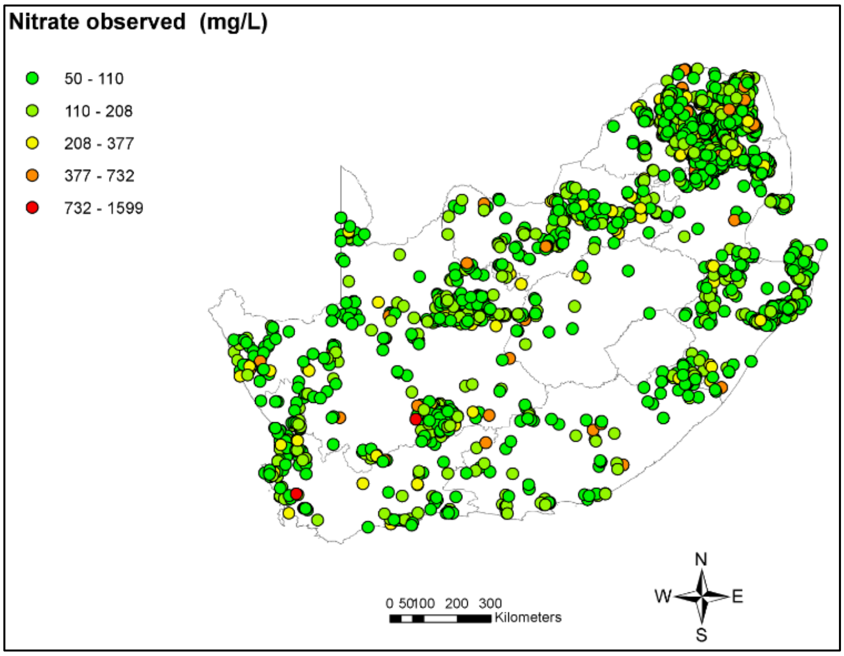


Figure 7-1: Distribution of nitrate concentration in groundwater in South Africa

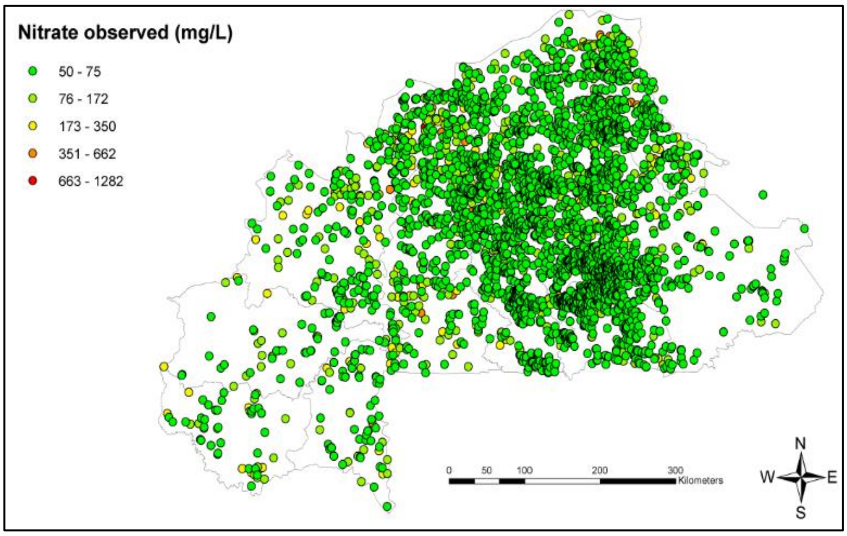


Figure 7-2: Distribution of nitrate concentration in groundwater in Burkina Faso

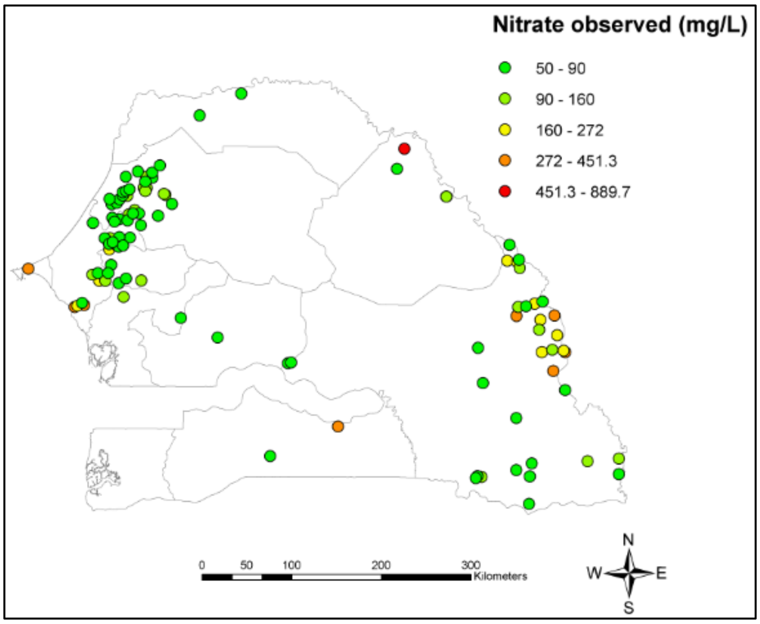


Figure 7-3: Distribution of nitrate concentration in groundwater in Senegal

7.3.2 Examining the distribution of nitrate data

The Q-Q plot, or quantile-quantile plot, is a graphical tool to assess the theoretical distribution of a data set. For example, if we run a statistical analysis that assumes our dependent variable is normally distributed, we can use a normal Q-Q plot to check that assumption. If the data does indeed follow the assumed distribution, then the points on the Q-Q plot will approximately fall on a straight line. The distribution of groundwater degradation parameters is often skewed. The log transformation of original data is therefore often used to reduce the skewness of original data. We applied the log transformation and used a 'qqnorm' function in R to visualize the distribution of our data. Theoretical quantiles of a normal distribution versus sample quantiles for the three regional data sets were checked, as shown in Figure 7-4. It is shown that even with a logarithmic transformation the assumption of normality does not appear to be satisfied for the regional datasets.

This is in contrast to the results obtained from a meta-analysis at the continental scale (Ouedraogo et al., 2017; *under review*). The Q-Q plot for Burkina Faso (Figure 7-4a) shows a staircase pattern of distribution, which means that some values are discrete. In other words, this Q-Q plot is obviously very different from a linear trend line and data are not normally distributed. Also, the Q-Q plot for the South Africa dataset does not support the normal distribution hypothesis (Figure 7-4b). A remarkable feature of the Q-Q plot for the Senegal data set (Figure 7-4c) is the prominent lower tail anomaly.

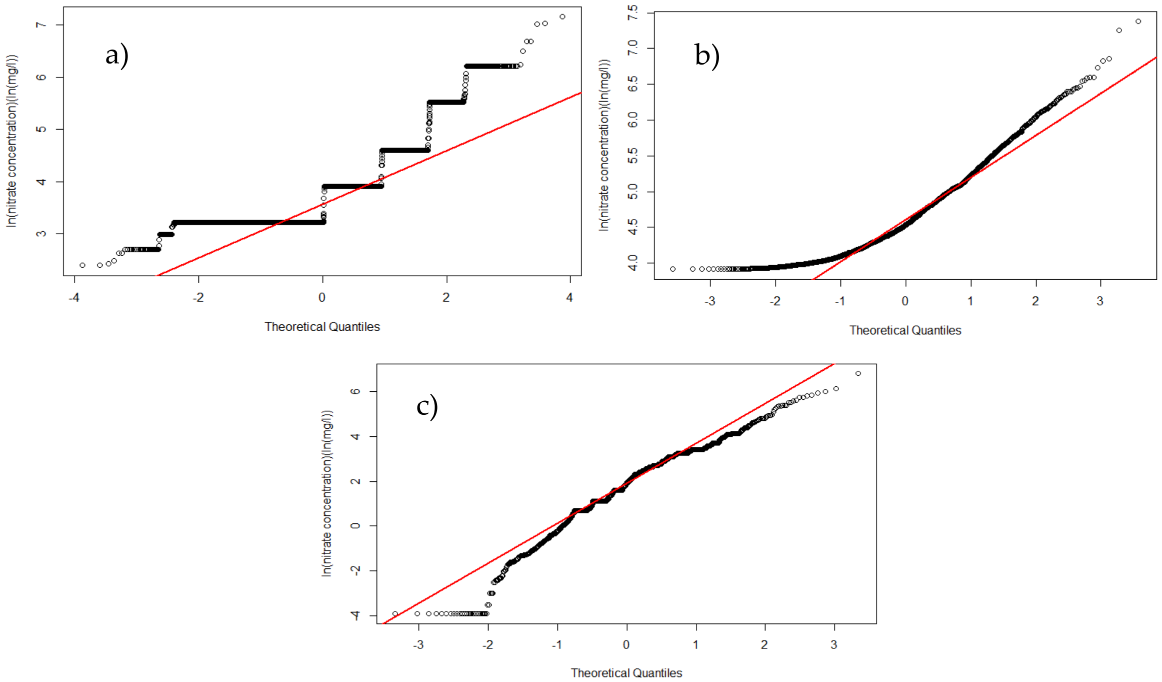


Figure 7-4: Q-Q plots for the three country data sets: a) Burkina Faso; b) South Africa; c) Senegal)

The non-normality of data poses problems with parametric methods such as multiple linear regression analysis. We, therefore, use in this study the non-parametric RF algorithm that is not constrained by the non-normality of the data.

7.3.3 Environmental variables

In addition to the nitrate measurement datasets, we also collected a total of thirteen spatial attributes, extracted from several high-resolution databases covering physical and anthropogenic attributes. These spatial attributes are related to land use, soil type, hydrogeology, topography, climatology, etc. Table 7-2 presents the thirteen explanatory variables, their spatial resolution, and their various main sources. All explanatory variables were integrated into a Geographical Information System (GIS) and processed in ArcGIS10.3™ in a raster format of 15 x 15 km^2 spatial resolution. This resolution was found to be the best compromise, considering the resolution of the different available datasets, the large extent of the study area, and the performance of our computers.

Table 7-2: Sources of the collected pan-African scale databases related to environmental parameters.

Explanatory variables	**Type of data**	**Units or Categories**	**Spatial resolution/Scale**	**Date**	**Data source(s)**
Land cover/land use	Categorical	-	300 m	2014	[1]UCL/ELIe-Geomatics (Belgium)
Population density	Continuous point	people/km²	2.5 km	2004	ESRI : www.arcgis.com/home
Nitrogen application	Continuous point	kg/ha	0.5° x 0.5°	2009	[2]SEDAC : www.sedac.ciesin.columbia.edu
Climate class data	Categorical	-	0.5°	1997	Global-Aridity values (UNEP, 1987)/ (UNESCO-IHE, Delft, The Netherlands)
Type of regions	Categorical	-	0.5°	2014	Global-Aridity values (UNEP, 1987)/ (UNESCO-IHE, Delft, The Netherlands)
Rainfall class	Categorical	mm/year	3.7 km	1986	UNEP: http://www.grid.unep.ch
Depth to groundwater	Categorical	m	0.05° x 0.05°	2012	British Geological Survey: www.bgs.ac.uk/
Aquifer type	Categorical	-	1:3750 000	2012	[3]GLiM data (Hamburg University)
Soil type	Categorical	-	1 km × 1 km	2014	ISRIC, World Soil Information: www.isric.org/content/soilgrids
Unsaturated zone (impact of vadose zone)	Categorical	-	1:3750 000	2012	GLiM data (Hamburg University)

Explanatory variables	Type of data	Units or Categories	Spatial resolution/Scale	Date	Data source(s)
Topography/slope	Continuous point	percentage (%)	90 m	2000	UCL/ELIe-Geomatics (Belgium) and [4]CGIAR/CSI (SRTM data)
Recharge	Continuous point	mm/year	5 km	2008	Global scale modelling of groundwater recharge (University of Frankfurt)
Hydraulic conductivity	Continuous point	m/day	Average size of polygon ~100km^2	2014	[5]GLHYMPS data (McGill University)

[1]Université Catholique de Louvain/Earth and Life Institute/Environmental sciences;

[2]Socioeconomic Data and Applications Center (SEDAC);

[3]The new global lithological map database GLiM: a representative of rock properties at the Earth's surface;

[4]Consultative Group for International Agricultural Research (CGIAR)/ Consortium for Spatial Information (CSI);

[5]A glimpse beneath the Earth's surface: Global Hydrogeology MaPS (GLHYMPS) of permeability and porosity.

7.3.4 Model development and validation approach

In this study, we used the RF algorithm for regression tasks rather than classification tasks. A detailed description of the RF method is given in Breiman, (2001a); and Culter et al. (2007). We present here a short summary of the RF method. The RF method (i) is non-parametric, (ii) does not over-fit, (iii) has high predictive power, and (iv) provides additional pieces of information (e.g. the importance of variables). The philosophy behind ensemble learning techniques, like RF, is based on the premise that its accuracy is higher than other machine learning algorithms because the combination of predictions performs more accurately than any single constituent model does (Rodriguez-Galiano et al., 2014). The individual decision trees in RF tend to learn highly irregular patterns, i.e. they overfit their training datasets. RF is a way of averaging multiple decision trees, trained on different parts of the same training dataset, with the goal of reducing the prediction variance (Hastie et al., 2008). RF modelling is appropriate for modelling the nonlinear effect of variables. It can handle complex interactions among variables, and is not affected by multicollinearity (Breiman, 2001b). RF can assess the effects of all explanatory variables simultaneously and automatically rank the importance of these variables in descending order (Li et al., 2015). The algorithm for RF consists of building a forest of uncorrelated trees. Each individual tree is grown using a randomised subset of predictor variables. The trees are grown to the largest extent possible without pruning, and they are aggregated by averaging them. Out-of-bag (OOB) samples are used to calculate variable importance and to get an unbiased estimate of the test set error, which is one of the advantages of RF because it means that there is no need for cross-validation (Oliveira et al.2012). The method essentially behaves as a ''black box'' since the individual trees cannot be examined separately (Prasad et al., 2006) and it does not calculate regression coefficients nor confidence intervals (Cutler et al., 2007). Nevertheless, it allows the computation of variable importance measures that can be compared to other regression techniques (Grömping, 2009). Within a very short period of time, RFs have become a major data analysis tool, and one which performs well in comparison with many standard methods (Heidema, et al.2006; Díaz-Uriarte et al.2006) (such as linear regression) and complex models (such as artificial neural networks and support vector machines). What has greatly contributed to the popularity of RF is the fact that it can be applied to a wide range of prediction problems, even if they are nonlinear and involve complex higher-order interaction effects, and also that RF produces variable importance measures for each predictor variable (Strobl et al.2007). The RF model has been successfully applied to various problems in the last few years, in (for example) genetic epidemiology, microbiology, ecology (Strobl et al.2007), and other fields related to the environment and water resources (Booker and Snelder, 2012; Zhao et al.2012).

In our previous study (Ouedraogo et al., 2016a; *under review*), a continental-scale nonlinear RF statistical model was developed by using a meta-database. The model had an excellent prediction capacity when comparing predicted versus observed ln-transformed nitrate concentration values for the training data, based on only 80 % of observations (R^2=0.97) (see Figure 7-5a) and predicted versus observed values for the test data, based on 20 % of observations (R^2=0.98) (see Figure 7-5b). Due to this and to the good results obtained at the continental scale, we have also used an RF in the present study to model groundwater degradation at the country level. The predictive ability or validation consisted of a comparison of model prediction and observed nitrate. The original dataset was therefore randomly divided into calibration samples (80% of total samples) and validation samples (the remaining 20%). Given that the predictors include both discrete and continuous variables, we implemented the CARET (Classification And REgression Training) package to determine the importance of explaining factors in the predictive model. The CARET package uses a method recommend by Strobl et al. (2007) that take accounts for bias associated with disparity in the number of levels contained in factorial variables. Strobl et al. (2007) suggested this alternative variable importance measure with a large number of categorical variables, which are selected against with a traditional random forest approach. To this end, we classified the relative importance of each variable for Burkina Faso in more detail.

All analyses were performed in the R statistical software version 3.2, using freely distributed packages.

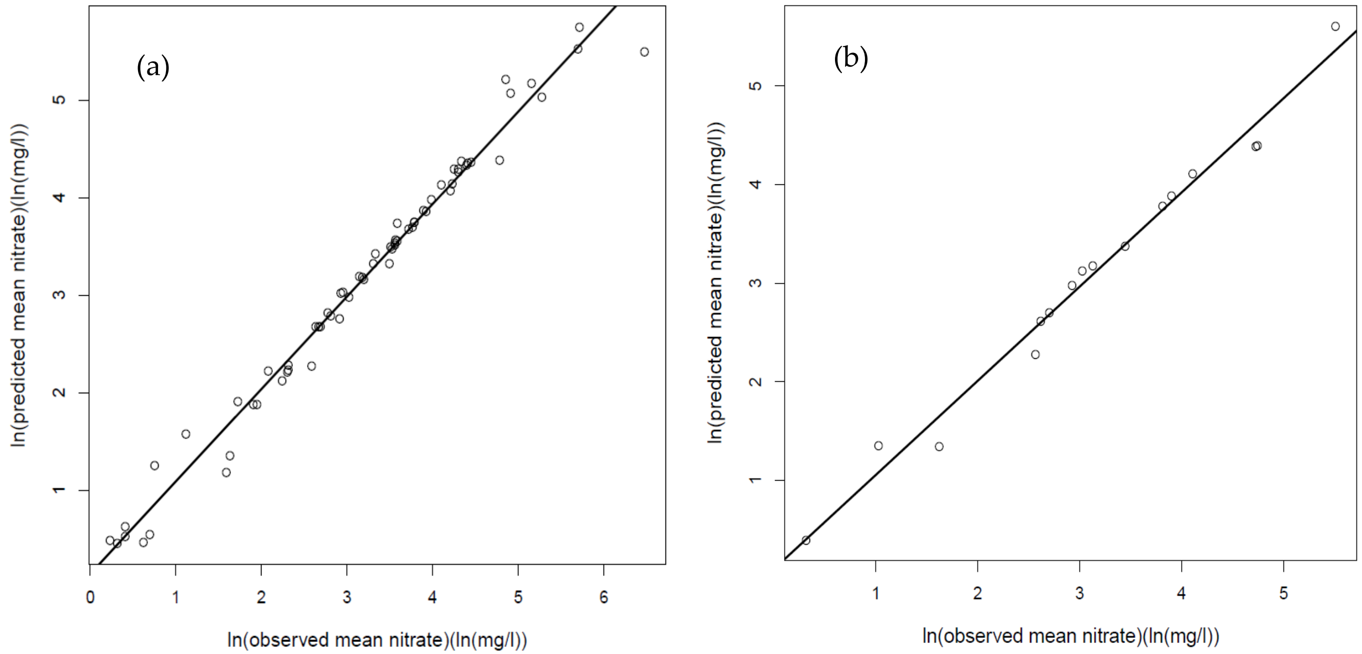


Figure 7-5: RF regression for observed and predicted log (ln) nitrate concentration on training dataset (a) and tested dataset (b) using the continental-scale nitrate data set.

7.4 Results

7.4.1 Validating the continental scale model with three countries datasets

We evaluated the predictive ability of the continental-scale RF regression model at the country level using NO_3^- data in Figure 7-6, Figure 7-7, and Figure 7-8 as the response variable. The validation results of this nonlinear method showed a poor performance at the country level compared to the calibration model (Ouedraogo et al., 2017; *under review*). The scatterplots of predicted versus observed of nitrate showed the wide range of predictions. For example, in Burkina Faso, the prediction is quite modest at R^2 =0.23 (Figure 7-6). Furthermore, in Senegal (Figure 7-7) and South Africa (Figure 7-8), we observed a very poor predictive ability (R^2<=0.1), with a coefficient of determination of 0.09 and 0.003 respectively.

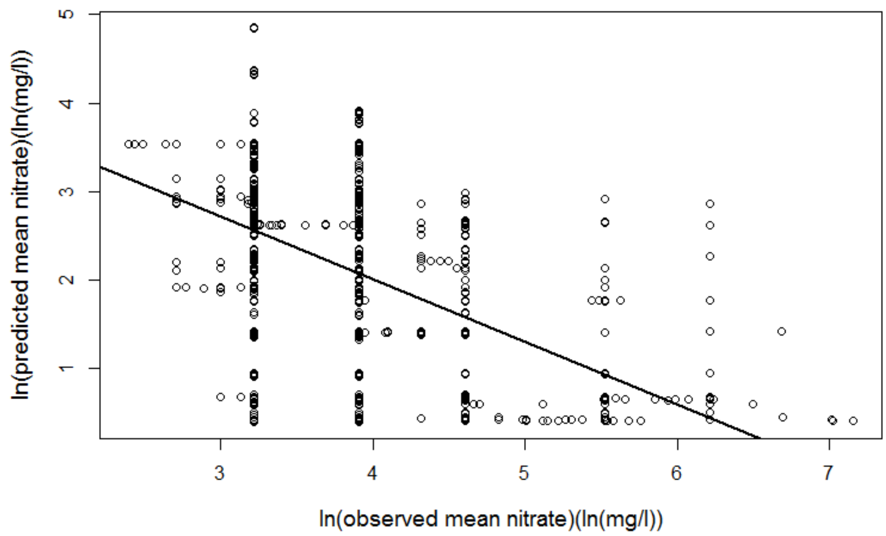


Figure 7-6: Validation results of the continental scale RFR model on the observed groundwater nitrate of Burkina Faso

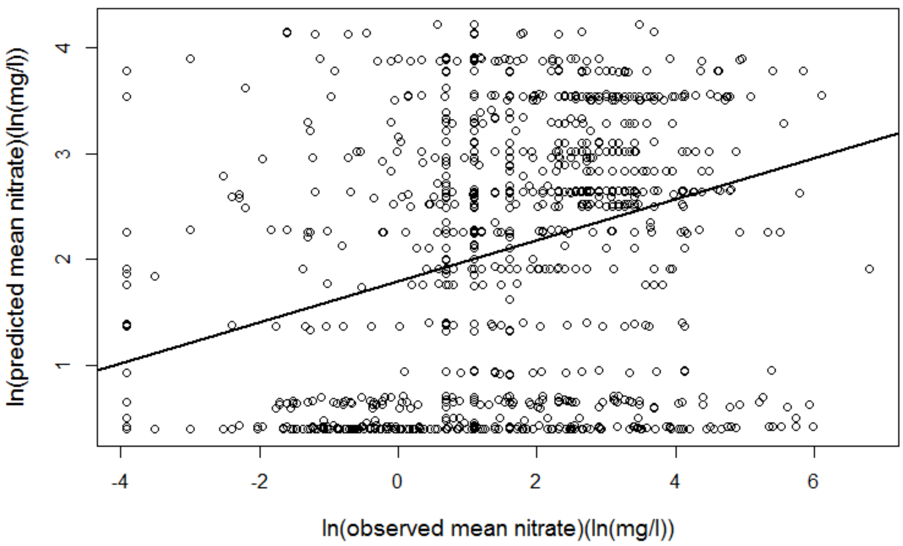


Figure 7-7: Validation results of the continental scale RFR model on the observed groundwater nitrate of Senegal

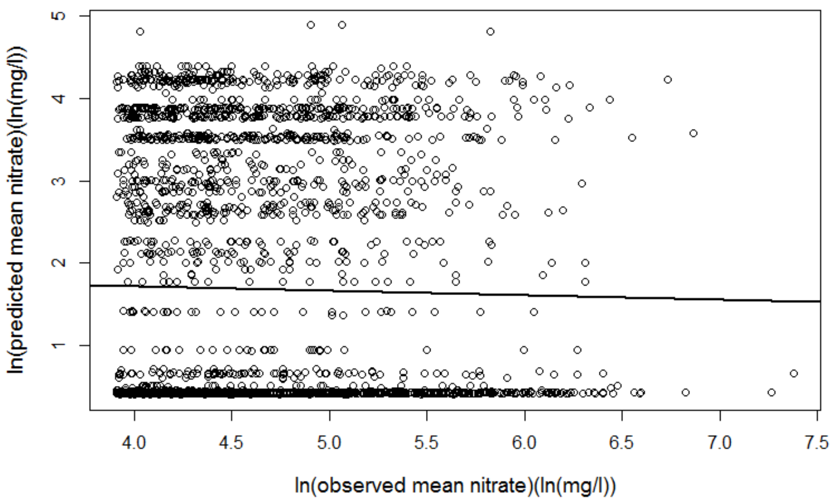


Figure 7-8: Validation results of the continental scale RFR model on the observed groundwater nitrate of South Africa

7.4.2. Re-calibration of nonlinear RF regression at country level

We recalibrated the RF model for each country using the country specific measured nitrate data. The recalibration procedure used 80 % of the country specific data for training dataset and 20 % for validation. The results of these recalibration showed variable results. For Burkina Faso (Figure 7-9a), we obtained very good results for the calibration (R^2 =0.91) and validation (R^2= 0.92) test. In contrast to this, the RF regression model failed to describe the data of the Senegal (Figure 7-10a) and South African (Figure 7-11a) data set. For those latter data sets we obtained R^2<=0.2 both in the calibration and in the validation step.

