Exploring Machine Learning techniques to identify nitrate sources in groundwater in National Mouhoun basin in Burkina Faso: the case of the Kou watershed

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Introduction

- Groundwater is subjected to many pressures, groundwater dependent functions and services;

- Groundwater protection and management implies an in-depth knowledge of the state of the available groundwater resource (quantity / quality) and groundwater vulnerability (likelihood of being negatively affected);

- Groundwater monitoring and modelling approaches are available to assess the state and vulnerability of groundwater.

Introduction: Groundwater resources in Africa

75 % of the African population depends on groundwater for basic water supply;

Groundwater used for other activities (irrigation, livestock watering, urban and industrial development, etc);

Groundwater demands will increase in future due:

- Population increase
- Climate change
- Need to combat growing food insecurity.

Context: Groundwater Pressures in Urban Areas

There may be 800 million people living in slums in sub-Saharan Africa by 2100.

Photo: Bwaise III , Kampala, Uganda- Robinah Kulabako

From Danert, K. (2015)

Groundwater pollution in Africa

Rapid urban development has resulted in many informal settlements!!!

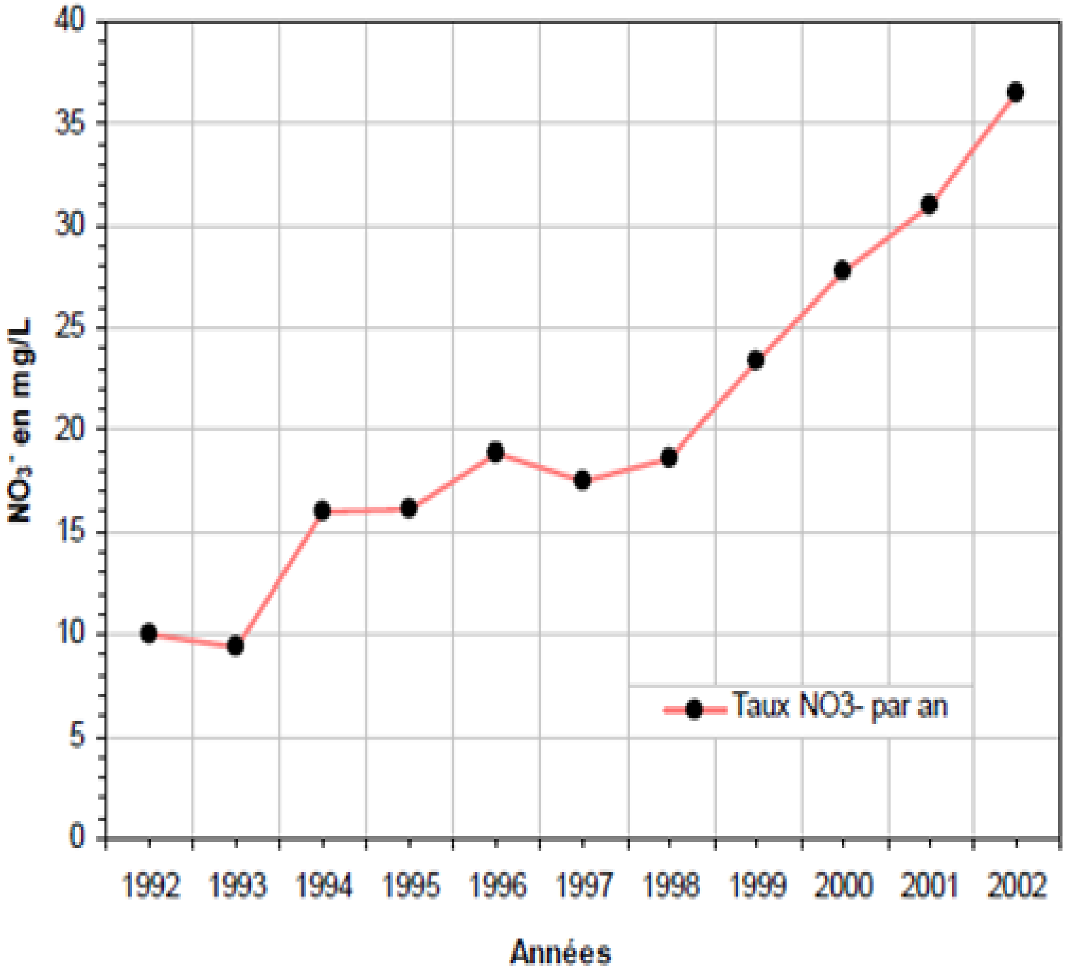
Poor sanitation

Urban agriculture

Sources of Nitrates and Emerging contaminants (ECs) in Groundwater/ Surface water