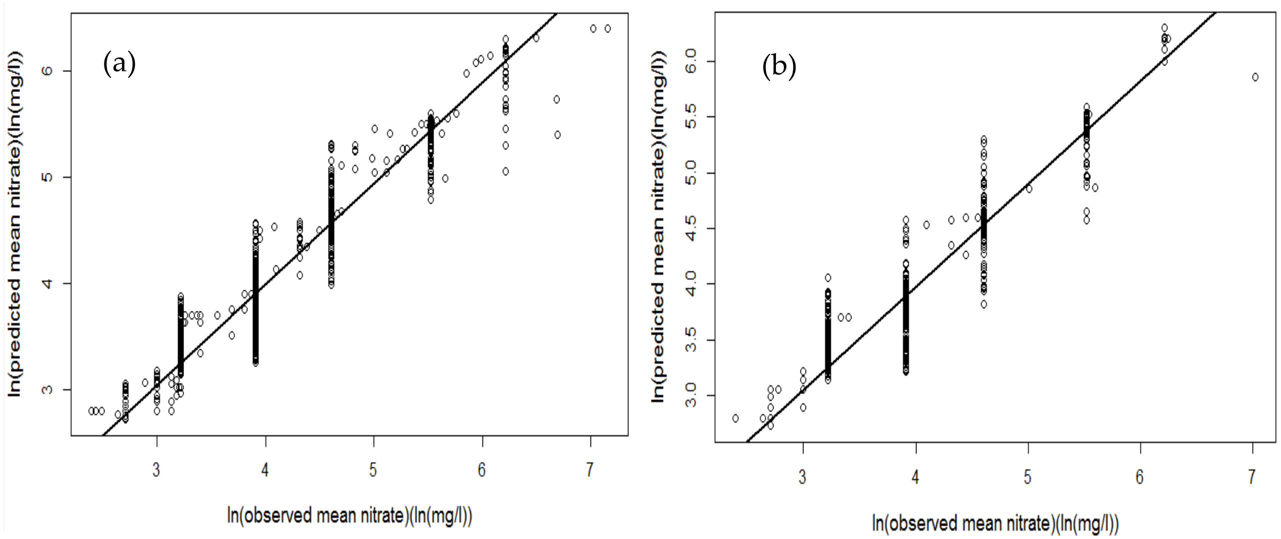


Figure 7-9: Log nitrate of observed versus predicted values for Burkina Faso

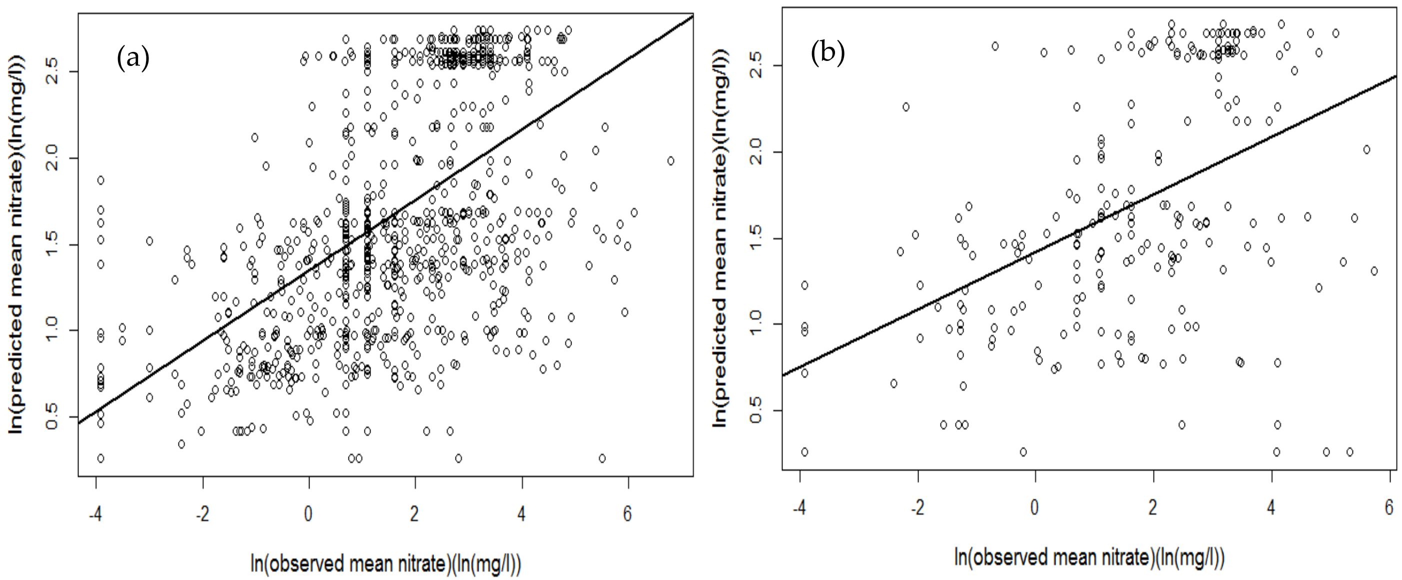


Figure 7-10: Log nitrate of observed versus predicted values for Senegal

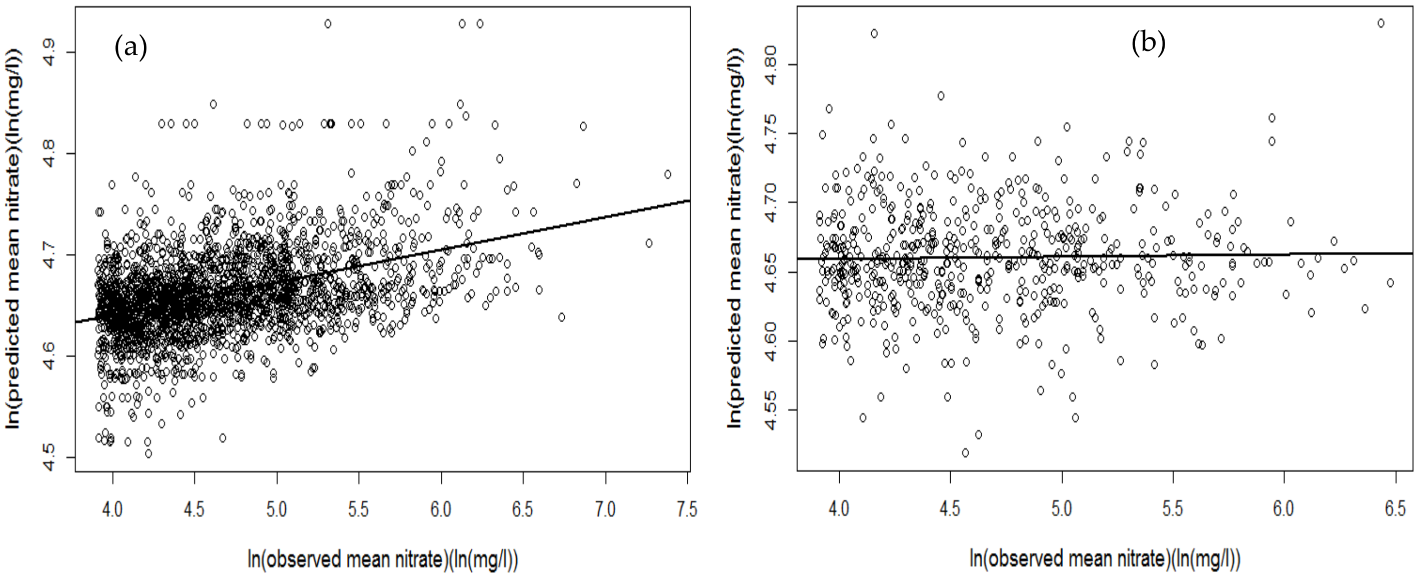


Figure 7-11: Log nitrate of observed versus predicted values for South Africa

7.4.3 Variable Importance Plots at country level

In Figure 7-12, we show for Burkina Faso the '*importance variable plots*' produced by the 'caret' package, which portrays the importance of twenty (20) first levels' of the factorial variable. Given the poor performance of the model for the Senegal and South Africa dataset, we cannot show this analysis for these 2 countries. By analyzing variable importance in Burkina Faso, we found that nitrogen fertilizer application, population density and recharge had the highest scores among all variables. This corroborates with earlier studies on nitrate pollution of African groundwater bodies (e.g. Mfumu et al. 2016).

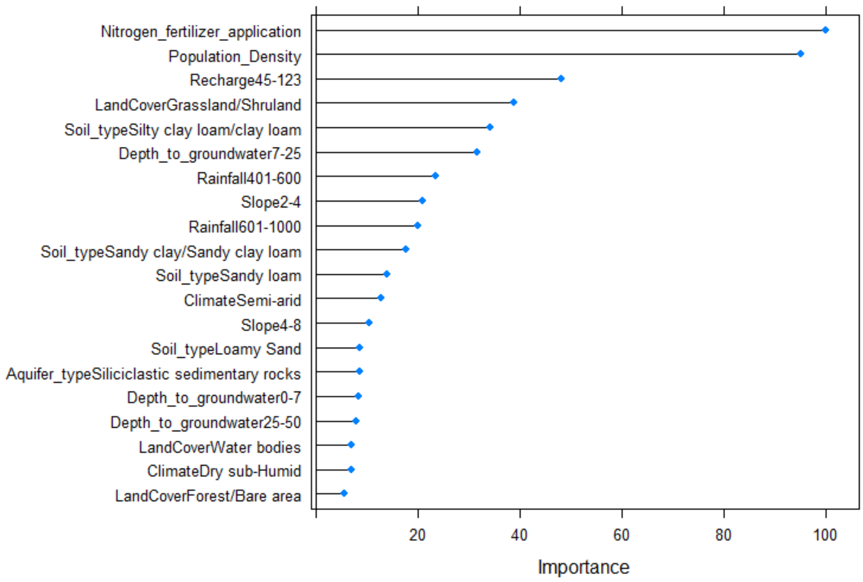


Figure 7-12: Variable importance plot for Burkina Faso

7.5. Discussion

Two prerequisites are necessary for large-scale modelling of nitrate pollution of groundwater on an operational basis (Refsgaard et al., 1999): firstly, access to readily available large-scale data of nitrate pollution and associated variables, making it possible to identify and validate an appropriate nitrate pollution model; and secondly, an adequate scaling, making it possible to apply the identified and validated model at another scale. The first prerequisite is often challenging when assessing nitrate pollution of African groundwater bodies. Not all the existing 'African' nitrate databases are generally available for modelling due to various, often institutional, restrictions (e.g. not publicly accessible, or available but with poor data). Also, not all databases maintained by African institutions contain harmonised and integrated datasets. For example, many databases are not harmonised in their contents or nomenclatures.

In view of these limitations, the present work tested the predictive ability of a nonlinear RF statistical model developed at the pan-African scale (Ouedraogo et al. 2016a; *under review*) and applied at a national level. We conducted this experiment using data collected from Burkina Faso, Senegal and South-Africa. While good results were obtained from the calibration and validation runs at the pan-African scale (Ouedraogo et al., 2016a; *under review*), these results could not be replicated at the country scale. The country-scale validation of the continental-scale model produced a R^2 of 0.003, 0.09, and 0.23 respectively for South Africa, Senegal and Burkina Faso. These poor results of the validation at the country scale show that the continental-scale model is not valid for making predictions at smaller scale. When recalibrating the model at the country scale, successful results could only be obtained for Burkina Faso. This shows that a similar model structure can be used to model nitrate pollution at the scale of Burkina Faso and the whole African continent, but that the model parameters are scale-variant. For Senegal and South Africa, the model structure of the continental-scale model cannot be used to predict pollution at the country scale. The regional model for Senegal and South Africa should therefore encompass other basin attributes for predicting nitrate concentrations (Schwarz et al. 2011; Dupas et al. 2013). For example, climate typically exhibits smaller variability within a region than across the continent (Schwarz et al., 2011). Hence, the role of climate in explaining nitrate contamination may become different at the regional scale as compared to the continental scale. The poor capacity to model nitrate pollution in Senegal and South Africa with a model type inferred from continental data may also be due to the poor quality of the data. Nitrate measurements collected for each country are derived from various climate zones, with no standard manuals or guidebooks describing the methods used to collect across the dataset. The data may therefore exhibit some bias, as we have mentioned in Section 7.3.1. There is no guarantee that the available nitrate point data from Senegal and South Africa are truly representative. For example, for the nitrate dataset of Senegal, the author of the dataset has declared that errors exist in the recorded data. For example, on the IGRAC (International Groundwater Resources Assessment Centre) Website, the data provider mentions: "No additional quality checks were performed and data should be used with caution. SADC-GMI and IGRAC accept no responsibility for accuracy of the data". Further, the low predictive ability of the continental scale model may be due to calibration issues. Indeed, by using logistic regression to explain non-point source (NPS) NO_3^- in groundwater, Gurdak and Qi (2012) argue that poorly predictive models are probably over-trained on the calibration data.

The rather good results when recalibrating the continental scale model at the country scale for Burkina Faso shows that (when the previously mentioned pitfalls are addressed) the structure of the continental-scale model can be maintained, but that the model parameters are scale-variant. The importance of scale effects has long been recognised by hydrologists, water resources managers and other water practitioners

(Refsgaard and Butts, 1999; El-Sadek, 2002; Gubler et al., 2011). Refsgaard and Butts (1999), for instance, affirm that model codes are generally scale-specific. According to Heuvelink and Pebsema (1999) (cited in El-Sadek 2002), there are three principal reasons for this: i) different processes are important at different scales; ii) input data availability is reduced at larger scales; and iii) the model's input and output undergo a change of 'support', i.e. the sample volume of field data changes between different spatial scales. Such general observations on scale dependency also hold for groundwater vulnerability and pollution modelling. Gurdak and Qi (2012), for instance, aimed to develop a statistical groundwater pollution model for the entire California Coastal Basin aquifer system (CCB) using explanatory variables that represent the source, transport, and attenuation (STA) of nitrate contamination in groundwater. They used a model initially inspired by the factors included in the DRASTIC vulnerability model. The first iteration of the CCB model had a poor fit to observations at the validation wells (R^2=0.064). Gurdak and Qi (2012) affirm that many DRASTIC model factors often identified as sensitive in national scale assessments were found not to be important when modelling contamination at the scale of the CCB. They recommended, for instance, to include dissolved oxygen (DO) as a sensitive parameter in the CCB-scale assessment. This suggests that explanatory factors and vulnerability models are highly sensitive to the scale of application. Four years later, Gurdak et al. (2016) examined these scale-dependencies in more detail and further illustrated the scale-dependency of the model and explanatory variables. They found that important differences in controlling factors were identified between the CCB- and national-scale models. They concluded by asserting that good management and policy decisions are best supported by models developed at the same spatial scale as the decision-making scale. Similar conclusions were obtained by Gross (2008), who affirmed that the explanatory factors may include challenges associated with scale or spatial autocorrelation. Vulnerability assessments and scale are therefore highly intertwined (NRC, 1993), not only in technical application but also in conceptualisation. Therefore, Fekete et al. (2010) proposed three recommendations to address scale issues in statistical groundwater pressure models: i) scale implications (both benefits and drawbacks) need more attention and documentation within vulnerability studies; ii) the choice of the appropriate spatial level driven mostly by data availability, policy demand, and aim of the concept should also be supported by theoretical considerations; and iii) the identification of appropriate types of scale (spatial, temporal) and types of nesting of phenomena (single-level, multi-level, and cross-level) should be a prior step to the conceptualisation of a statistical groundwater pressure model.

In addition to the limitation related to the scale transition, we acknowledge that in our study the model is subjected to the classical uncertainties and modelling errors. Indeed, model predictions at the regional scale are likely to be contaminated by several different modelling errors (Donigan and Rao, 1986; NRC, 1993). According to Mulla and Addiscott (1999), these errors include modelling structure error, experimental data measurement error, model parametrization errors and, as mentioned above, scale transitions errors. Errors in model structure occur when the process and the assumptions represented by the model fail to represent reality. The example could be a model which simulates solute transport using the convective dispersive equation for a region in which two-region or macropore transport is significant. The scale-transition error is due to errors in extrapolation caused by spatial and temporal averaging of model parameters (Destouni, 1993), or due to bias caused when the calibration site is not representative for the region (Beven, 1993). Mulla and Addiscott (1999), argue that the scale-transition error is also due to the fact that processes which dominate broad patterns and trends at the larger scale may be obscured by other processes that dominate at the smaller scale. An example is the description of groundwater contamination by nitrate-nitrogen at the regional scale in terms of regional patterns in precipitation, depth to groundwater, and soil texture. At local scale, variations in nitrate leaching to groundwater may more strongly be controlled by management practices such as the amount and timing of N fertilizer application than by local variations in precipitation, depth to groundwater, or soil texture. To conclude, these authors affirm that the rigorous validation of models at different scales is difficult for a variety of reasons.

7.6 Conclusion

To develop effective groundwater protection programs, we need to understand how natural and anthropogenic factors determine groundwater degradation. Within this paper, we evaluate the ability of a statistical model that was designed for predicting groundwater contamination by nitrates at the scale of the African continent to predict groundwater contamination by nitrates at the scale of individual African countries. We assess the results using datasets on groundwater contamination by nitrates from Senegal, Burkina Faso and South Africa. The assessment was poor for the Senegalese and South African dataset, but good for the Burkina Faso dataset when recalibration of the continental scale model was considered. Many of the difficulties and limitations within this validation study were data-related and resulted from, among others, lack of homogeneous nitrate data at the African scale, and uncertainties related to the explanatory variables. For example, the first limitation occurred when the model was used to predict the distribution of nitrates at the country scale. Additionally, uncertainties or bias in the reference data (coarse explanatory variables) were found to distort the performance of the model validation at the country level. This study highlights the necessity of developing a national-level political programme for the characterisation of groundwater vulnerability, firstly by constructing a good database of groundwater quality data, and secondly by building a robust vulnerability predictive model for each country. The continental-scale model does not account either for local point sources of nitrate, or for features and processes that may promote focused recharge. Therefore, the continental scale model may not be appropriate to support local-scale decisions. To improve this poor predictive ability, future modelling efforts must address the many modelling errors related to model structure, model parametrization and, in particular, scale-transition.

Besides the validation and recalibration, we have sought to determine the relative importance of the variables that determines nitrate contamination. Our results revealed that population density, nitrogen fertiliser application rate, groundwater depth, recharge rate, land cover and rainfall are the most important variables contributing to nitrate pollution in groundwater.

In summary, our study showed that RF regression can be an effective technique for predicting nitrate contamination at the continental and country scale. Yet, caution should be paid to data quality. Better data availability and better quality data would, of course, help to make model predictions more accurate in the future. We therefore encourage national and regional agencies to strengthen the groundwater quality monitoring programs. This echoes Goal 6 of United Nations Sustainable Development Agenda, which recommends the establishment or expansion of water quality monitoring programmes at a national, regional and global scale.

Chapter 8 Time dynamic pollution risk modelling of groundwater at the African scale[5]

[5] ***Ouedraogo, I***., *Girard, A., Defourny, P., Vanclooster, M., and Jonard, F. (2017). Time dynamic pollution risk modelling of groundwater at the African scale. To be submitted in Hydrological Sciences Journal.*

8.1 Abstract

Groundwater pollution risk modelling is an important asset to improve groundwater management and protection. In a previous study, we proposed a method for mapping groundwater vulnerability and pollution risk at the pan-African scale based on a "static" hypothesis (Ouedraogo et al. 2016). However, some of the parameters taken into account by this method may vary significantly over time such as recharge, land use, etc. Hence, vulnerability and pollution risk should also be considered as a time dynamic groundwater property. In this chapter, we assess the time dynamic behaviour of groundwater pollution risk at the continental scale, using the parametric DRASTIC model. We use the most recent continental scale data on soil, topography, land use, geology, hydrogeology, and climate in a Geographical Information System at the resolution of 15x15 km^2 to implement the approach. We compared continental scale groundwater pollution risk for the years 1990, 2000 and 2010. The elaborated pollution risk maps show important variations of the spatial distribution of pollution risk between the three years. The maps reveal that changes are mainly concentrated in the area of the Nile Delta, in areas around the Lake Victoria, in North Africa, and in coastal West-Africa (predominately in Nigeria). The increase of pollution risk is mainly related to the increase of the density of population of settlements areas in these regions.

The proposed method for modelling the time dynamic groundwater pollution risk can support the monitoring of SDG Goal 6 which includes a focus on preserving our freshwater resources for potential future threats.

8.2 Introduction

While groundwater represents 15 % of total renewable water resources in Africa, an estimated of 75 % or more of the population relies on it as their main source of drinking water (UNEP, 2010). However, degradation of groundwater by overexploitation and contamination is the most serious water resources problem in Africa (Xu and Usher, 2006; MacDonald et al., 2013). Many unprotected groundwater resources are vulnerable to NPS (non-point source) contamination (Gurdak, 2014). In such a context, to manage and protect groundwater resources, a set of pollution risk assessment methods have been developed to estimate the potential for NPS groundwater pollution and to identify primary factors influencing the contamination level. According to Quevauviller (2008), a key step in assessing pollution risks is based on the analysis of the groundwater vulnerability (ease with which groundwater may be contaminated by human activities). Groundwater vulnerability assessment is therefore pivotal in groundwater pollution prevention and control (Huan et al. 2012 cited in Huang et al., 2017). It provides a method for evaluating the sensitivity of groundwater to contamination and scientifically defensible information for decision makers. More than a hundred methods for assessing the vulnerability of groundwater pollution have been developed around the world (Amharref et al., 2015). Traditionally, these methodologies have been based on a "static" hypothesis that groundwater pollution risk does not change significantly over time (Butscher and Huggenberger, 2009). One of the traditional groundwater vulnerability models used is the DRASTIC method (Aller et al.1985; 1987). Based on this method, pan-African groundwater pollution vulnerability was mapped in an earlier study (Ouedraogo et al., 2016).

Yet, groundwater vulnerability and pollution risk are strongly dependent on factors such as depth to water, recharge, and land use and land cover conditions, all of which are influenced by climate conditions (Li, 2012). A warming climate, for example, could alter the vulnerability of shallow aquifers by affecting depth of the water table and recharge (Toews and Allen, 2009; Scibek and Allen, 2006; Pointer, 2005). Ducci (2005), affirms that patterns of regional groundwater pollution vulnerability will vary between drought, average, and wet periods. To this regard, it is important to introduce the time component in groundwater vulnerability and pollution risk assessments.

In recent years, some studies have attempted to integrate the temporal dimension to investigate groundwater vulnerability evolution under varying environmental conditions and climate change (Luers et al. 2003; Dennis and Dennis, 2012; Albuquerque et al. 2013; Pórcel et al. 2014; Stevenazzi et al. 2015; Amharref et al. 2015; Xi et al. 2016; Paradis et al., 2016). For instance, Dennis and Dennis (2012) introduced time dynamics in the DART vulnerability method to investigate climate change impact on groundwater vulnerability for South-Africa aquifers. Stevenazzi (2015) focussed in their pollution risk assessment on the relation between temporal changes in groundwater contamination and land use. Others compared vulnerability maps elaborated for different years, which highlights the key factors in the aquifer vulnerability variation (Saouini, 2014; Amharref et al. 2015).

In this chapter, we assess the time dynamic groundwater pollution risk at the continental scale of Africa. In other words, we seek to develop a modelling approach to better understand the relationships between groundwater pollution risk and time dynamic drivers of this pollution risk such as land use. The incorporation of the time dimension into groundwater pollution risk map will facilitate the transfer of knowledge and information to decision-makers and is considered pivotal for the monitoring of groundwater systems, as for instance suggested in the SDG-6 monitoring strategy.

8.3 Material and methods

8.3.1 Groundwater vulnerability modelling framework

In a previous study, we determined the groundwater pollution risk at the pan-African scale using the Composite DRASTIC index (Ouedraogo et al., 2016). The Composite DRASTIC index or CD index is an adaptation of the DRASTIC vulnerability index with the addition of a new parameter to define the risk associated with land use (L). In this chapter, we used a multiplicative approach to combine land use with DRASTIC and to assess pollution risk. The same method was used by Meunier (2012). Indeed, according to Baghapour et al. (2016), this method allows achieving greater accuracy in the estimation of the nitrate pollution risk. The method uses the following equations to assess pollution risk:

$$VI = DwDr + RwRr + AwAr + SwSr + TwTr + IwIr + Cw\mathrm{Cr} \quad (1)$$

$$DVI = VI * LU \quad (2)$$

where VI is the dimensionless DRASTIC Vulnerability Index; D (Depth to groundwater), R (Recharge), A (Aquifer type), S (Soil media), T (Topography), I (Impact of vadose zone) and C (hydraulic conductivity) are the seven variables (or parameters) contributing to groundwater vulnerability and subscripts r and w are the corresponding ratings and weights. In equation (2), DVI is the Dynamic Vulnerability Index which is dimensionless and LU refers to the potential risk associated with land use. The higher the DVI, the greater the groundwater pollution risk. Each of DRASTIC index parameter of equation (1) was assigned ratings and a numerical weighting to reflect its relative importance in estimating groundwater pollution potential. According to Merchant (1994), ratings are intended to reflect the relative significance of data values (mapped "classes") within each factor. Typical weights assigned to each parameter, following guidelines as given in the DRASTIC documentation (Aller et al., 1987) (See Table 4.1 in Chapter 4). The weights for assessing time dynamic pollution risk are considered constant (Ehteshami et al. 1991). Table 8-1 show for each DVI variable the designated rating. They vary from 1 to 10, with higher values describing greater pollution.

We deployed the general modelling framework as illustrated in Figure 8-1, which is an adaptation from Huang et al. (2017). It shows the combined interactions of climate and land use change on groundwater vulnerability and pollution risk.

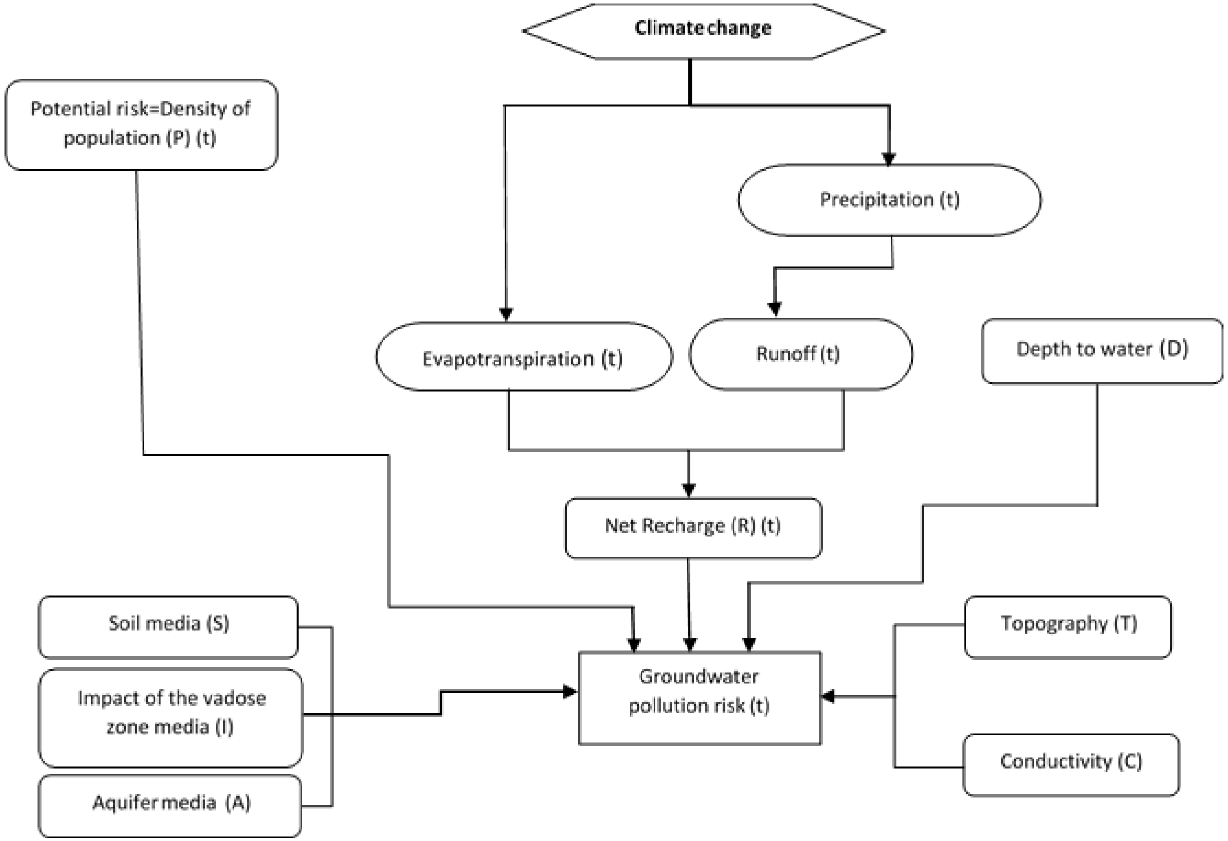


Figure 8-1: Impact of climate change, land use change, and environmental factors on groundwater (modified from Huang et al. 2017)

In general, land use and land cover are major attributes determining specific vulnerability and pollution risk. In this regard, due to the difficulty to build dynamic land use and land cover data sets, we used the normalised density of population (P) as a proxy for land use. This is consistent with our previous study showing that population density is one of the most relevant factors that explain the nitrate contamination at the African scale (Ouedraogo and Vanclooster, 2016a).

Table 8-1: Weight, Range and Rating and of the DRASTIC parameters and Land-Use parameter (based on Ouedraogo et al., 2016, and Girard, 2017)

	Depth to groundwater (D)(m)	**Net recharge (R) (mm/yr)**	**Aquifer media(A) (type)**	**Soil media (S) (type)**	**Topography (T) (%)**	**Impact of the vadose zone (I) (type)**	**Hydraulic conductivity (C) (m/day)**	**Land use (P) (people/km²)**
Rating	Weight:5	Weight:4	Weight: 3	Weight:2	Weight:1	Weight:5	Weight:3	Weight:1
1	>250	0-45	-	Clay	>18	-	<0.010	0-50
2	100-250	-	-	-	-	-	0.010-0.038	50-100
3	50-100	45-123	Acid plutonic rocks Intermediate plutonic rocks Basic plutonic rocks Metamorphic rocks	Clay loam Silty clay loam	12-18	-	-	100-150
4	-	-	-	Sandy clay Sandy clay loam	-	Acid plutonic rocks Intermediate plutonic rocks Basic plutonic rocks Metamorphic rocks	0.038-0.127	150-200
5	25-50	-	-	Loam	8-12	-	-	200-250
6	-	123-224	Siliciclastic sediments	Sandy loam	-	Siliciclastic sediments	0.127-0.345	250-300
7	-	-	-	Loamy sand	-	Unconsolidated sediments		300-350
8	7-25	224-355	Unconsolidated sediments	-	4-8	Water bodies	0.345-0.569	350-400
9	-	>355	Acid volcanic rocks Intermediate volcanic rocks	Sand	2-4	Acid volcanic rocks Intermediate volcanic rocks	-	400-450
10	0-7	-	Basic volcanic rocks Mixed sedimentary rocks Carbonate sedimentary rocks Evaporites	-	0-2	Basic volcanic rocks Mixed sedimentary rocks Carbonate sedimentary rocks Evaporites	> 0.569	>450

8.3.2 Data sources

To estimate the dynamic aspect of groundwater pollution risk at the continental scale of Africa, we used several data with various spatial resolutions and grouped them into two categories, i.e., static and dynamic parameters. We transformed the data to the reference resolution of 15x15 km^2 as proposed by Ouedraogo et al. (2016). We obtained the dynamic groundwater risk map, after classifying and assigning relative ratings and weights, then overlaying the individual maps in a GIS.

8.3.2.1 Dynamic Parameters Mapping

This part will summarize the changing of groundwater net recharge, and density of population as land use proxy. For both dynamic parameters, mapping was elaborated on the basis of the data developed by Girard (2017). This mapping was done for 1990, 2000 and 2010.

Net Recharge (R) affected by climate change

The '*Net Recharge*', R and is a function of the precipitation. R represents the amount of water per unit area of land penetrating the ground surface and reaching the water table. It is thus influenced by the amount of surface cover, the slope of the land surface, the permeability of the soil and the amount of water that recharge the aquifer. Climate change will alter the hydrological cycle, including spatial and temporal changes in precipitation and evaporation (Huang et al., 2017). A number of investigations such as Gogu and Dassargues (2000); Raupach et al. (2013) suggested that climate change will affect directly groundwater recharge. We inferred R from the data prepared by Girard (2017). Due to lack of dynamic data of recharge evolution at the African scale, the relation in equation (3) was proposed as a tool to examine possible groundwater recharge trends in response to climate change:

$$R = P - ET - Q \tag{3}$$

where R is the recharge (mm), P is the total Precipitation (mm), ET is actual evapotranspiration (mm), and Q is the Runoff in mm. These factors used to prepare recharge map data were extracted from Global Land Data Assimilation System Version 2 (https://earthdata.nasa.gov/). The recharge map ratings (Figure 8-2) were assigned values following the classification suggested by Ouedraogo et al. (2016).

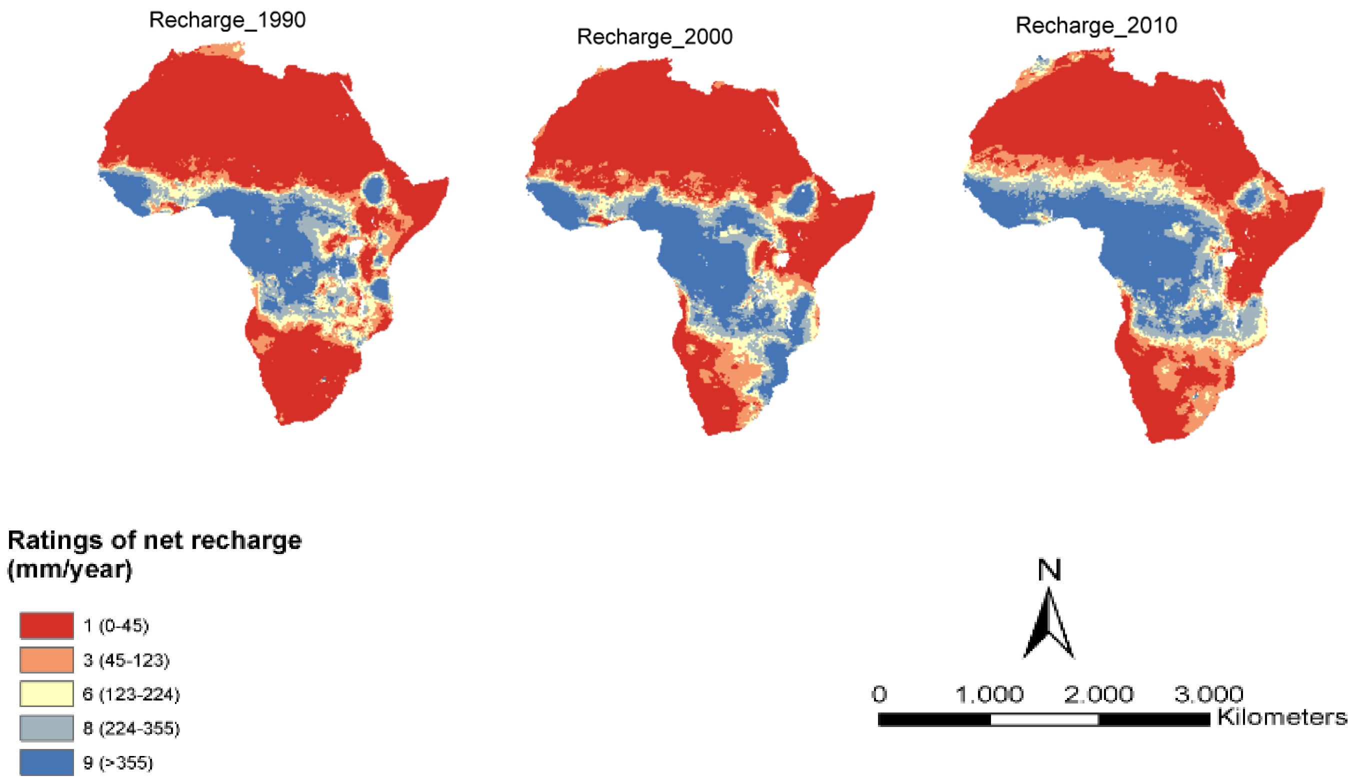


Figure 8-2: Rating of Recharge (R) map in Africa for 1990, 2000, and for 2010

The standard classification of recharge map is similar for the tree years. Africa has areas with low net recharge rate (<50 mm/year) for which a rating of 1 is assigned, and areas with high recharge ranges (>225 mm/year), particularly in Central Africa and a portion of western Africa for which a rating of 9 is assigned. We observe an average variation of the recharge between 2000 and 2010. For example, the variation can be observed near the Lake Victoria and Ethiopia in East Africa and Morocco in North Africa. These two maps indicate that climate change could affect groundwater net recharge.

Density of Population (P)

The second dynamic factor was '*density of Population'*, P. The population density is commonly represented as the number of people per square kilometers (person/km^2). According to Alemayehu et al. (2006), who analysed the case of Addis Ababa, Ethiopia, the impact of the human population on surface and groundwater is increasing with the development of industry and population size. These authors affirm that the state of groundwater contamination in this city is similar to the reality of large cities in many developing countries. The level of groundwater contamination tends to rise with the increasing human population, particularly in urban areas and the low level of economic development. Indeed, recently a study carried out by Lapworth et al.(2017), affirms that faecal waste is the largest source of contamination in urban (and rural) groundwater, in particular where there is high-density housing with poor and/or inadequate sanitation facilities and treatment of faecal waste. These authors say that this situation is common in low-income areas of most major and growing urban centres in Africa. Therefore, the "P" factor represents the distribution of potentially causative agents, considering that groundwater pollution is mainly human-caused. Data on population density at the African scale for the year 1990, 2000 and 2010 were developed by SEDAC and prepared in a raster grid by Girard (2017) (Figure 8-3). This factor was normalized and assigned ratings from 1 to 10. Ratings were obtained from a previous study (Vaezihir and Tabarmayeh, 2015; Girard, 2017) and adapted for our study area.

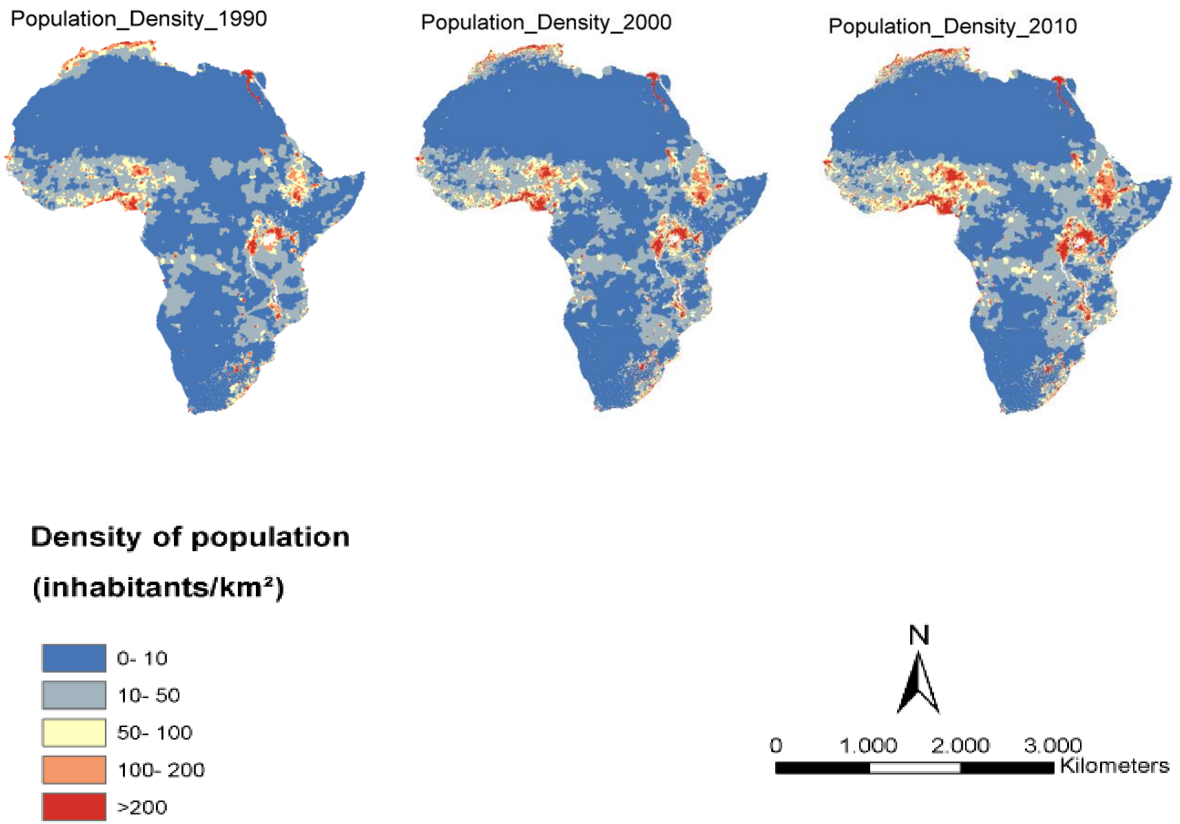


Figure 8-3: Rating of Density of Population (P) map in Africa for 1990, 2000, and for 2010

8.3.2.2 Data of Static Parameters

The '*Depth-to-water-table*' (D), is the vertical distance from the land surface to the top of the saturated zone in the aquifer. It represents the distance that a potential contaminant must travel before reaching the aquifer. Consequently, the D will have an impact on the degree of interaction between the percolating contaminant and the sub-surface materials (air, minerals, water) and, therefore, on the degree and extent of the physical and chemical attenuation and the degradation process (Rahman, 2008). In general, the vulnerability for pollution decreases with D. Furthermore, with climate change over time, depth to water level in Africa is not static. However, in our case study, due to the absence of groundwater level variation between the three considered years, we assumed that the parameter D is "static". The D value was calculated from the data as presented by Bonsor et al. (2011). The original value of this parameter was not continuous and was obtained in a categorical data format. The rate varies from 0 to more than 250 m bgl across the African continent. The assigned D ratings vary between 1 to 10, according to the classification of Ouedraogo et al. (2016). Due to the importance of this factor in groundwater vulnerability to pollution, we decided to show explicitly the map of this static parameter (Figure 8-4).

The aquifer type or aquifer media is also considered a static variable. The '*Aquifer media*', *A*, refers to a type of consolidated or unconsolidated material which hosts the aquifer (Ersoy and Gültekin, 2013). The A map was inferred from three main data sources: (1) the high resolution global lithological database (GliM) of Hartmann and Moosdorf (2012); (2) the global permeability estimates of Gleeson et al.(2011); and (3) the African hydrogeology and rural water supply map of MacDonald et al. (2008). Africa has many different hydrogeological environments, but five of most important were categorized in the study: unconsolidated sediments, siliciclastic sediments, carbonate rocks, crystalline rocks and volcanic rocks

(Gleeson et al., 2014). The ratings of the A map were set according to the classification of Ouedraogo et al. (2016).

For implementing the pollution risk model, we further assessed soil characteristics, topography (slope), the characteristics of the vadose and the hydraulic conductivity at the pan-African scale. Soils serve as the dominant sink for retention of pollution (Barrett and Burke, 2002), and impact the leaching of pollutants to deeper horizons. For this study, the soil map of Africa was inferred from the data processed by Hengl et al. (2014). Slope affects the likelihood that a contaminant deposited on the land surface will infiltrate through the soil (Li and Merchant, 2013). Low slope of area tends to retain water for longer periods, which allows a greater recharge of water and a greater potential for contaminant migration. The slopes were derived from the 90-meter Shuttle Radar Topography Mission (SRTM90) database. The vadose zone is a layer in between the aquifer and the soil zone. The vadose zone properties determine the attenuation behavior of the materials that are located above the groundwater table and below the soil. The vadose zone is also where processes of biodegradation, neutralization, mechanical filtration, chemical reactions, volatilization, and dispersion may occur (Aller et al. 1987). Similar to the aquifer parameter, the vadose zone parameter was elaborated on the basis of the GLiM data and the African hydrogeological map. The parameter was based on each parent material type that is the same as for aquifer media. Hydraulic conductivity is a property of an aquifer that describes the ability of water to move through the aquifer. According to Rahman A. (2008), an aquifer with high conductivity is vulnerable to substantial contamination as a plume of contamination can move easily through the aquifer. Hence, areas with high hydraulic conductivity values are more susceptible to contamination. We inferred the hydraulic conductivity map from the global hydrogeological map of permeability and porosity, as produced by Gleeson et al. (2014).

All these factors were considered static in this study.

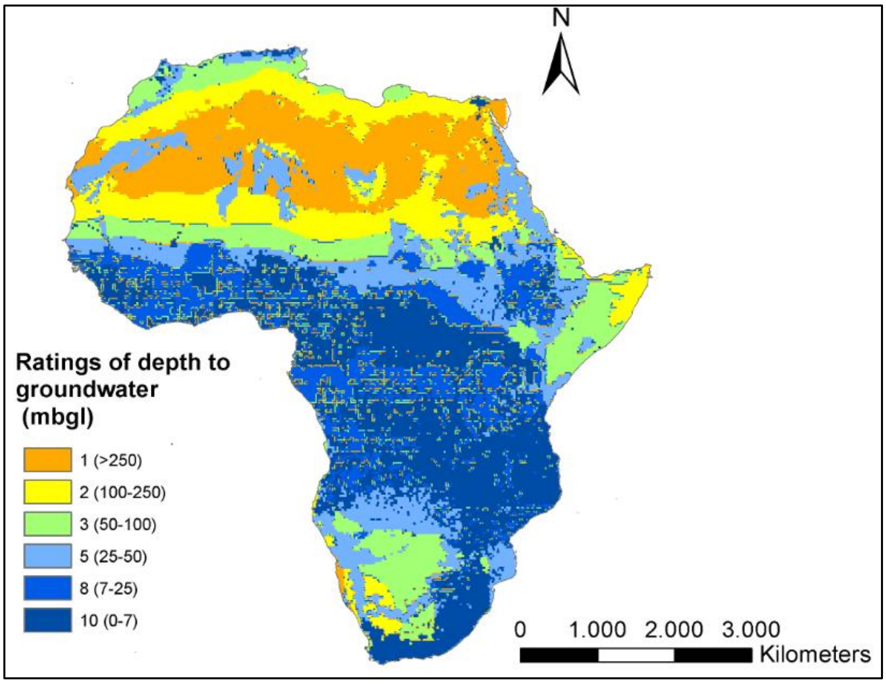


Figure 8-4: Depth to groundwater (D) rates map for Africa

The dynamic pollution risk maps were computed for three years (1990, 2000, and 2010) and were implemented using the ArcMap Raster calculator.