- Treated wastewater discharge to surface water
- Manure/sludge application to soil
- Urban waste water drainage
- Managed aquifer recharge
- Animal waste lagoons
- Transport networks
- Water treatment
- Septic tanks
- Landfill

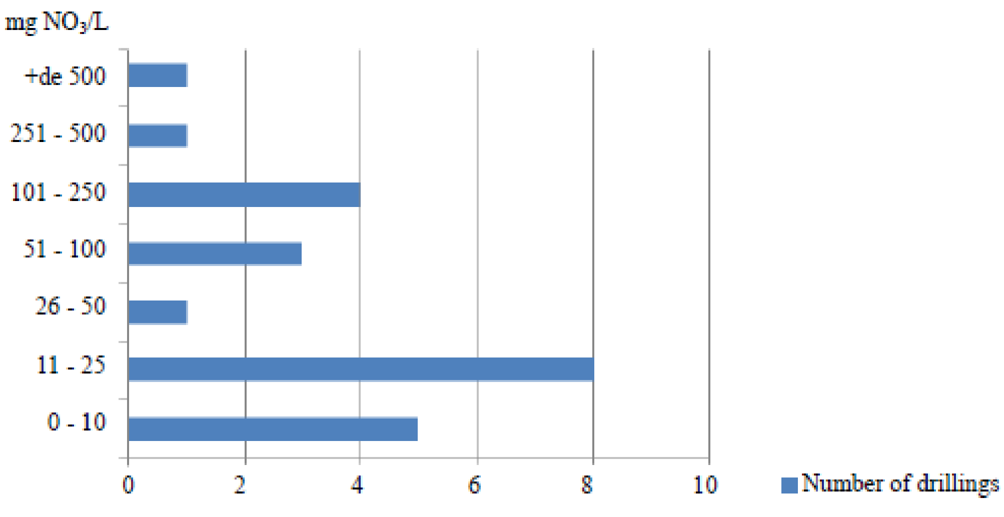
Example of Groundwater pollution with nitrates in Abidjan/Ivory Coast



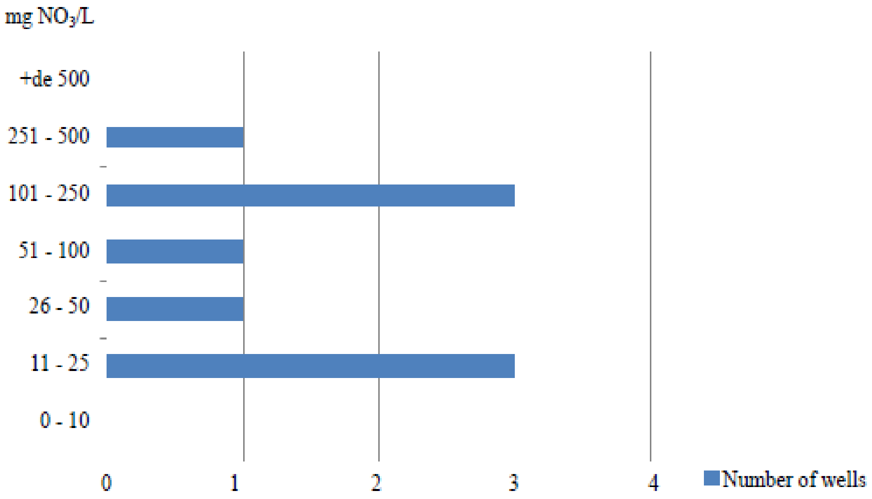
Source: Ahoussi et al.,2013

Pressure on groundwater quality in Burkina Faso

Why high nitrates concentrations in the wells and drillings of the Sourou Valley in Burkina Faso? Survey 2006-2014 **by Rosillon et al.2014**



Nitrates contents (per classes) in drillings water samples.