8.4 Results and discussion

8.4.1 Dynamic maps of the groundwater pollution risk

The results of the spatial pattern of DVI index are presented in Figure 8-5. It is important to keep in mind that the DVI index is a continental index and that it should be used to identify areas that will be negatively impacted by land change with respect to groundwater. The risk index indicates the relative level of susceptibility to groundwater pollution. The pollution risk index is divided into five equal interval classes ranging from very low to very high. The DVI exhibits significant space and temporal variability. Areas of higher vulnerability are shown in red with areas of lower vulnerability in green. We observe that pollution risk is significant in North Africa, West Africa (mainly Nigeria), the Lake Victoria or Great Lakes Regions in East Africa, Horn of Africa (Ethiopia) and the Nile Delta in Egypt. This is consistent with the previous findings of Ouedraogo et al. (2016). The maps elucidate the important effect of P on pollution risk which is consistent with previous studies (Xu and Usher, 2006; M'mayi, 2014; Ouedraogo and Vanclooster, 2016a). The highest values are located in the Western part of Africa (Nigeria). When looking at the time dynamics, we observe that the pollution risk increases in the highly vulnerable areas. Vaezihir and Tabarmayeh (2015) affirm that risk of groundwater pollution is directly related to population density which increases with the population growth in urban areas. As mentioned above, Lapworth et al. (2017) demonstrated that the greatest nitrate contamination was in groundwater sources in settlements with extremely high population densities (over 40,000 people per km^2). Many authors affirm that informal settlements are associated with high levels of nitrate, nitrite, and organic compounds (Gwebu, 2003; Ren et al., 2003; Wright, 1999). For example in the city of Harare (Zimbabwe), rapid urbanisation and the lack of low-cost accommodation have led many people to settle (formally or otherwise) on previously land in Epworth, south-east of the city (Zingoni et al. 2005). Half of the population of Epworth makes use of the groundwater resources for their domestic water supply. This number increases as high as 77 % in the most recently-settled area. According to Love et al. (2006), the Epworth settlement thus showed major problems with levels of nitrogen (representing nitrates) and coliform bacteria in groundwater. This is a cause for concern, since the area has a high water table and high population density, leading to an elevated risk of contamination for shallow wells supplying half the population of the settlement with water (Love et al., 2006). Urban growth exhibits high rates in parts of East & West Africa. Urban low income population growth is very high (Lapworth et al.2017). But, while the evidence indicates that the lower-income households are substantially more vulnerable to anthropogenic impacts on water quality (Yang et al, 2013), few studies have specifically examined the extent to which groundwater quality trends impact the poor and their wellbeing (UPGro, 2017). By studying recently groundwater and poverty in sub-Saharan Africa, UPGro (2017) argues in theirs report that: "*a greater vulnerability is likely for several reasons. First, the poor are less likely to have access to treated, piped water and hence more likely to rely on shallow groundwater for drinking. Second, the urban poor are more likely to live in densely populated areas, where sanitation and waste disposal are inadequate, and contamination risks are highest. This is evidenced by the study of Sorensen et al. (2015a), which notes that groundwater contamination was most extensive in areas of low cost housing. Third, low-income groundwater users are more likely to have poorly constructed wells, with inadequate or absent protection measures and rudimentary lifting devices. Fourth, the poor are less likely to undertake household water treatment*." Furthermore, according to Jourda et al. (2006), among the major threats to the urban aquifer in Abidjan, there is the absence of an institutional framework.

With respect to the desert of Sahara, due to low population density and agricultural land use, we observed a low pollution risk. The relative risk with respect to a reference year is given in Figure 8-6. We observe three poles the high-risk with an increase groundwater vulnerability to pollution (50 to 100 % over 20 years). The South of Sahara is also facing a very high level of risk (> 100 % in 20 years). The Nile delta presents a contrasted evolution which is much less clear. Finally, the coasts of Morocco, Algeria and Tunisia and the south-eastern region of Lake Victoria are marked by a 10 to 50 % reduction in the risk of pollution over the same period. In overall, the Figure 8-6 illustrates a significant increase in pollution risk for the Sudan-Sahel belt of Africa and around the Great Lakes Region between 1990, 2000, and 2010. The absolute change in pollution risk is given in Figure 8-7. This figure confirms the findings in Figure 8-6.

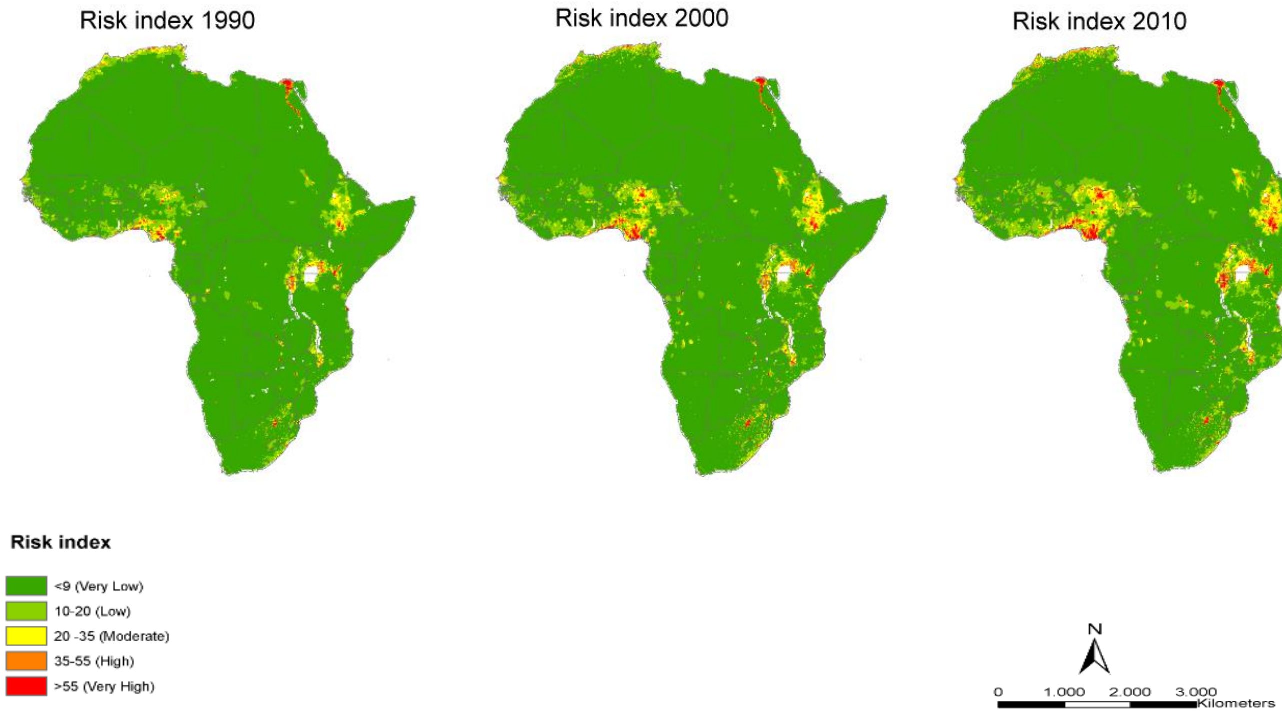


Figure 8-5: Groundwater pollution risk for 1990, 2000, and 2010

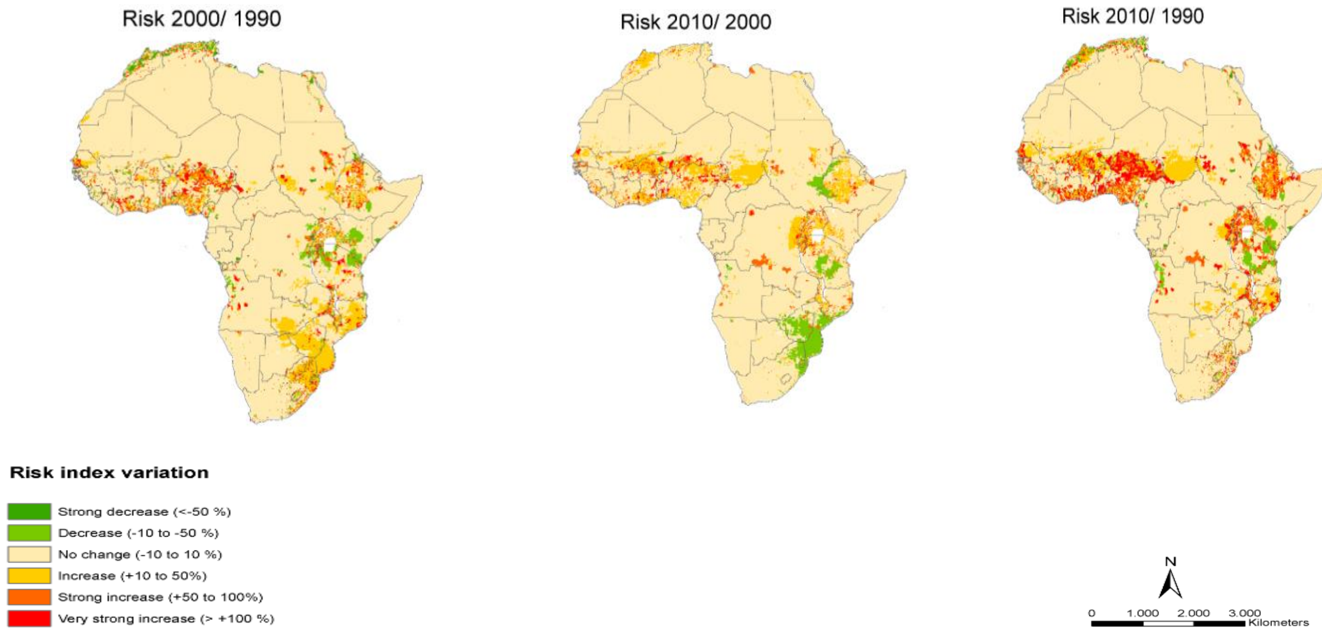


Figure 8-6: Relative comparison of groundwater pollution risk for 1990, 2000, and 2010

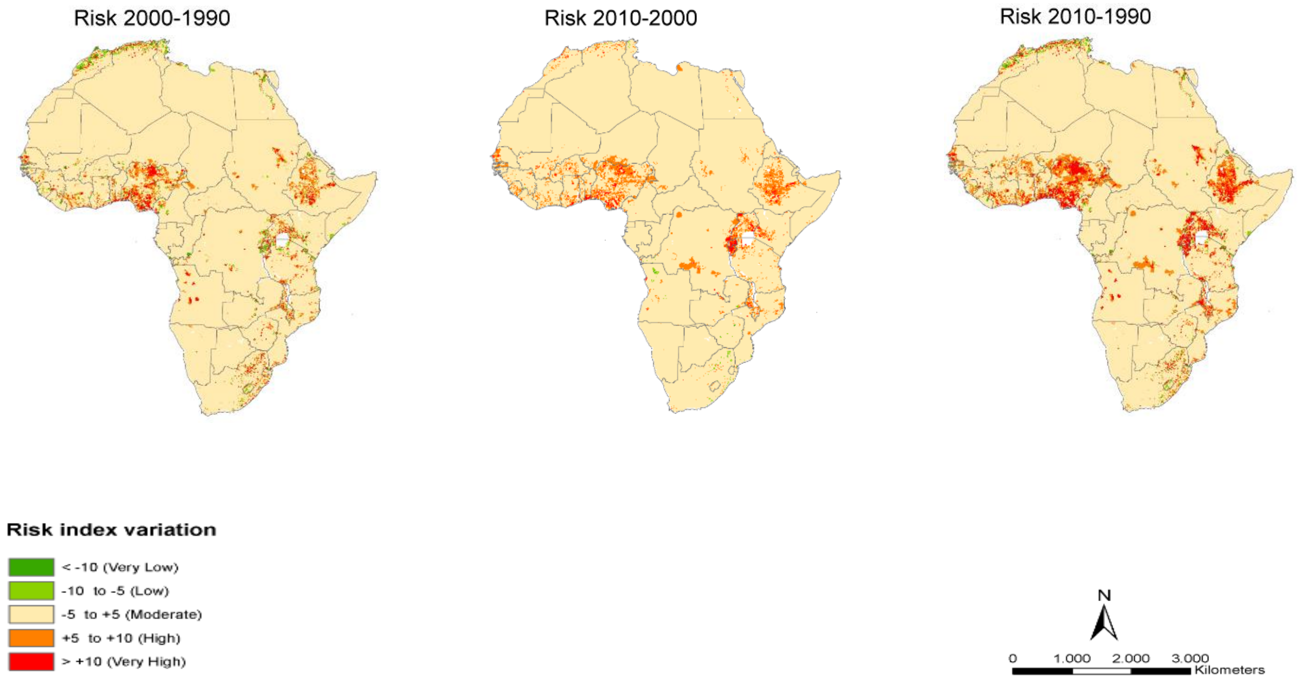


Figure 8-7: Absolute comparison of groundwater pollution risk for 1990, 2000, and 2010

Table 8-2 presents the results of the increasing trend from low to very high pollution risk during the period of 20 years computed from the Figure 8-5. The values in this table confirm that the pollution risk for groundwater in Africa increased considerably. For example, the percent from 1990 to 2010 in pollution risk class of high and very high were 0.55 %, 0.87 %, 1.26 %; and 0.29 %, 0.48 %, 0.76 % respectively, which demonstrates that the surface of the risk of pollution follows an increasing trend. The results of this table confirm the visualization observed on the three maps in Figure 8-5. The results of Table 8-2 are also represented in the diagram (Figure 8-8) to a better visualization.

Table 8-2: Percent of different pollution risk classes

	Pollution risk class				
Year/period	Very low	Low	Moderate	High	Very high
Year 1990	91.98 %	5.5 %	1.66 %	0.55 %	0.29 %
Year 2000	81.63 %	6.49 %	2.50 %	0.87 %	0.48 %
Year 2010	86.79 %	7.94 %	3.22 %	1.26 %	0.76 %

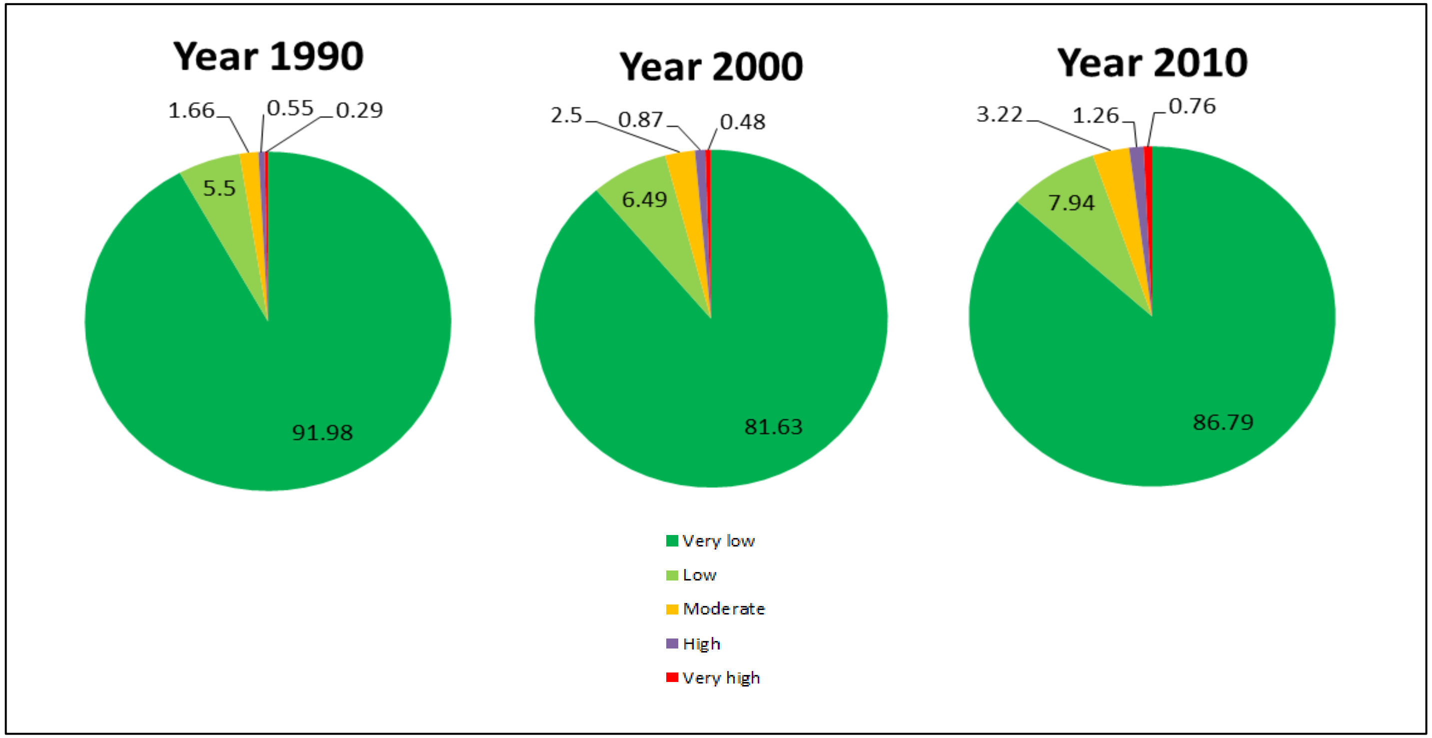


Figure 8-8: Diagram in percentage of pollution risk for 1990, 2000, and 2010

8.4.2 Limitations of the study

In this study, we modelled the time dynamic groundwater pollution risk at the African scale in terms of a set of explaining natural and anthropogenic factors. These factors were combined in a linear model to model groundwater vulnerability and pollution risk. However, according to Li and Merchant (2013), it is recognized that the actual physical processes leading to groundwater contamination are not necessarily linear and often involve complex mechanisms such as pollutant transport, dilution and dispersion, adsorption, and chemical and biological transformation. Furthermore, Ouedraogo et al. (2017) demonstrated that the best statistical model to explain groundwater nitrate contamination at the African scale is a nonlinear model. The linear model used in this study can over- or under-estimate groundwater pollution risk. Still, the linear modelling approach has a significant advantage in that it simplifies complex groundwater contamination processes and can facilitate rapid regional evaluation based on well recognized key environmental and anthropogenic factors.

It should be noted that the groundwater pollution risk maps developed for this research portray only the risk of pollution on a continental scale, and cannot be used to interpret incidences of actual local groundwater contamination. A low pollution risk does not mean that there is no risk of contamination; it simply means that the geology and hydrogeology of the area provide more natural (or intrinsic) protection to the groundwater resources in the given environment. One must look at the land use activities and potential hazards associated with such activities to predict the likelihood of contamination. However, these maps provide a preliminary assessment of the dynamic aspect of groundwater pollution risk at the African scale, and may also support risk assessment when combined with specific hazards. In addition, the modelling results are also subject to the uncertainty from resampling of the relatively coarse resolution climate data, natural factors and anthropogenic data. In addition to climate change data uncertainties, other uncertainties are associated with data sources, such as for example depth to groundwater described by Bonsor et al. (2011).

8.5 Conclusion

By introducing the time dimension to assess trends in groundwater vulnerability is an innovative approach to study the pollution risk. In this study, the DVI index was calculated and mapped at the African scale to identify areas that experienced possible changes in pollution risk of groundwater between 1900 and 2010. This mapping approach was based on public available data. The results identified regions in Africa where groundwater may represent a major threat due to the anthropogenic pressures changes over time. The pollution risk degree of African groundwater varies from very low to very high. We observed that the spatial pattern of pollution risk at the pan-African scale has changed over the time between 1990, 2000 and 2010. Groundwater vulnerability to pollution greatly varies across Africa. This variation was clearly visualized for example in North Africa, in the Nile Delta, and in West Africa. The zone with the highest pollution risk at the scale of the continent is the Western Africa area, which is highly urbanized and densely populated. These results suggested that with the growing population, who generates rapid urbanization with many slums and increasing water demand, the groundwater vulnerability and pollution risk would also increase.

Although there are limitations to the assessment of the dynamic groundwater vulnerability, particularly the absence of depth to water changes for the continent. However, these maps represent the existing data and allow for preliminary interpretation of the spatiotemporal evolution of groundwater in Africa, in terms of climate and land use change. Vulnerability maps and groundwater pollution risk maps are basic tools to assess the efficacy of land use planning toward groundwater protection.

As more data become available over time (e.g. water level change), this result may be reassessed and updated for characterizing the dynamic aspect of African aquifers. Future work will implement sampling design through Africa and provide data for testing the model robustness.

Notwithstanding the many limitations, the modeling approach used here appears well-suited for linking groundwater vulnerability with climate change and population density as a proxy for land use change. The simple DVI model allows modelling the time dynamic pollution risk at the pan-African scale using public available data. This can, therefore, provide an important tool for the sustainable groundwater resources management in Africa. The model could be used to monitor the achievement of SDG Goal 6 in Africa which includes a focus on preserving freshwater resources for potential future threats. For example, this research could perhaps aid groundwater managers at the African scale such as African Ministers Council on Water (AMCOW) in selecting prioritizing areas for future groundwater monitoring and protection.

Chapter 9 Conclusion and Perspectives

9.1 Main findings

Groundwater vulnerability maps are largely considered to be an essential component of sustainable land use planning and management in developed and especially in developing and underdeveloped countries (Sorichetta, 2010). Groundwater vulnerability maps represent the final result of implementing a spatial model to depict the relative susceptibility of groundwater to contaminant loads applied over the land surface. Thus, characterising the vulnerability to contamination of groundwater resources, particularly in shallow aquifers, should help decision-makers to evaluate current land use practices, make recommendations, implement regulation changes and/or introduce new rules in order to better prevent or minimise groundwater contamination and hence preserve its quality. To this end, Wang et al. (2014) affirm that the water quality in Africa is facing severe challenges. Therefore, the improvement of water quality and wastewater treatment is of vital importance to achieve the SDGs (Sustainable Development Goals). In this thesis, we filled a significant knowledge gap in groundwater pollution pressures at the continental scale of Africa by developing methods for assessing groundwater vulnerability to pollution at the pan-African scale in space and time. We also identified key environmental factors that explain nitrate pollution in groundwater and finally validate these methods.

The first objective of this thesis was to assess groundwater vulnerability to pollution at the pan-African scale. We, therefore, aimed identifying which aquifer systems/groundwater resources and settings are most vulnerable to degradation. Necessary data for land use, soil, topography, and geological and hydrogeological features in the study area were collected from different sources. To do asses this vulnerability we deployed the empirical DRASTIC index model and GIS techniques at the pan African scale. Seven environmental parameters including “depth to water”, “net recharge rates”, “aquifer media”, “soil media”, “topography”, “impact of vadose zone”, and “hydraulic conductivity” were used to represent the natural hydrogeological context. These data have been compiled into a 15x15 km^2 resolution geodatabase for the African continent and used to build the seven parameters of the DRASTIC vulnerability index. In Chapter 4, we attained our first objective by showing clearly; through mapping that groundwater resources in Africa are vulnerable and subject to pressures. In short, the first pan-African groundwater vulnerability and pollution risk map developed in the thesis showed that areas under very high and high pollution risk are mainly characterised by shallow groundwater systems. Inversely, low contamination risks are observed for the large sedimentary basins in North Africa, and a small portion of Eastern and Southern Africa. These groundwater systems are situated at greater depths. The risk map of groundwater pollution in Africa shows that water resources are mainly under pressure in large agricultural basins. A validation of the DRASTIC based vulnerability approach is also shown in this Chapter 4. To this, we used nitrate concentration data at the pan-African scale were inferred from a literature meta-analysis (Ouedraogo and Vanclooster, 2016a). Results of validation show a good match between nitrate concentration and the groundwater pollution risk classes, i.e. the results of the map agree with the actual nitrate pollution situation reported in the literature. High nitrate concentrations detected in the literature coincide with high intrinsic vulnerability and high pollution risks. This illustrates the consistency between the calculated vulnerability and groundwater pollution risk using generic data on the one hand, and the observed contamination on the other. A scatterplot between the nitrate concentration in groundwater and the DRASTIC map shows that groundwater pollution risk is consistent with observed nitrate inferred from the literature. The relation between maximum nitrate concentration and the intrinsic vulnerability and the risk for pollution is respectively of $R^2 = 0.89$ and $R^2 = 0.65$. We conclude that the first main objective of this research shed, therefore, light on the pollution problem posed by shallow groundwater in Africa.

Our second main objective was to build a meta-database of nitrate through a meta-analysis of the available literature, to develop a statistical model and to identify environmental factors that explain nitrate pollution in groundwater at the pan-African scale. This objective was fulfilled in Chapters 5 to 6. In these chapters, the available literature data for nitrate are used. Statistical and regression analyses are used to identify the key factors that significantly influence nitrate concentration in groundwater. Statistical methods range from simple descriptive statistics of nitrate data to more complex statistical analyses that include nonlinear techniques. Groundwater contamination by nitrates is reported throughout the African continent, except for a large part of the Sahara desert. The observed nitrate concentrations range from 0 mg/L to 4625 mg/L. In Chapter 5, the analysis of correlation through the graphical box plot has highlighted that nitrate contamination is important in shallow groundwater systems and strongly influenced by population density and recharge rate. Nitrate contamination is, therefore, a particular point of concern for groundwater systems in urban sectors, and for the effect of agricultural practices on groundwater. Multiple Linear Regression (MLR) is performed to identify the relevance of anthropogenic factors and natural factors for nitrate pollution in groundwater (Chapter 5). The MLR model for the log-transformed mean nitrate concentration uses "the depth to groundwater", "groundwater recharge rate", "aquifer type" and "population density" as explanatory variables. The total variability explained by the model is 65%. This suggests that other variables may be needed to explain the reported nitrate concentrations. These findings highlight the challenges in developing appropriate regional databases to predict groundwater degradation. The MLR shows that the population density parameter is the most statistically significant variable. This authenticates the theory that leaking cesspits and sewer systems are considerably causing nitrate contamination of groundwater predominantly in urban areas. We identified a similar MLR model for the log transformed maximum nitrate concentrations. Yet, for this latter attribute, the explained variation using the simple MLR techniques (i.e. 42 %) remains small.

In spite of weaknesses and uncertainties caused by a moderate heteroscedasticity from residuals in the MLR model, the modelling approach presented is appealing. To avoid some limits MLR such as heteroscedasticity, we suggested non-linear modelling techniques as an alternative to MLR such as Random Forest (RF) techniques. Such techniques have the potential to improve the quality of explanation and eventually prediction. RF allowed the explanatory variables to be classified according to their importance ranking, and better explain the relationships between nitrate concentrations in groundwater (Chapter 6). The results of MLR compared to RF in Chapter 6 illustrated that the RF outperforms as compared to MLR in modelling of pan-African nitrate concentration.

The two statistical approaches developed in Chapters 5 and 6 have demonstrated the unambiguous link between population density (urban areas, agricultural activity) and pollution of groundwater by nitrates. Recently, Lapworth et al. (2017) affirms supporting the findings of Ouedraogo et al. (2016). According to the findings of Sorensen et al. (2015a), the majority of African wastewater is currently discharged without treatment. This last affirms that contamination is most extensive within shallow wells sited in areas of low-cost housing, due to inadequate sanitation, household waste disposal, and, significantly, poor well protection and construction. And the lack of quality water and poverty drive untreated wastewater use in urban and peri-urban agriculture. This is a common pattern in sub-Saharan Africa and other poor regions where there is no economic capacity to afford conventional sanitation and wastewater treatment facilities. This poses health, environmental and agriculture risks if no additional measures are applied (Mateo-Sagasta and Burke, 2012). Furthermore, by studying nitrate pollution of groundwater by pit latrines in developing countries such as the peri-urban areas surrounding Dakar, Sénégal, Abidjan, Côte d'Ivoire, and Abomey-Calavi, Benin in the summer of 2014, Templeton et al. (2015) highlighted the risk posed by pit latrines to groundwater quality in terms of nitrate pollution, specifically in low-income, densely-populated peri-urban areas with only basic forms of onsite sanitation and high water tables. Also, Graham and Polizzotto (2013) affirm that latrines are important sources of groundwater contamination in Africa. A recent study of UPGro (2017) on groundwater and poverty in sub Saharan Africa affirms that some aspects of groundwater access may be disadvantageous to the poor. Indeed, according to the UPGro (2017) report, in rural areas, shallow groundwater accessed by poorer households in or near river beds or via shallow hand-dug wells may be more contaminated than deeper groundwater which may be accessed by wealthier households. Boy-Roura (2013) affirms that financial cost are also associated to poor water quality. Because, nitrate pollution in groundwater implies additional drinking water treatment, construction of new wells, monitoring of other safe drinking water actions (Boy-Roura, 2013).

In addition to the density of population, which is the top relevant variable found in both techniques, other factors affect the pollution of nitrate in groundwater. These comprise nitrogen fertiliser application and natural factors such as recharge, depth to groundwater, rainfall, and aquifer characteristics. Therefore, the study of the occurrence and transport of nitrate in groundwater requires acknowledgment of complex relationships among these different variables.

Our third objective presented in Chapter 7, consisted of using regional datasets of nitrate measured in groundwater for validating nonlinear statistical modelling at the pan-African scale. While the model calibration at the pan-African scale showed very good results, the validation step showed a disappointing predictive ability at the regional scale. We concluded that nitrate measurement data at a regional scale cannot reasonably be used to accurately validate the continental-scale groundwater statistical model, due mainly to a scale issue. Some aspects related to the scale issues in remote sensing were reviewed by D'Andrimont (2017).

A final objective, presented in Chapter 8, consisted to integrate dynamic drivers of pollution risk such as land use and climate in the continental scale vulnerability and pollution risk modelling approach. The conclusions drawn from this Chapter indicated that the groundwater vulnerability to pollution across Africa varies also considerably in time. We observed that the spatial pattern of pollution risk at the pan-African scale has changed over the time between 1990, 2000, and 2010. The zone with the highest pollution risk at the scale of the continent is the Western Africa area, which is highly urbanized and densely populated. We found that the percent in pollution risk class of high and very high changed during 20 years from 0.55 % to 1.26 %; and from 0.29 % to 0.76 % respectively, which demonstrates that the surface of the risk of pollution follows an increasing trend.

9.2 Implications for science and policy: Addressing the challenges

This thesis research participates indirectly in achieving SDG 6, which includes a focus on preserving our freshwater resources. As highlighted in this thesis research, groundwater contamination and pollution problems are a growing threat to African continental development and urgently need to be addressed. The map shows an interpretation of the groundwater resources map of Africa in terms of groundwater sensitivity towards pollution. Continued concern about contamination of groundwater resources makes vulnerability assessments important tools for water-resource managers and policy makers (Gurdak, 2014). The conception of the vulnerability map is to assist both laymen and professionals in water resources. In our study, we make an assessment of the vulnerability of groundwater at the pan-African scale. We validated the approach based on a meta-analysis of pollution caused by nitrates. We see possible applications in many management domains.

First, a groundwater vulnerability map at the pan-African scale did not exist yet. Many previous products in this domain have been developed but merely focused on quantitative aspects, such as the groundwater map (WHYMAP, 2008; MacDonald et al. 2012; Altchenko et al. 2014), the drought vulnerability map for Africa (Naumann et al. 2014) and the global map of vulnerability to floods and droughts (Jaroslav Vrba (UNESCO-IHP), Andrea Richts (BGR), 2015). Only recently have water quality aspects been addressed at these large scales, such as Ippolito et al. (2015) who developed a global pesticide runoff vulnerability map with a generic indicator model. With respect to groundwater pollution, issues were addressed for specific pollutants such as arsenic and fluoride contamination in groundwater (Amini et al. 2008a, and 2008b). However, no general vulnerability map is available. With our study, we fill this existing gap.

Second, large-scale vulnerability maps raise the awareness of policy makers and water managers about the vulnerability of this precious water resource system and increase the overall concern to develop appropriate protection programmes.

Third, improving the assessment of water quality at a large-scale should be based on the appropriate monitoring. This assessment is needed to evaluate the compliance of different countries with overall political commitments, such as the commitment to reach sustainable water management in the WFD in Europe, or to reach the SDG at the UN level. Hence, smart monitoring of water quality at a large scale is needed. We believe that smart monitoring of groundwater quality should be based on vulnerability. Monitoring should be concentrated primarily in areas that are vulnerable. Hence, vulnerability maps can help to optimise the smart large-scale monitoring programme.

Fourth, we believe that vulnerability can be very useful for rural and urban planning. Vulnerability can help to identify those locations that deserve particular protection in urban and rural development projects and programmes.

The pollution risk map should serve as a general guideline for planners and decision-makers with land-use development issues. It is also useful to scientists in government agencies and consulting companies. Furthermore, it is designed to make the general public aware of the pollution risk of water resources and to direct their attention towards the rational use and protection of both groundwater and surface water resources. In this respect, this research could serve as a good example for establishing a pan-African groundwater network like the strategies employed in Europe and the United States to establish large-scale groundwater monitoring networks and groundwater protection programmes. Groundwater protection and alleviation at the pan-African scale is not optional and acknowledging the role of groundwater is paramount to successfully implementing the SDGs. Remediation should be developed at both the continental and regional scale. The solutions that can be proposed to mitigate and improve the situation have been partially addressed by Xu and Usher, (2006):

i. Political will: Groundwater quality protection is closely related to the government policy towards economic development and the political will for sustainable development and utilisation of resources. Our study may increase support for AMCOW (African Ministerial Council on Water) to proceed with groundwater protection programmes at the pan-African level. For example, the implementation of resolutions at the Pan-Africa Conference on Water (December 2003 in Addis-Ababa/Ethiopia) organized by AMCOW, are a good start for correct regulation of policies for successful protection of water resources.
ii. Capacity building and technical skills: Africa has little capacity to challenge groundwater degradation and there is a need to boost this capacity through appropriate capacity building programmes. As an example, capacity building can be increased by (a) the establishment of more formal networks of African universities working on water and sanitation; and (b) improving communication by increasing access to internet facilities.
iii. Knowledge dissemination: Awareness of groundwater resources in Africa is low. There is a need to improve the knowledge of groundwater systems for decision-makers and for the broader public. This thesis may contribute to the increase in groundwater awareness. For example, in Africa, the number of technical people involved in groundwater studies is small.

In addition to these 3 main solutions above, which we recommend to decision-makers, we think that the African decision-makers for water resources must urgently elaborate groundwater protection programmes that are based on groundwater monitoring and data management. Such programmes can be boosted through a multilateral organisation such as the African Groundwater Commission or SADC, ECOWAS, the Nubian Aquifer Regional Information Systems (NARIS), The North Western Sahara Aquifer System (NWSAS) (better known under the acronym SASS for its French name "Système Aquifère du Sahara Septentrional"). Various institutions are working in many countries but they are scattered, isolated and uncoordinated. Groundwater management organisations should be created and connected with existing river basin organisations. Cooperation between neighboring countries is, therefore, a requirement if we are to reduce the risks of degradation and allow the sustainable use of these shared resources.

The African groundwater pollution index maps in this study could be used for feasibility studies to be conducted at a regional scale and in assessing the relative differences in pollution potential between regions. These maps support the possibility of using nitrate as an indicator tool for water management. It is hoped that these maps will encourage regional planners to conduct further feasibility studies to pursue economically feasible pond-based small-scale supplemental groundwater pollution treatment schemes. Conflicts related to transboundary aquifer management often exist, especially when the resource is limited or overexploited and exposed to toxic waste.

We think that groundwater monitoring in Africa needs to be addressed as a matter of priority. Based on the research conducted in this thesis, several factors for nitrate pollution have been highlighted. Of great concern is the fact that for many of these factors, the currently available datasets show that very little attention has been paid to the constituents in most groundwater monitoring programmes. Two sources of nitrate pollution are highlighted: urban areas and agricultural domains. High nitrate concentrations have been found to occur from sources ranging from agricultural fertilisers to pit latrines to explosives companies. There is no directed programme to monitor nitrate in urban and peri-urban areas and hence there is a gap in information.

The pan-African map is intended for continental (multicountry) or sub-regional (e.g. ECOWAS, SADC, IGAD region) use and has several limitations because it does not reflect local conditions. Each map type should only be used for the purpose for which it was produced (Vrba and Zaporozec, 1994). Areas of high risk on the map have a high potential for nitrate contamination but are not necessary contaminated. A low vulnerability does not mean that there is no risk of contamination; it simply means that the geology and hydrogeology of the area provide more natural (or intrinsic) protection to the groundwater resources. Despite the issue of possible bias and uncertainties noted in the dataset collected for this dissertation, we are very optimistic about the robustness of the models for predicting contamination at the continental scale.

Firstly, for example, the model of MLR that was obtained used population density, shallow groundwater, aquifer type, and recharge as explanatory variables. This is consistent with a study from UNEP/DEWA (2014) in 11 countries across Africa which stated:

- "The level of protection at the wellhead strongly influences the quality of the well water. This is a vital aspect of protecting groundwater quality. Sanitation must not be delinked from Groundwater Protection".
- "Recharge from multiple sources influences groundwater microbial and chemical water quality".
- "The magnitude of contamination is also strongly affected by the population density and socio-economic setting".
- "Groundwater pollution and vulnerability issues are affecting all developing countries with increasing urbanisation".

Secondly, the RFR results presented in Chapter 6 show that this is a promising technique for modelling groundwater degradation because of its ability to provide meaningful analysis of nonlinear and complex relationships such as those found in hydrogeological studies. The RFR model determined the factors that significantly influence nitrate pollution, which are: aquifer type, rainfall, and density of population. The explained high variation of the RFR paves the way for creating water quality maps at the continent scale. Such maps are considered essential tools for developing groundwater management and development programmes, including transboundary groundwater management.

The statistical tools presented here are designed to give a continent-wide view of groundwater contamination by nitrates and to encourage the development of more qualitative national and sub-national models and assessments to support the development of groundwater-based adaptation strategies for current and future climate variability. Inevitably these results can be improved. They should be viewed as a first attempt to provide quantitative statistical modelling of nitrate contamination in groundwater for Africa and furthermore provide a strong basis for future studies when homogeneous data without bias will be available at the African scale.

Notwithstanding some limitations related to data, the simple Dynamic Vulnerability Index (DVI) model allowed modelling the dynamic aspect of pollution risk at the pan-African scale using public available data. This is therefore an important tool for the sustainable groundwater resources management in Africa. The DVI could be used to monitor the achievement of SDG Goal 6 in Africa which includes a focus on preserving freshwater resources for potential future threats.

All methodologies presented in this thesis can be easily applied both to larger areas, and small areas, and used as a decision support tool for evaluation of legislative and management measures, aiming to reduce nitrate contamination risks. Although the present work was directed toward the vulnerability of groundwater to agricultural chemicals, of which nitrate was the exemplar, the methods developed in the course of this study are not specific to agricultural chemicals in groundwater. The same approach could easily be applied to other forms of pollution such as fluoride and arsenic.

An example of indirect implication for science and policy of this Ph.D. research:
In a new landmark study just published by Lapworth et al. (2017), reviewed all the available data and studies on urban groundwater across the continent and build up a map of aquifer pollution risk. The Figure 9-1 showed the spatial distribution of the 31 studies included in the analysis of nitrate in urban groundwaters. Unlike that recent study, the analysis described in this paper differentiates boreholes from shallower groundwater sources, incorporates one measure of nitrate load into the aquifer (population density), and explicitly accounts for sample size variation between studies via random effects meta-regression.

New pollution risk maps for Africa to help with achieving safe water for everyone

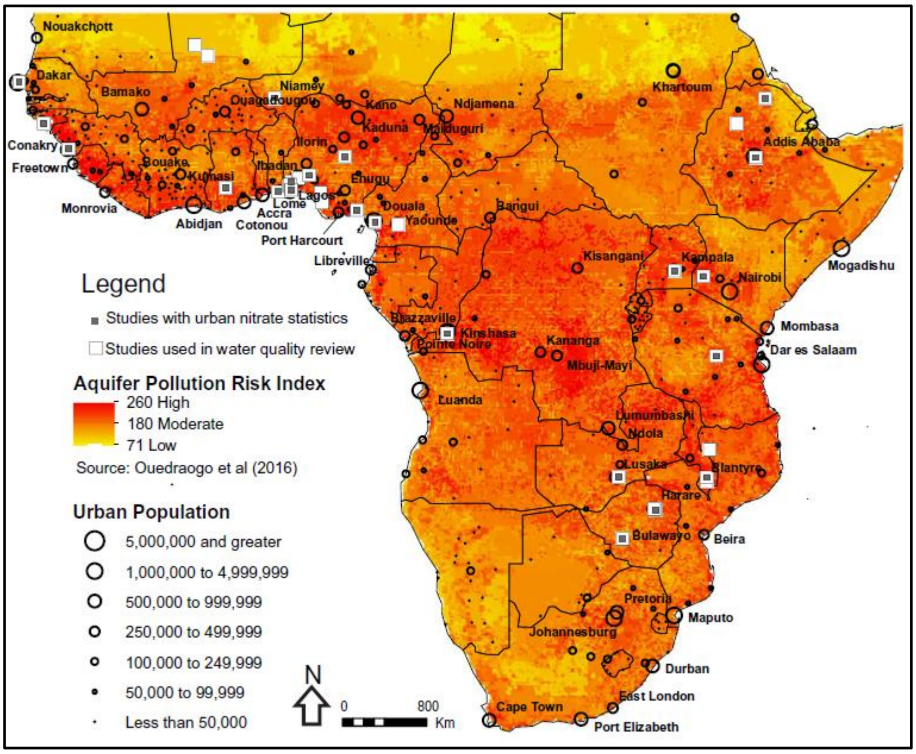


Figure 9-1: Media Release: World Water Day 22 March. Relationship between urban centres in sub-Saharan Africa (SSA) and estimated aquifer pollution risk using an intrinsic aquifer modelling approach (Ouedraogo et al. 2016). The location of studies included in the paper are shown. Major cities in SSA are shown and are from the ESRI cities dataset (2006) (Lapworth et al.2017).

From his study, the lead researcher, Dr. Daniel Lapworth, of the British Geological Survey, said: "Despite the risk to the health of millions of people across the continent, very little is routinely monitored. If there is any chance of achieving the Sustainable Development Goal targets – and adapting to climate change – it is essential that governments and water utilities routinely monitor groundwater quality and take appropriate action to protect their precious water resources."

"However, we are excited that our research through has developed a low-cost and robust way for measuring groundwater quality(Sorensen et al.2015b), and this approach is being rolled out in our work in Africa and India."

This interview is for Media Release for Responding to UNICEF/WHO report on Safely managed drinking water. Accessed online October 2nd 2017: https://upgro.org/2017/03/13/new-pollution-risk-maps-for-africa/.

9.3 Limitations of the study and perspectives for future research

In spite of the achievements described previously, this study has several limitations.

First limitation, the pan-African groundwater vulnerability to pollution map developed in Chapter 4 is intended for continental (multicounty) use or sub-regional use and has also several limitations. For example, the overall utility of a vulnerability map is dependent on the scale at which the map has been compiled, the scale at which data were gathered, and the spatial resolution of mapping (NRC, 1993). The notion of scale is central to the thesis. Vulnerability maps, which are the most visible products from groundwater vulnerability assessment, are subject to inherent uncertainty (Gurdak et al., 2007). Factors influencing NPS contamination are never completely realised and thus spatial and temporal representations (GIS data coverage) of these variables are subject to uncertainty. This uncertainty can be compounded and propagated through the analysis of the final mapped product, as Heuvelink et al. (1989) and Gurdak et al. (2007) have demonstrated. Consideration of error propagation is particularly relevant and should be addressed when using continuously distributed random variables within GIS-based vulnerability maps (Gurdak, 2008). Furthermore, in this research as noted in Chapter 4 is that the explained variability in the boxplots and scatterplots is still rather low, showing that quite some scope exists to calibrate and to improve the proposed vulnerability and groundwater risk mapping procedure. In our study, we use the linear model to modelling dynamic aspect of groundwater vulnerability to pollution risk. The linear model used in this study can over- or under-estimate groundwater pollution risk. Because it is recognized that the actual physical processes leading to groundwater contamination are not necessarily linear and often involve complex mechanisms such as pollutant transport, dilution and dispersion, adsorption, and chemical and biological transformation (Li, 2013). Furthermore, it was demonstrated that the best statistical model to explain groundwater nitrate contamination at the African scale is a nonlinear model (Ouedraogo et al. 2017). Thus, use linear model to modelling groundwater vulnerability to pollution presents some limits.

Second limitation, the information gained from the analysis of historical groundwater quality data was restricted to Nonpoint-Source (NPS) nitrate contamination, due to data availability in general. Therefore, NPS NO_3^- data was one of the major constraints with regards to developing the modified DRASTIC model. For a large part of Africa there is very little or no systematic monitoring of groundwater. To this regard, Baisch (2009) affirms that Africa is not only suffering from water shortage but also from data shortage. Furthermore, according to Fan et al. (2013), Africa is the most data-poor region with limited records (<0.001%) of global shallow groundwater records. Therefore, in the absence of a systematic data monitoring programme, we compiled groundwater nitrate pollution data at the pan-African scale from different sources in published literature and personal contacts with local water authorities. Thus, lack of available data and its relation to the scale of the map are major limitations. Our database of nitrate was based on approximately 250 published studies. We acknowledge that bias exists in our dataset and this bias may be due to multiple reasons, as stated in Chapters 5 and 6. In conclusion to these chapters we state that the main weakness or the major constraints of the modelling at the pan-African scale lies in the unavailability of a homogeneous data set on nitrate contamination, particularly the lack and uneven distribution of nitrate measurement points. Therefore, results from these analyses should not be over-interpreted. Whilst the data provide a useful preliminary assessment of the nitrate contamination in groundwater at the African scale, there are clear limitations. Unsurprisingly there are no consistent measurement datasets that can be explored at a continental scale; at larger scales, much of this information is also patchy, both spatially and temporally. Non-traditional data sources such as literature data (for example meta-analysis) may, therefore, be useful substitutes for some traditional measurement data. The data used in this study is derived predominantly from literature. The data come from different sources (reviewed journal article, a book of articles, or other grey literature) and the methods (such as isotopic analysis) used to collect and produce the results of each study are not the same. They should therefore not be treated as traditional nitrate measurements. Certain studies in our dataset address specific groundwater nitrate contamination to water supplies, others address groundwater nitrate contamination to heavy irrigation areas, others couple the two issues (water supply and irrigation), and other studies address the nitrate pollution in mining zones, etc. The different natures of these studies constitute a possible bias. In spite of potential problems caused by possible sampling bias, the data set was used to explain the environmental/physical factors that contribute to nitrate pollution in groundwater at the African scale. Variables not found to be significant in the statistical modelling at the pan-African scale (such as soil) or not considered or available during model calibration (such as irrigation or denitrification/age) can affect nitrate leaching locally, so the map or the statistical model should not be used for local management decisions.

A third and last limitation of this study was observed during validating of continental scale groundwater diffuse pollution model by using regional datasets describes in Chapter 7. The discrepancy between a model applied exclusively to a meta-database of measurements of nitrate and nitrate contamination from different countries has already been identified as a major obstacle to the validation of the continental scale model at the regional scale. At this regard, Gubler et al. (2011) affirm that the problem of comparing model simulations made at one scale to measurements taken at another scale has no simple solution. Certain investigators such as Konikow and Bredehoeft (1992) and Oreskes et al. (1994) affirm that in environmental systems, complete validation of a model is *a priori* an impossible task. Also, the scale issues involved in the application of GeoPEARL at the regional scale were met by Leterme (2006) in his thesis research. It affirms that finding a framework for the evaluation (or validation) of leaching studies at the regional scale is indubitably a major challenge in hydrological science. Furthermore, Leterme (2006) mentioned that model validation is never totally achieved, but the validation status can be qualified via the model performance in different case studies (increasing confirmation; Beven, 1995). Thus, this problem of validation met in this study highlights the necessity of developing a national level political programme for characterisation of groundwater vulnerability by first constructing a good database of groundwater quality data and secondly building a robust predictive vulnerability model for each country.

The original goal of this study was to formulate a method for mapping groundwater vulnerability to pollution at the pan-African scale. This goal has been fully met. Results derived from this research are a good start in supporting UN Sustainable Development Goals agenda for water quality. The present work has opened up much more potential for investigation than initially envisaged. The method employed in groundwater vulnerability to pollution at the African scale is not the most sophisticated in terms of the current state of the art in modelling groundwater vulnerability to pollution, but it is by no means invalid and can hold their ground scientifically, because having proven effective elsewhere. However, in view of above remarks on limitations, some progress must be made toward again. In further pursuit of that research, several steps should make.

The most important step is to link groundwater vulnerability model with uncertainty analysis and modify the theoretical framework of the method. Particularly the calibration of DRASTIC can be explored to better represent the weights. Loague and Corwin (1996) declare that the utility of relatively simple vulnerability maps, produced at the regional scales with geographic information system technology, is undermined by significant uncertainties related to model and data errors. To this regard, Honnungar (2009) investigated the limitations arise due to the spatial and temporal variability of input (data and resolution), data processing methods (sampling and interpolation methods), subjectivity in assigning weights and ratings by decision-makers, and non-linear relationships between the hydrogeological parameters using MCDM such as DRASTIC model. Furthermore, Fortin (1998) gave an example of analysis of the propagation of spatial errors by integrating multisource data in DRASTIC groundwater vulnerability. Furthermore, Murat et al. (2004) studied a proposal to monitor uncertainty associated with spatial data processing for aquifer vulnerability mapping and GIS. However, the authors faced many problems and lost time trying to quantify propagation errors compared to efforts spent on running the DRASTIC model. Then they conclude that it is relatively simple to produce a specific map of groundwater vulnerability.

In addition, another main challenge that undermine further development of this methodology is, the statistical modelling validation and difficulties in taking into account, the scale transitions error in the model. Furthermore, synergies between different spatial resolutions should also be explored. This research could involve including best available GIS dataset from a local scale to improve the model's performance at regional scale. Indeed, in assessing groundwater vulnerability, it will be interesting to work towards a bigger set of indicators to see which of the indicators not used can contribute to improving the final outcome. To this regard, there are other variables such as, age of groundwater, denitrification, GDP per capita, degree of sanitation, physical-chemical variables (pH, temperature, and electrical conductivity), distance from urban solid waste, distance from irrigation canals, etc., that had not been included in this initial research. These additional parameters can reveal other more important relationships in the assessment of groundwater vulnerability. This will open up exciting possibilities in groundwater pollution studies as new research challenges.

For example, using maximum entropy modelling (Maxent), a machine learning method, to build environmental models for predicting and validating the potential global distribution of a problematic alien invasive species (the American bullfrog), Ficetola et al. (2007) concluded that integrating large-scale environmental layers with data collected at a more local scale, and combining climatic data with information on human activities, can greatly improve the prediction of invasion risk. Leterme (2006) affirms that a classical approach is to include other variables in the model validation. Therefore, better data availability of course, would help to make model predictions more accurate in the future.

Due to simplification adopted to calculate recharge map in Chapter 8 (see equation 3) to produce time dynamic groundwater pollution risk, a new groundwater recharge could be calculated using the WaterGAP Global Hydrology Model (WGHM) like in Döll and Fielder (2008). Then, we propose as another perspective is to the use of the approach developed by Li and Merchant (2013) in modelling framework that employs four sub-models, namely climate change scenarios, a land use change (LUC) model, recharge and groundwater level models, and a modified DRASTIC model, linked within a GIS framework. For example, to illustrated how climate change can affect the physical and geochemical processes that that in turn affect groundwater quality in many ways, the author Li proposed in Fares (2016), a conceptual framework. It gives an overview of mechanisms through which climate variability and change could affect groundwater quality (See Figure 9-2). In addition, a future research could be undertaken to evaluate the effects of urban growth on groundwater quality in Africa by using the techniques of time-dependent methods developed by Stevenazzi et al. (2015).

Another new research agenda may focus on the following area: the development of physically based models that can account for the key processes influencing nitrate fate and transport in groundwater and their interactions involving climate change. To this regard, Fares (2016) argues that process-based modeling methods account for physical processes of water movement and the associated fate and transport of contaminants in a quantitative manner, and hence can produce relatively accurate estimates of pollutant concentration. For example, in 2005, Sinkevich et al. implemented the Generalized Preferential Flow Transport Model (GPFM) to map areas with high risk of contamination by agrochemicals. Tiktak et al. (2006) used EuroPEARL, a one-dimensional, mechanistic pesticide leaching model, in a GIS to map pesticide leaching at the Pan-Europe scale. Furthermore, Almasi and Kaluarachchi (2007) employed a soil nitrogen dynamic model to estimate nitrate leaching to the aquifer and then used the MODFLOW and MT3D to simulate the fate and transport processes of nitrate in the groundwater system. The method developed by Almasi and Kaluarachchi (2007) is illustrated in Figure 9-3. Also, MODFLOW could be explored in the future to developed a new pan-African scale groundwater pollution map because de Graaf et al.(2015) presented a global-scale groundwater model (run at 60′ resolution) using

MODFLOW to construct an equilibrium water table at its natural state as the result of long-term climatic forcing. In addition to this new challenge, spatially distributed models could be explored at the African scale in the future, because Refsgaard et al. (1999) used spatially distributed simulation model to study large-scale modelling of groundwater contamination from nitrate leaching. For example, Pulido-Velazquez et al. (2015) coupled a watershed agriculturally based hydrological model (Soil and Water Assessment Tool, SWAT) with a groundwater flow model developed in MODFLOW, and with a nitrate mass-transport model in MT3DMS.

Another approach recommended to improve the efficiency of groundwater vulnerability assessments is to compare Multicriteria decision making (MCDM) such as GOD groundwater vulnerability and the DRASTIC vulnerability index. In order to explore a new MCDM tool, we suggest that land use or human activities be split in various categories of different weights and rating: agricultural practices oriented on crop cultivation, on arable lands on cattle breeding, on grassland production, industrial activities (factories producing nitrate fertilizers and chemicals based on nitrate components), nitrate storage areas and waste disposal sites, unsewered urban areas, open pit mining areas and deep mining areas (e.g. mining of saltpeter). In addition, tools such as isotopes analysis could be used to investigate groundwater pollution.

The lack of the data is the major challenge, but this issue can be solved by promoting at a regional scale collaboration between countries and regional institutions in Africa. Notwithstanding this issue of data availability, we recommend as a perspective to use a scientific sampling procedure with standard procedures in the process of groundwater quality monitoring. To reduce human related errors, a qualified team and not the homeowners themselves should be in charge of the collection of data at the country level. .

In addition to these new challenges discussed above, new processing capacity (storage, speed, etc.) could improve the mapping capability.

Although the development of a new tool for estimating groundwater vulnerability to pollution at the African scale is not really relevant or indispensable, it is of interest to finalize the methodology for the establishment of the DRASTIC index. This will help to integrate the uncertainty associate at large scale coarse data, evaluate the effects of scale, resolution, sampling and improve the validation step during the downscaling. Also, our modelling framework can be potentially adapted to model other types of substances or pollutants such as arsenic or electrical conductivity and could be applied in other regions.

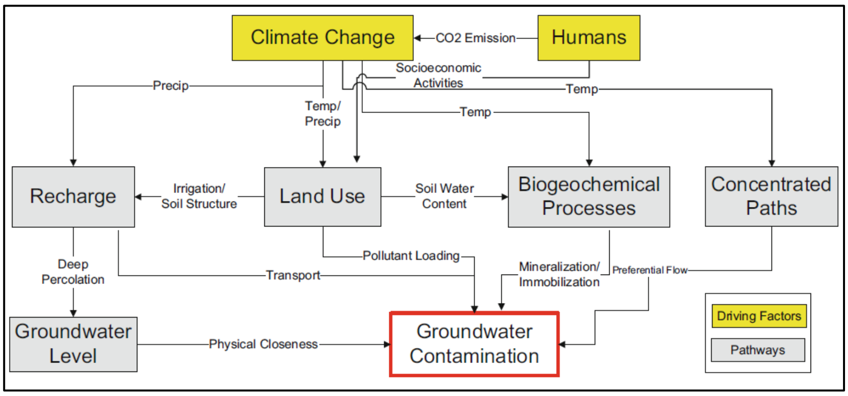


Figure 9-2: Pathways that climate change can affect groundwater quality (in Fares, 2016)

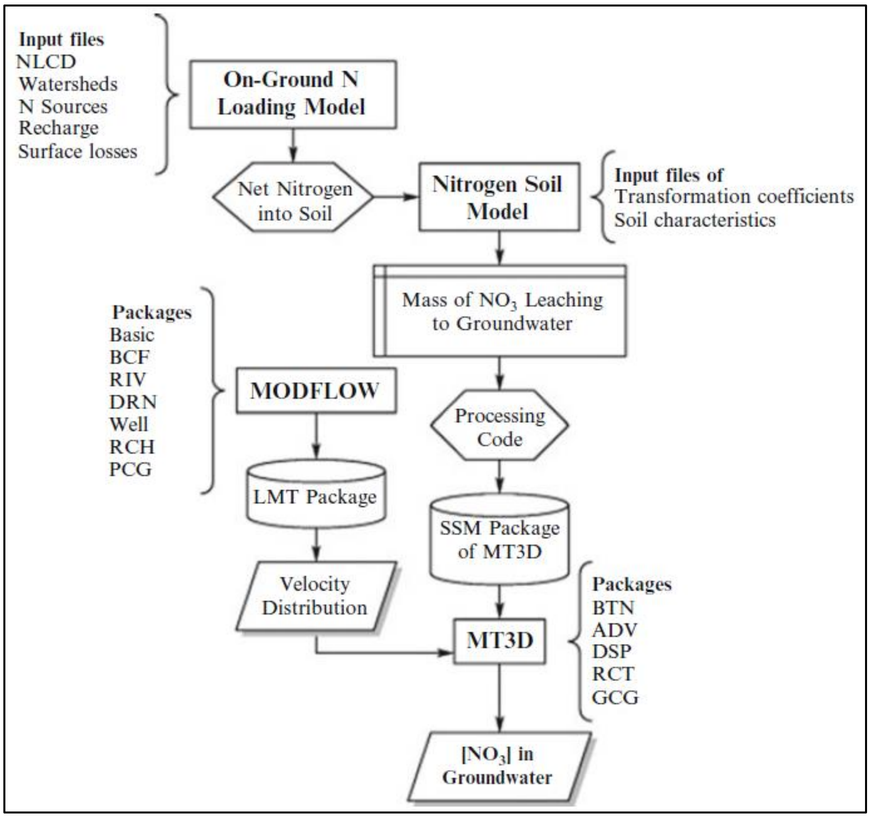


Figure 9-3: Flowchart for modeling nitrate contamination in groundwater using physical models (from Almasri and Kaluarachchi 2007 in Fares, 2016)

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Appendices

Appendix A

Maximum nitrate concentration analysis

Normality of maximum nitrate

Figure A-1 shows conventional and logarithmic histograms for the maximum nitrate concentration full data sets. We can observe that the log transformed maximum nitrate concentration is normally distributed.

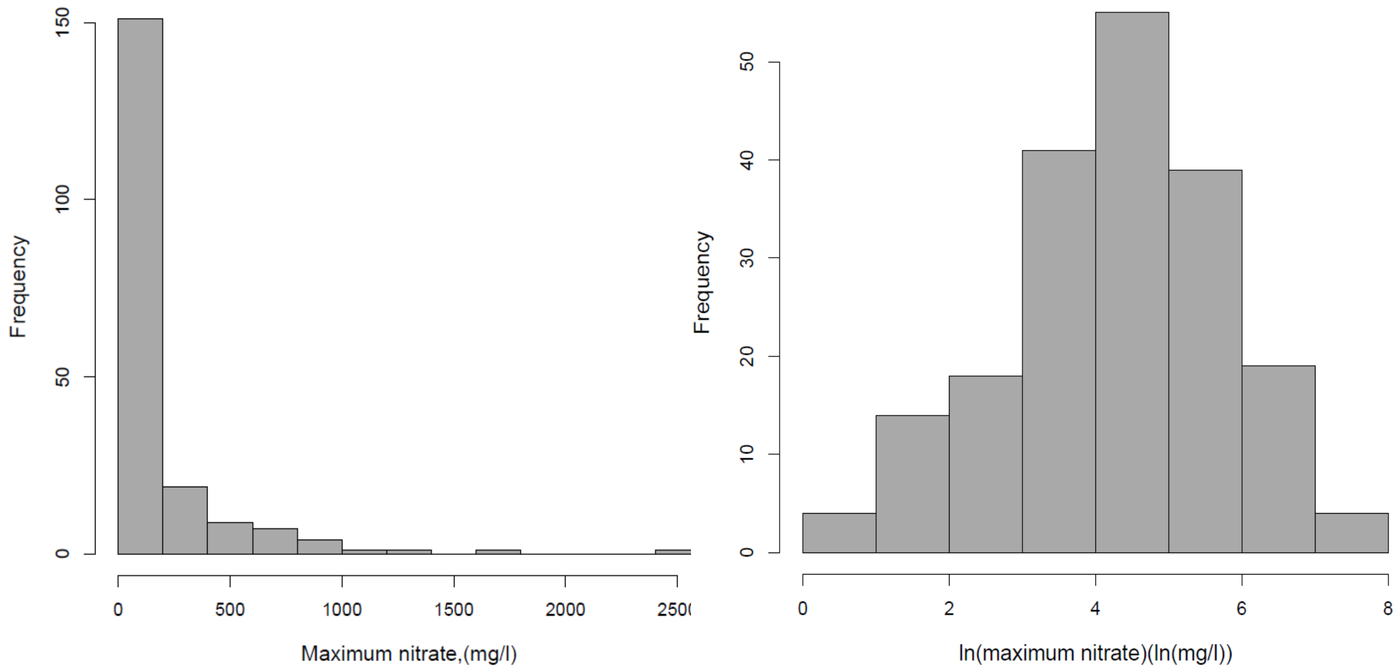

Figure A-1: Histograms of maximum nitrate concentration and log transformed maximum nitrate concentration.

Correlation between explanatory variables and log transformed maximum nitrate concentration

Except the box plot of land use parameter in Figure A-2, all the others box plots represent the environmental factors that influence the log transformed maximum nitrate concentration.

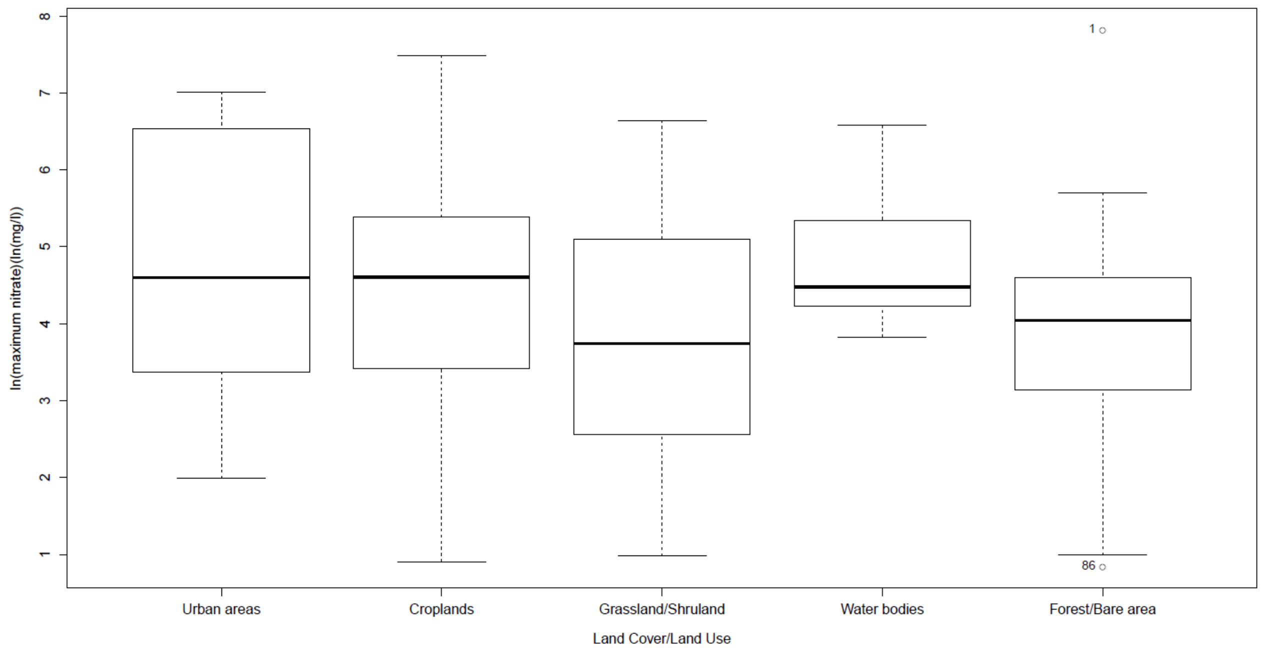

Figure A-2: Log transformed maximum nitrate concentration for different land use classes.

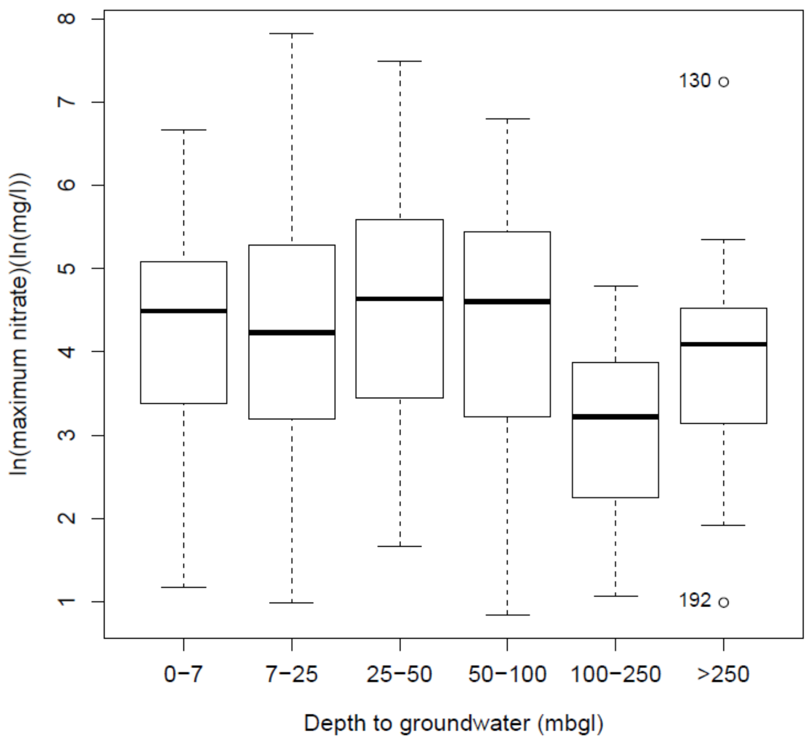

Figure A-3: Log transformed maximum nitrate concentration for different groundwater depth classes.

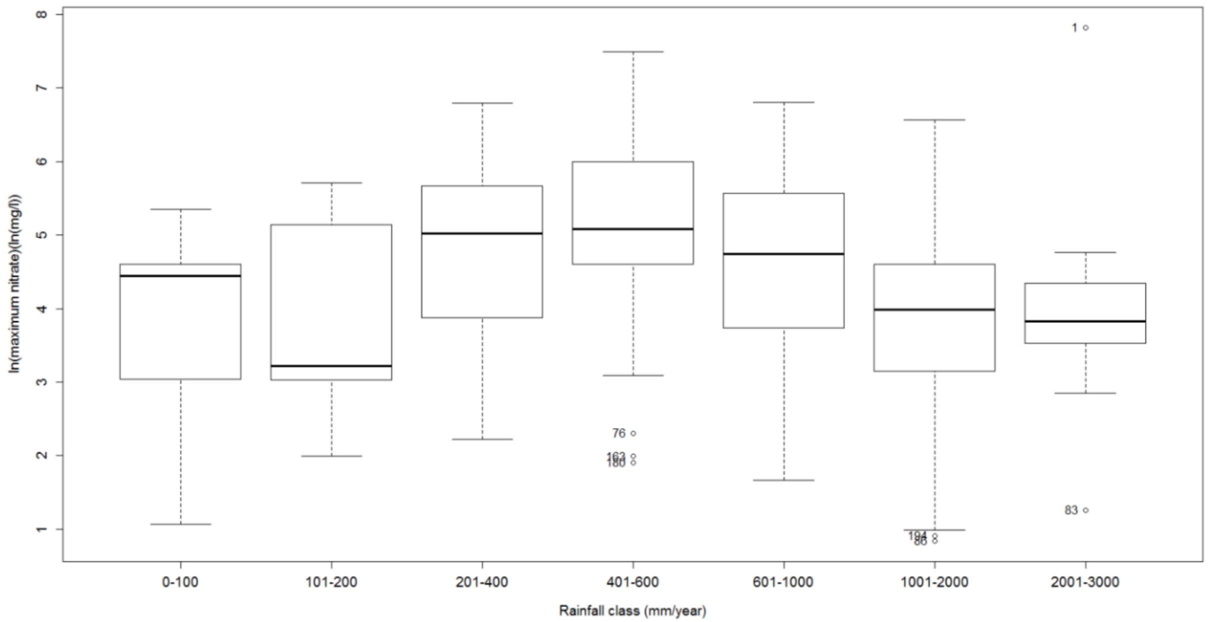

Figure A-4: Log transformed maximum nitrate concentration for different rainfall classes.

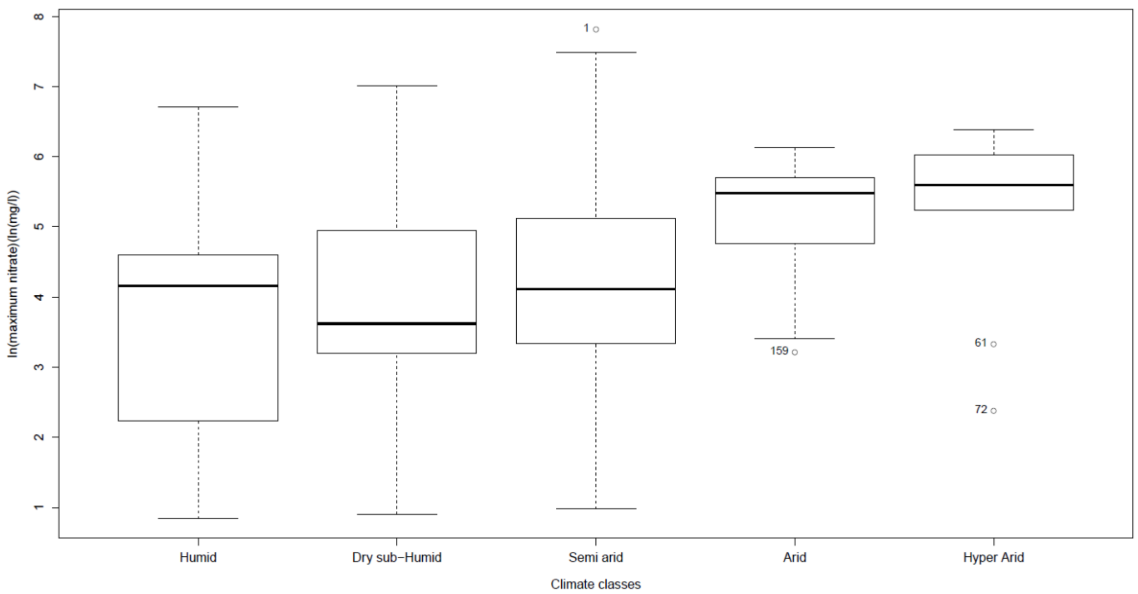

Figure A-5: Log transformed maximum nitrate concentration for different climate classes.

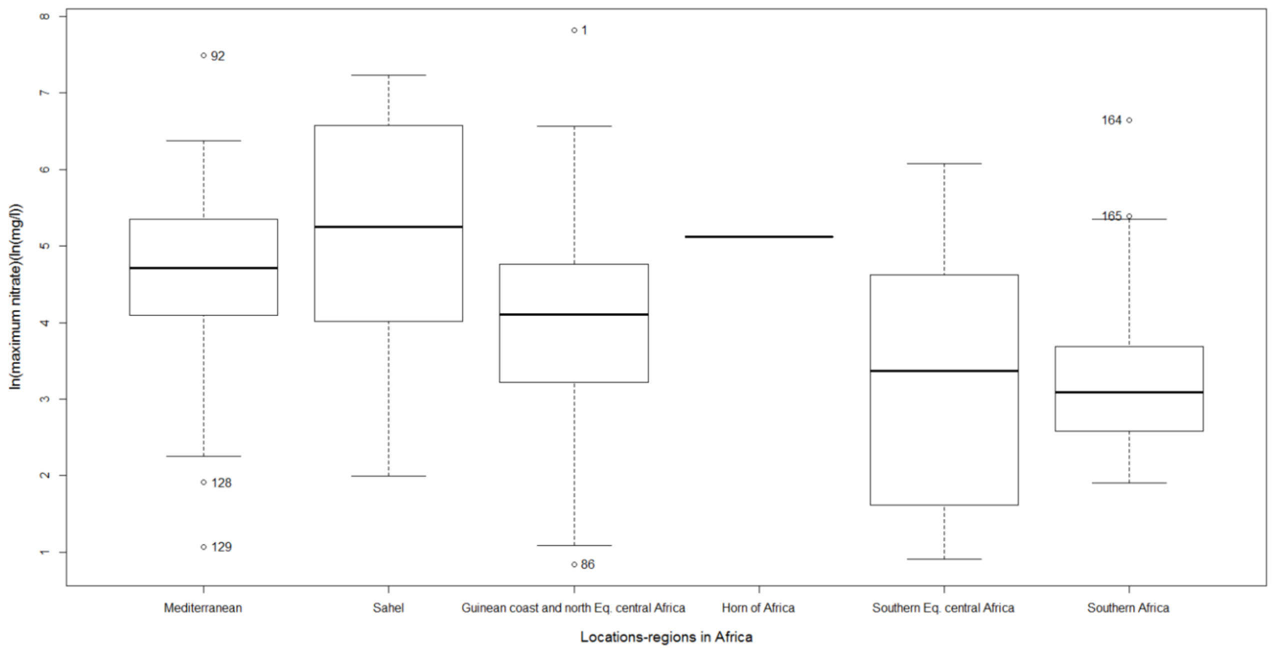

Figure A-6: Log transformed maximum nitrate concentration for different regions classes

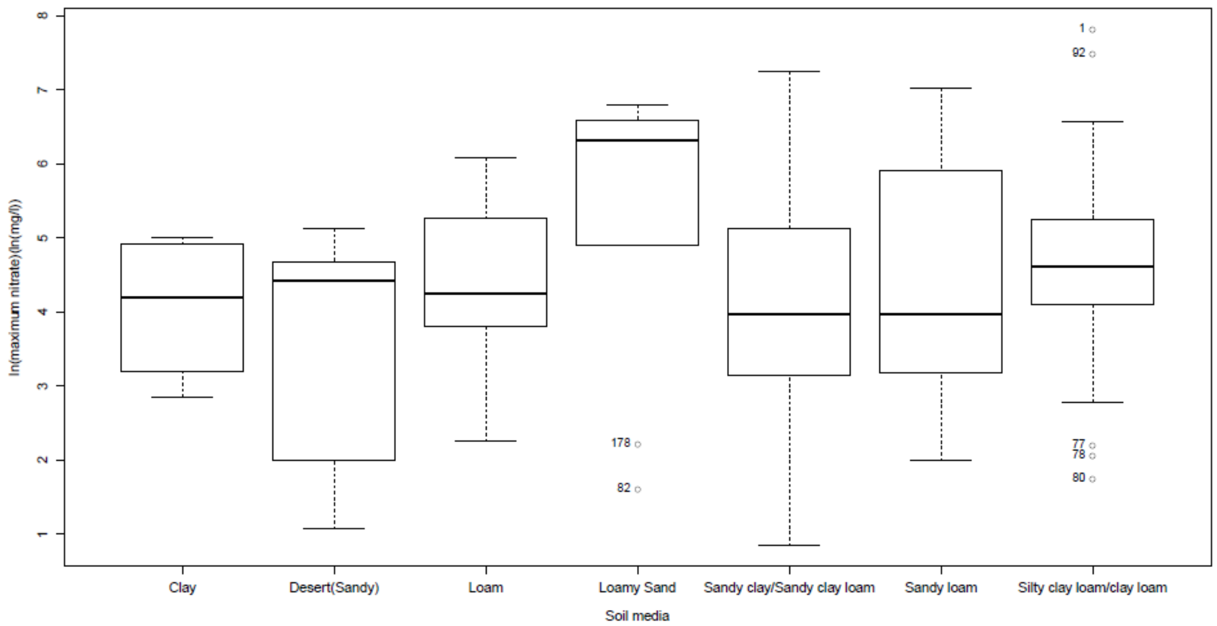

Figure A-7: Log transformed maximum nitrate concentration for different soil classes.

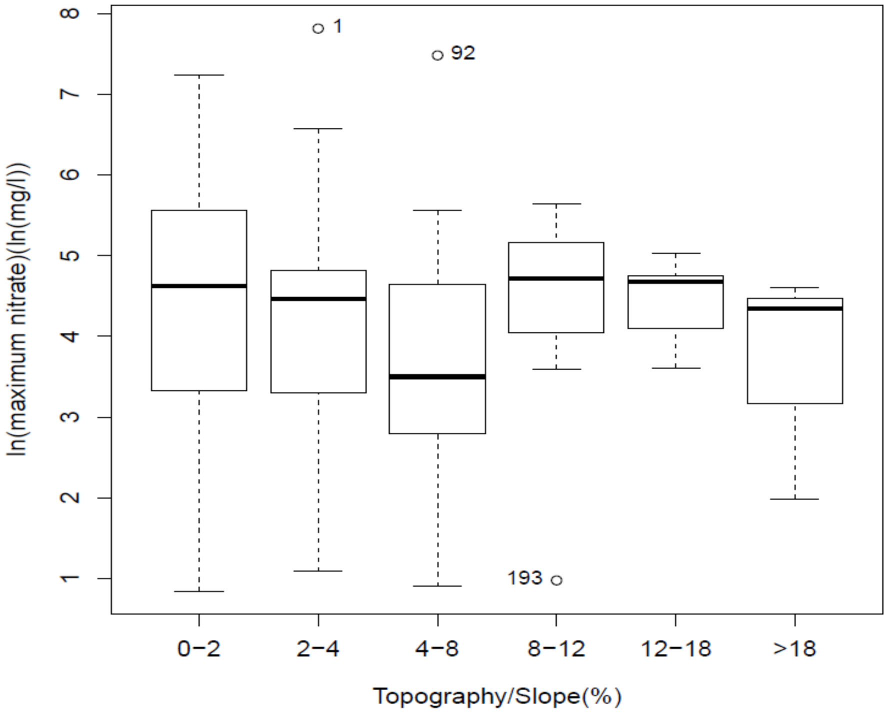

Figure A-8: Log transformed maximum nitrate concentration for different slope classes

Results of the maximum concentration modelling

The same methodology used to develop the log transformed mean nitrate concentration predict model was used for the log transformed maximum nitrate concentration at the pan African scale. The log transformed maximum nitrate model had 6 factors in the final model which are significant: (1) depth to groundwater (shallow groundwater), (2) soil media, (3) topography, (4) rainfall, (5) climate class, and (6) regions type. The Akaike's Information Criteria (AIC) for the best model is AIC =-1.75. Student statistic t values are used to check for statistical significance of variables categories in the final model. The regression coefficients of final model are presented in Table A-1. The model has a relatively good fitness and explains 42 % of the maximum nitrate occurrences at the pan Africa scale. The observed versus predicted values displays a very low p-value of 1.581e-08 <0.001 indicating that the model fit is acceptable (Figure A-9). The parameter coefficients provide an indication of the importance of the explanatory variable on the log transformed maximum nitrate concentration.

Parameter coefficients in Table A-1 shed a light on predominant processes influencing maximum nitrate contamination of groundwater at the pan African scale. The sign of the coefficients indicate whether they proportionally increase or decrease the amount of nitrate delivered to groundwater. Shallow groundwater (0-7m) present a positive sign indicating that nitrate concentration increases while the great depth (100-250 m) has a negative sign. These two categories of depth are statistically significant in the model.

In Table A-1, the silty clay loam/clay loam of soil media is the only category statistically significant and have a positive sign indicating that nitrate increases for this soil type. The others categories of soil type are not significant (p-value>0.05) and present the positive correlation except desert (sandy) category. This negative sign of desert sandy could be explained in fact, that in these areas (North Africa mainly), groundwater bodies are at great depths, thus reducing the nitrate pollution.

Parameters coefficients for topography have for all categories positive signs. The category (2-4%) is statistically significant (p-value <0.1) According to Ouedraogo et al. (2016), a gentle slope (0-4%) is dominating the largest part of Africa. From this study, we can extrapolate and conclude that the low slopes contribute also at the groundwater pollution by nitrate at the pan African scale.

The rainfall coefficients showed in table are negative signs. The rainfall corresponding at (1001-2000 mm/year) is the most statistically significant (p<0.05). The negative sign indicate that the rainfall contribute to dilute the rate of nitrate in groundwater, thus decreasing the concentration.

The climate class regression coefficients are all negative signs. Among the categories of climate class, three are statistically significant at p-value <0.05, except the hyper-arid climate with a p-value > 0.05. The humid climate class is the most significant, reflecting the high risk to nitrate pollution in these zones.

Parameter coefficients for region type have positive or negative signs depending on whether they promote the increase or decrease the amount of nitrate delivered to groundwater. Regions having positive signs include the Horn of Africa region, the Mediterranean region and Sahel region, while Southern equatorial central Africa region and Southern Africa region have negative signs (see Table A-1). The Sahel region and Southern Africa region are statistically significant at $p<0.05$.

A probability plot of model residuals indicates that they follow a normal distribution (Figure A-10). Therefore, a transformation of the independent variables for regression was unnecessary. Figure A-11 illustrated the residual analysis of the maximum nitrate concentration. The majority of observations are in the range of -2 to 2 with a few outliers. These outlier observations could influenced the results of model and limited the robustness.

Tableau A-1: Optimal linear regression using logarithm maximum nitrate as independent variable.

Coefficients:				
	Estimate	Std. Error	t-value	Pr (>|t|)
(Intercept)	3.89203	1.31110	2.969	0.00345 **
Depth [0-7]	0.81209	0.39525	2.055	0.04152 **
Depth [7-25]	0.41959	0.42070	0.997	0.32008
Depth [25-50]	0.11368	0.47776	0.238	0.81223
Depth [50-100]	0.34814	0.41597	0.837	0.40386
Depth [100-250]	-1.72804	0.57873	-2.986	0.00327 **
Soil media [Desert(Sandy)]	-0.07092	0.86606	-0.082	0.93483
Soil media [Loam]	0.97788	0.77816	1.257	0.21068
Soil media [Loamy Sand]	0.94832	0.79749	1.189	0.23613
Soil media [Sandy loam]	0.78280	0.81088	0.965	0.33580
Soil media [Silty clay loam/clay loam]	1.41521	0.70290	2.013	0.04573 **
Soil media [Sandy clay/Sandy clay loam]	0.79318	0.68114	1.164	0.24594
Topography [0-2]	1.22962	0.76397	1.610	0.10945
Topography [2-4]	1.29656	0.77731	1.668	0.09724*
Topography [4-8]	0.90060	0.78908	1.141	0.25542
Topography [8-12]	0.83524	0.85754	0.974	0.33151
Topography [12-18]	0.57584	0.89963	0.640	0.52302
Rainfall [101-200]	-1.28433	0.67780	-1.895	0.05989*
Rainfall [201-400]	-1.30949	0.71233	-1.838	0.06785*
Rainfall [401-600]	-0.95014	0.72779	-1.306	0.19357
Rainfall [601-1000]	-1.30688	0.75678	-1.727	0.08609*
Rainfall [1001-2000]	-1.81435	0.71197	-2.548	0.01175**
Rainfall [2001-3000]	-1.36421	-1.36421	-1.629	0.10516
Climate class [Humid]	-1.39950	0.30886	-4.531	1.13e-05 ***
Climate class [Dry sub-Humid]	-0.90813	0.34871	-2.604	0.01006**
Climate class [Semi-arid]	-0.76395	0.29024	-2.632	0.00931 **
Climate class [Hyper Arid]	-0.28891	0.49427	-0.585	0.55968
Mediterranean region	0.34746	0.38715	0.897	0.37080
Sahel region	1.15109	0.38408	2.997	0.00316 **
Horn of Africa region	1.72708	1.45046	1.191	0.23551
Southern Eq. central Africa region	-0.43528	0.38600	-1.128	0.26113
Southern Africa region	-0.90444	0.39805	-2.272	0.02439 **
Residual standard error: 1.224 on 162 degrees of freedom				
Multiple R-squared: 0.42				
F-statistic: 3.788 on 31 and 162 DF, p-value=1.581e-08 < 0.001				

Note: Statistical significance: ***p<0.001; **p<0.05; and *p<0.1.

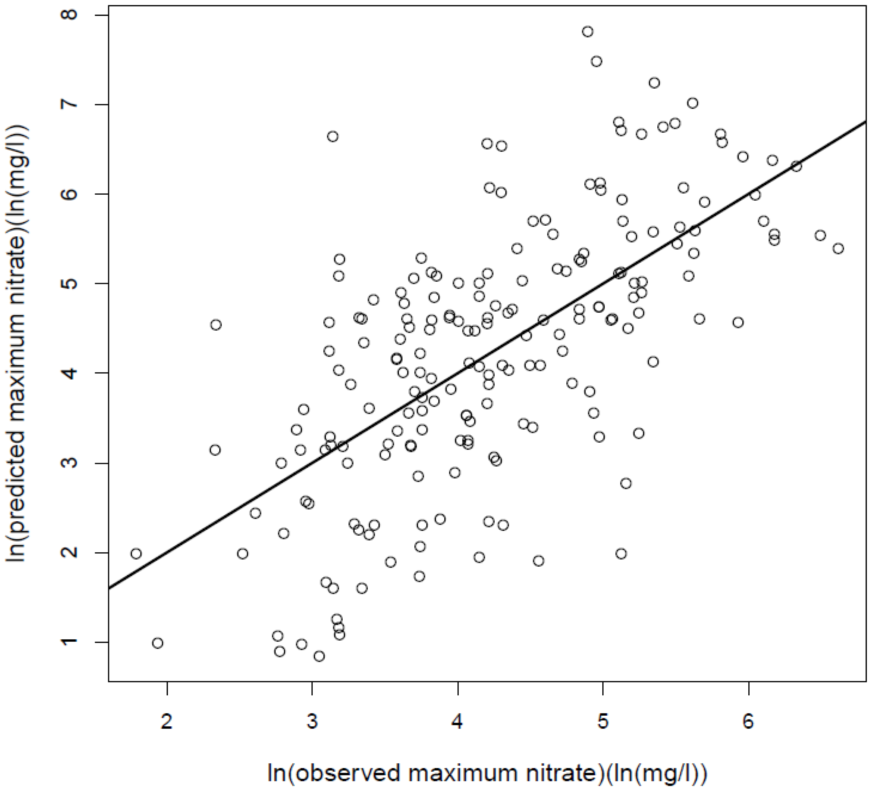

Figure A-9: Observed versus predicted log transformed maximum nitrate concentration (**R^2=0.42**).

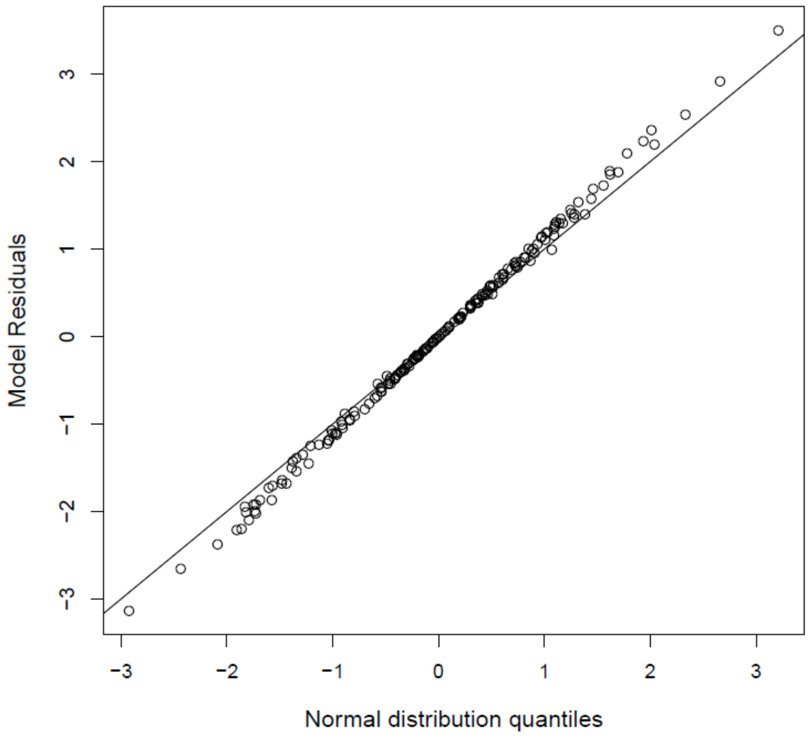

Figure A-10: Normal probability distribution of model residuals for log transformed maximum nitrate concentration.

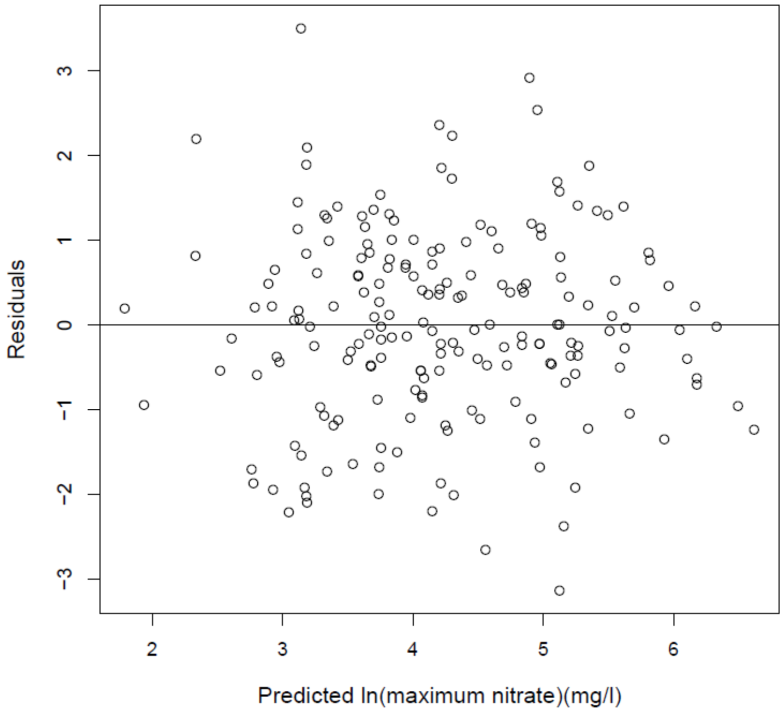

Figure A-11: Relation between residuals and predicted log transformed maximum nitrate concentration.

Appendix B

Minimum nitrate concentration analysis

Normality of minimum nitrate

Figure B-1 shows conventional and logarithmic histograms for the minimum nitrate concentration. Despite the log transformation, a non-normal distribution is observed. This may be due to many outliers in these dataset.

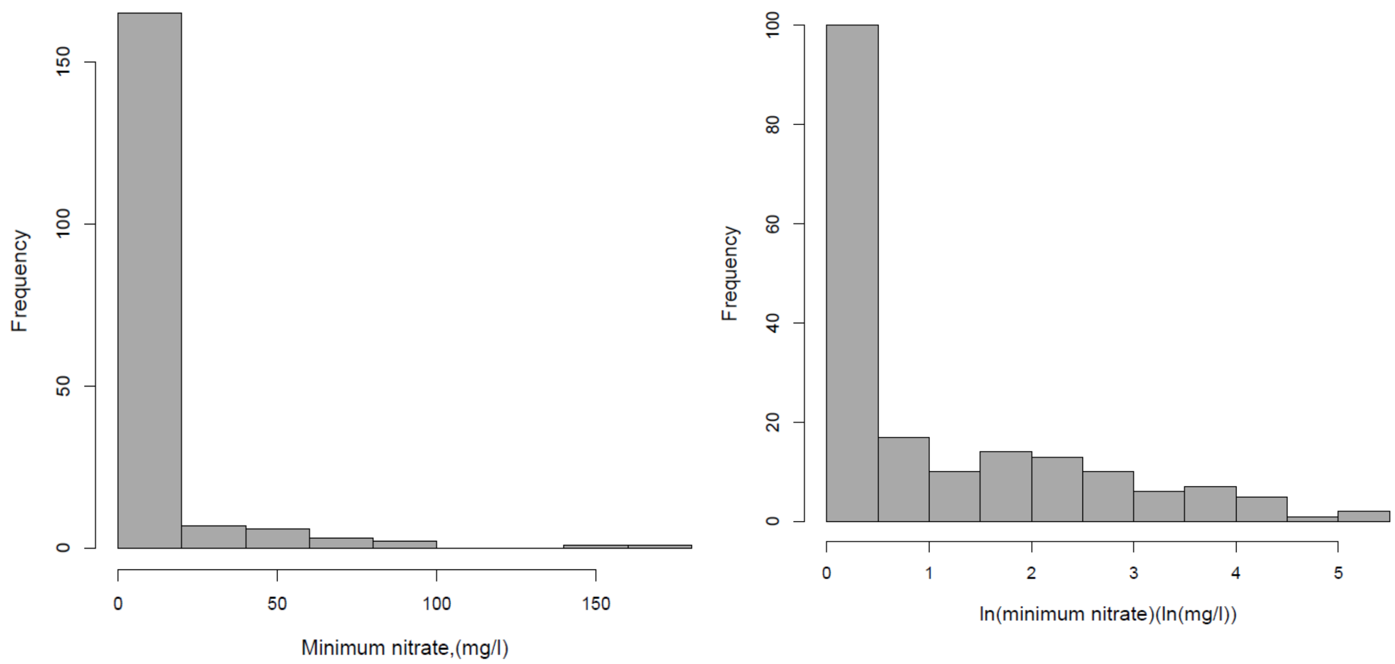

Figure B-1: Histograms of the original and log transformed minimum nitrate concentration

Correlation between explanatory variables and log transformed minimum nitrate concentration

Except the box plot of land use parameter in Figure B-2, all the others box plot diagrams represent the environmental factors that influence mainly the rate of minimum nitrate concentration and are illustrated in Figure B-3 to Figure B-7.

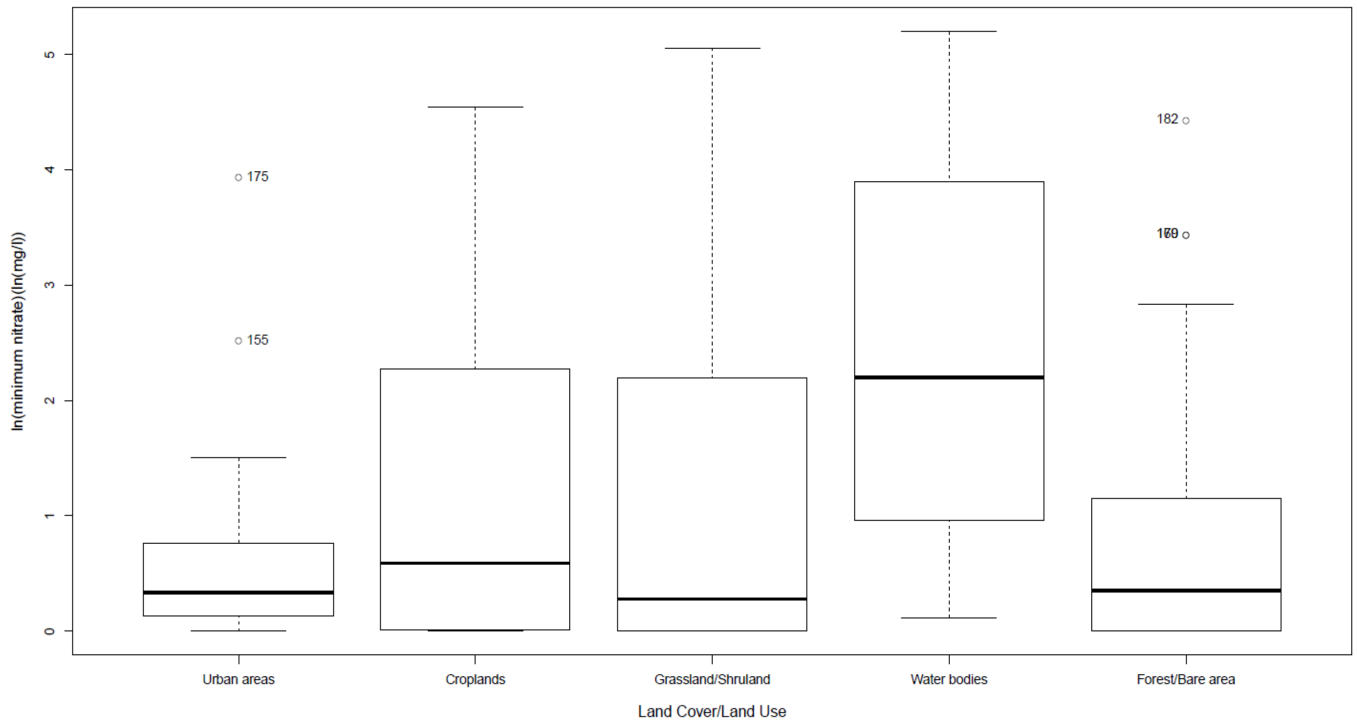

Figure B-2: Log transformed minimum nitrate concentration for different land use classes

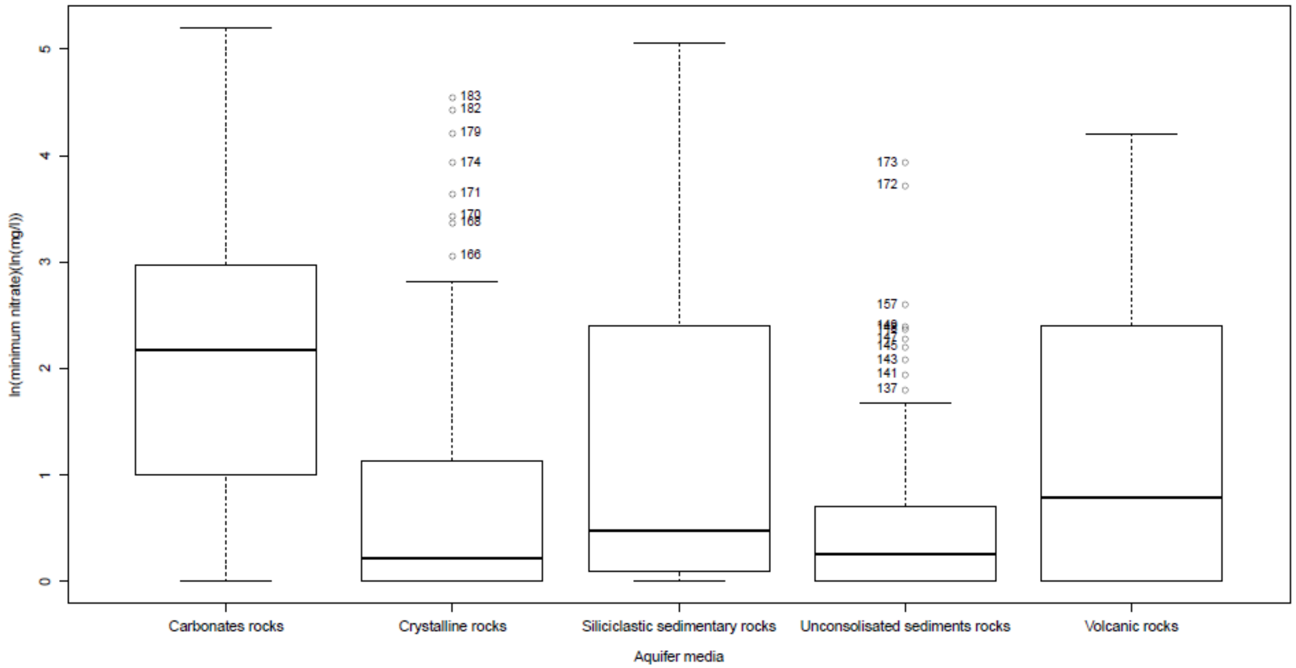

Figure B-3: Log transformed minimum nitrate concentration for different aquifer system classes

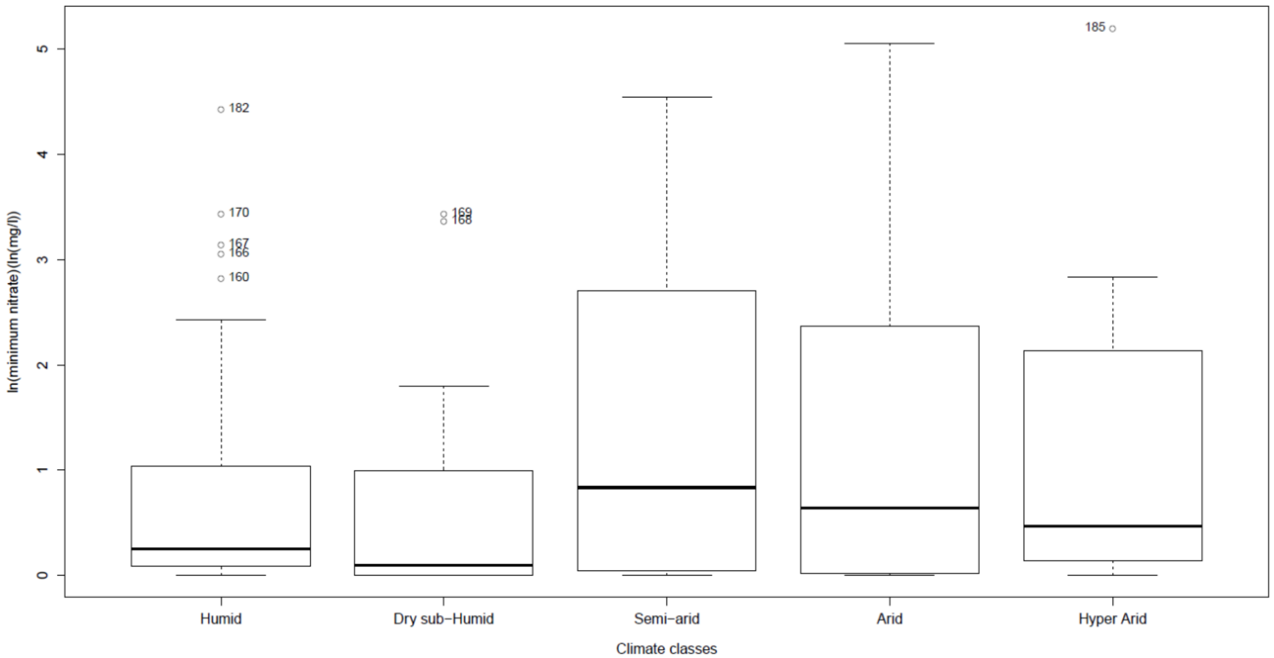

Figure B-4: Log transformed minimum nitrate concentration for different climate classes

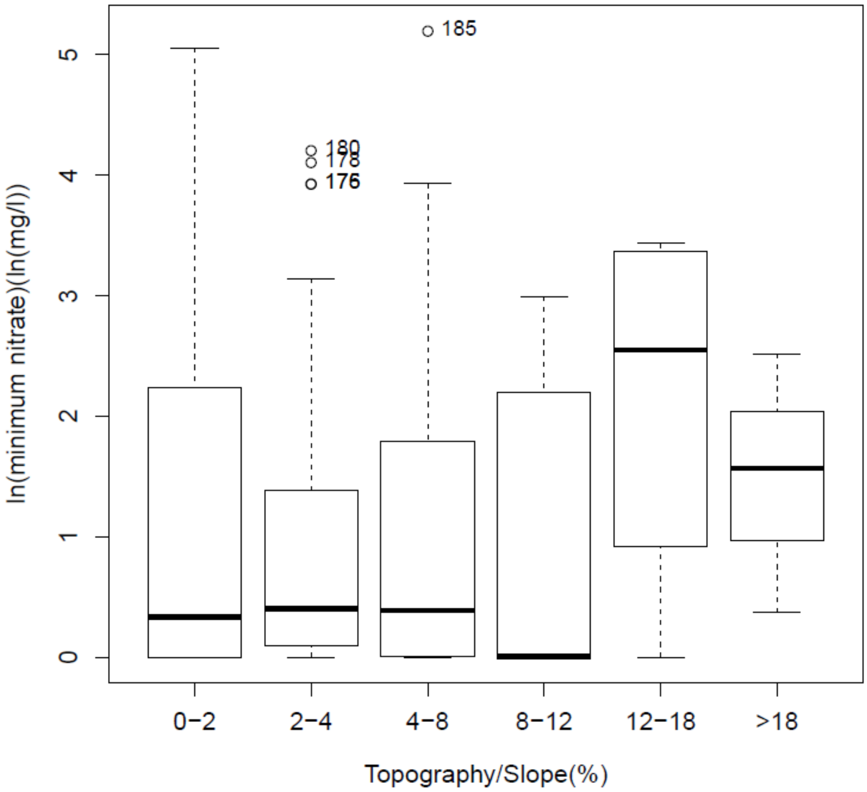

Figure B-5: Log transformed minimum nitrate concentration for different slope classes

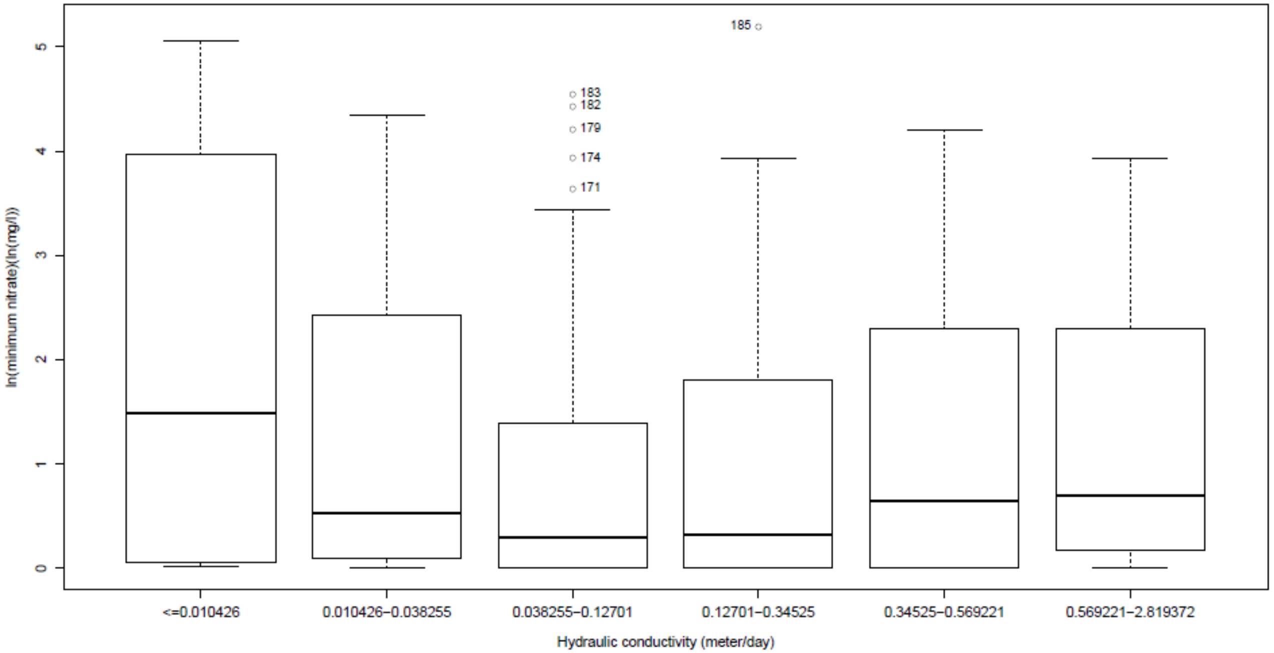

Figure B-6: Log transformed minimum nitrate concentration for different hydraulic conductivity classes

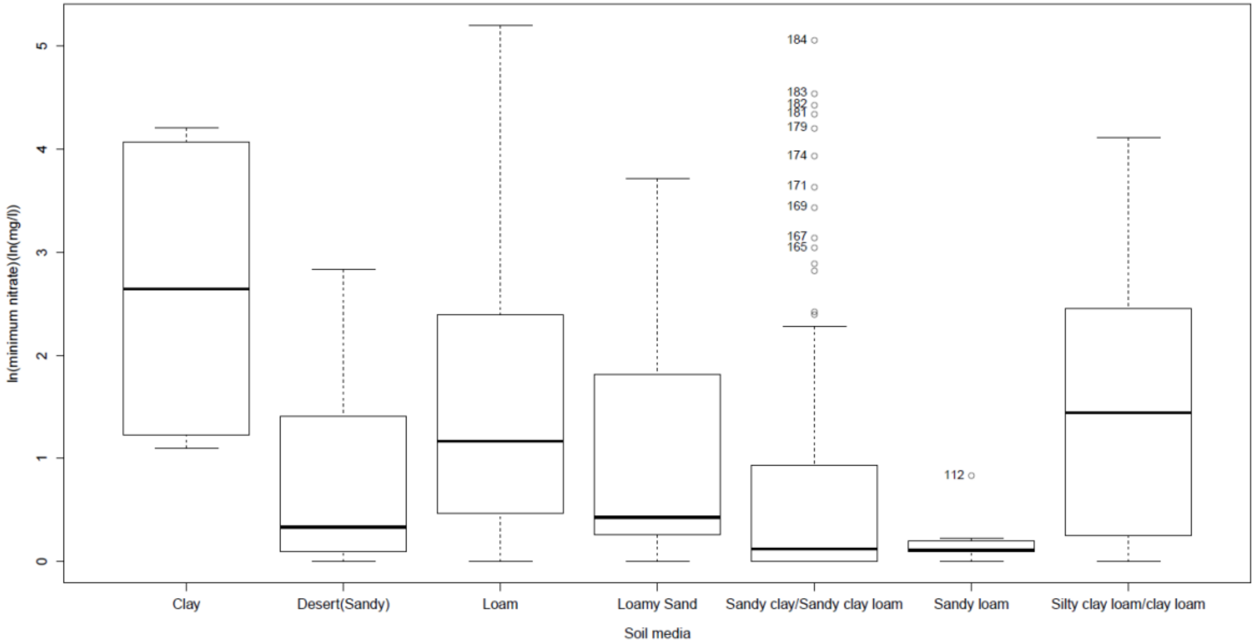

Figure B-7: Log transformed minimum nitrate concentration for different soil classes

Appendix C

Framework of questions for thesis

<table>
<tr><td colspan="5">Overall goal:
Develop knowledge on the state of groundwater at the pan African scale, supporting the monitoring of the implementation of the UN Sustainable Development Goals agenda.</td></tr>
<tr><td colspan="2">Knowledge gap</td><td></td><td colspan="2">Research Question</td></tr>
<tr><td>Knowledge Gap 1</td><td>Groundwater vulnerability to pollution at the pan-African scale is not known.</td><td></td><td>Research Question 1</td><td>How can we map, with a high spatial resolution, the possible pressures on groundwater at the pan-African scale?</td></tr>
<tr><td>Knowledge Gap 2</td><td>Groundwater pollution at the pan African scale is not assessed.</td><td></td><td>Research Question 2</td><td>How can we use the power of meta-analysis, to build, through the published literature a pan-African meta-database of groundwater pollution for nitrates as a proxy of general pollution?</td></tr>
<tr><td>Knowledge Gap 3</td><td>Environmental drivers contributing to groundwater pollution risk at the continental scale are not quantified.</td><td></td><td>Research Question 3</td><td>How can we use a meta-database to develop statistical models which allow explaining the origin of nitrate pollution with environmental factors?</td></tr>
<tr><td>Knowledge Gap 4</td><td>Groundwater pollution risk at the pan African scale has not been modelled.</td><td></td><td>Research Question 4</td><td>How valid are the statistical models for predicting nitrate pollution in African groundwater?</td></tr>
<tr><td>Knowledge Gap 5</td><td>Monitoring of groundwater pollution at the pan African scale is not operational</td><td></td><td>Research Question 5</td><td>How can we integrate time dimension in the statistical models to predict time course of groundwater pollution risk at the pan African scale?</td></tr>
</table>

Publications and Conferences

List of publications in international peer-reviewed journals: published, submitted or to be submitted.

1) **Ouedraogo, I**., Defourny, P., Vanclooster, M. (2016). Mapping the groundwater Vulnerability for pollution at the pan-African scale. Science of the Total Environment, Vol. 544, p. 939-953.DOI: 10.1016/j.scitotenv.2015.11.135.
   Impact factor: 4.900 (2016)

2) **Ouedraogo, I.,** and Vanclooster, M.(2016). Shallow groundwater poses pollution problem for Africa. In: SciDev.Net. 4 pp, http://hdl.handle.net/2078.1/169630

3) **Ouedraogo, I.,** and Vanclooster, M. (2016). A meta-analysis and statistical modelling of nitrates in groundwater at the African scale. In: Hydrology and Earth System Sciences, Vol. 20, no.6, p. 2353-2381. DOI: 10.5194/hess-20-2353-2016.
   Impact factor: 4.437 (2016)

4) **Ouedraogo, I.,** Defourny, P., and Vanclooster, M.(2017). Modeling groundwater nitrate concentrations at the African scale using Random Forest Regression Techniques. Accepted 24th April to review in the special issue on Groundwater in Sub-Saharan Africa for Hydrogeological Journal (HJ) (*in progress, book expected in December 2017*).
   Impact Factor : 2.109 (2017)

5) **Ouedraogo, I**., Defourny, P., and Vanclooster, M.(2017). Validating a continental scale groundwater diffuse pollution model using regional datasets. Submitted June 23rd to Environmental Science and Pollution Research (ESPR) journal for IAH2016 special issue. (*Under review*).
   Impact Factor: 2.741 (2016)

6) **Ouedraogo, I**., Girard, A., Defourny,P., Vanclooster, M., and Jonard, F. (2017). Time dynamic pollution risk modelling of groundwater at the African scale. *To be submitted in Hydrological Sciences Journal.*

7) **Ouedraogo I.,** and Vanclooster, M. (2017)**.** Evaluation de la vulnérabilité des eaux souterraines africaines. "La lettre du RIOB" -, no.25, p. 9 (Juin 2017). http://www.riob.org/pub/RIOB-25/

Conferences and workshops
Oral Presentations

1) Vanclooster M, S. Petit, P. Bogaert, **I. Ouedraogo** and A. Mfumu, 2017. Recent advances in groundwater vulnerability mapping. In: Modelling for sustainable groundwater management. Tunisian chapter of IAH. Tunis 23-28 October 2017. Keynote lecture.
2) **Ouedraogo, I.,** Defourny, P., and Vanclooster, M. (2017). *Modelling nitrate concentrations at the pan-African scale: A random forest approach*. 1st Atlas Georesources International Congress AGIC 2017. Hammamet, Tunisia 20-22 March 2017.

3) **Ouedraogo, I.**, Defourny, P.; Vanclooster, M. (2015). *Mapping the groundwater vulnerability for pollution at the pan African scale.* European Geosciences Union (EGU) General Assembly (Vienna (Austria), du 13/04/2015 au 17/04/2015). In: *Geophysical Research Abstracts*, Vol. 17, p. EGU2015-8794 (April 2015).

4) **Ouedraogo I.,** Defourny P., and Vanclooster, M. (2015)**.** *Nitrate in African groundwater: Crossing a meta-database of nitrate contamination with a groundwater vulnerability and risk map.* Meeting 14/01/2015 at IGRAC in Delft/ The Netherlands.

5) Vanclooster, M., Mfumu K. A., **Ouedraogo, I.** (2014). *"L'union fait la force or how different approaches should be combined to assess groundwater vulnerability at the regional scale"*. IAH 2014 (Marrakech, Maroc, du 15/09/2014 au 19/09/2014).

6) **Ouedraogo, I.**, Defourny, P.; Vanclooster, M. (2014). *"Advanced mapping of pollution pressures of Africa groundwater bodies"*. Symposium International Afromaison of May 16th 2014 in Delft/.The Netherlands.

Poster Presentation

1) **Ouedraogo, I.,** Defourny, P., Girard, A., and Vanclooster, M. (2017). Time dynamic modelling of groundwater vulnerability at the African scale. "Africa, Groundwater and the Sustainable Development Goals", London (United Kingdom) (25/10/2017)."IAH British - INESON Lecture 2017"- p. 6.

2) **Ouedraogo, I.,** Defourny, P., and Vanclooster, M. (2016). *Modelling groundwater nitrate concentrations at the pan-African scale using Multiple Regression and Random Forest Statistical Models*. Poster at 43rd IAH CONGRESS from 25 to 29 September 2016, in Montpellier - France.

3) **Ouedraogo I.,** Defourny P., and Vanclooster, M. (2014**).** *Groundwater pressure mapping in Africa*. "PhD Day ENVITAM", Louvain-la-Neuve (Belgique) (05/03/2014).Communication à un colloque (Conference Paper) - (Poster - Abstract).

4) **Ouedraogo, I.**, Vanclooster, M. (2015). *A statistical model to predict groundwater vulnerability against pollution: a support to design groundwater quality monitoring program*s. Workshop Exploring new data for SMART monitoring of water SDG targets (IHP-HWRP) (Maastricht (The Netherlands), du 30/11/2015 au 01/12/2015).

Other works

1) Co-promotion du Master en bio-ingénieur: **Arthur Girard. (2017).** Modélisation spatio-temporelle de la pollution diffuse des eaux souterraines à l'échelle africaine;

2) Mise en ligne pour libre accès des données de thèse sur la plateforme de « International Hydrological Programme-Water Information Network System » (IHP-WINS) le 31/03/2017 **:** http://ihp-wins.unesco.org/layers/geonode:gwpollriskafrio

❖ ***Works in DEA (Diplôme d'Etudes Approfondies in French):***

1) **Ouedraogo I.,** (2009) – Contribution à l'étude hydrodynamique de la nappe du littoral dans la banlieue de Dakar, Mémoire de DEA, Univ. Cheikh Anta Diop Dakar, 95pp.

2) **Ouedraogo, I.,** Sambou, S., et Tamba, S. (2009). *Interaction between groundwater and surface water in coastal area: strategies definitions against flooding in suburbs of Dakar*. Communication orale à la 3ème conférence AMMA (Analyses Multidisplinaires de la Mousson Africaine) du 20- 24 Juillet 2009 à Ouagadougou (Burkina Faso). Communication orale.

3) **Ouedraogo, I.**, Sambou, S., et Tamba, S. (2010). *Surface water and groundwater interactions in coastal area of Dakar suburbs: using computer system to definite strategies against flooding*. Abstract à la 6th World Friend Conference Fez – Morocco 25-29 October 2010 (presentation de poster).

4) **Ouedraogo, I**., Sambou, S., BabaSy, M, O; Amwata, D, A. (2010). *Using groundwater numerical model to understand hydrodynamics behaviour in coastal area of Dakar (Senegal) suburbs***.** 10th International Symposium on Stochastic Hydraulics et 5th International Conference on Water Resources and Environment Research (joint Water 2010 symposium) , 5-7 Juillet 2010 au Québec (Canada) (article rédigé).

5) **Ouedraogo, I.,** Sambou, S., Tamba, S., BabaSy, M.O. (2011). *Study by groundwater numerical model in coastal area of Dakar (Senegal) suburbs*. 6èmes Journées Scientifiques du 2iE, 4-8Avril 2011 à Ouagadougou/ Burkina Faso. http://journees-scientifiques.2ie-edu.org/js2011/sessions/pdf/ouedraogo_i.pdf

6) Comte, J., Banton, O., Sambou, S., Travi, Y., and **Ouedraogo, I.** (2012). *"L'aquifère des sables de la presqu'île de Dakar (Sénégal) : état de la ressource et impacts anthropiques.*" Dix-huitièmes journées techniques du Comité Français d'Hydrogéologie de l'Association International des Hydrogéologues. «Ressources et gestion des aquifères littoraux. Cassis 2012»: 276-274. http://www.cfh-aih.fr/images/DOCS/2-Colloques/Colloque_2012_aq_lit_cassis/articles/POSTER-COMTE-et-al.pdf