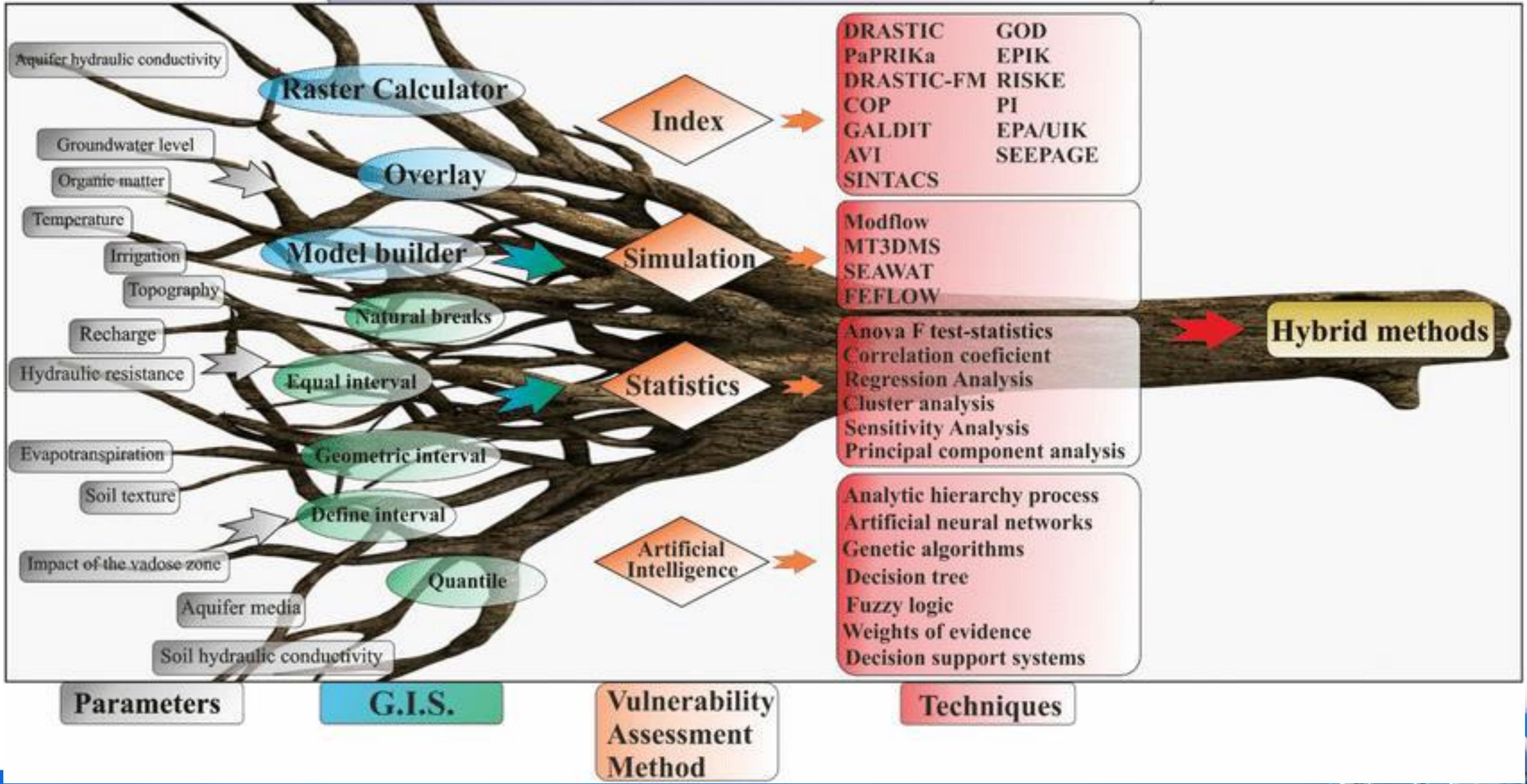


Nitrates contents (per classes) in wells water samples.

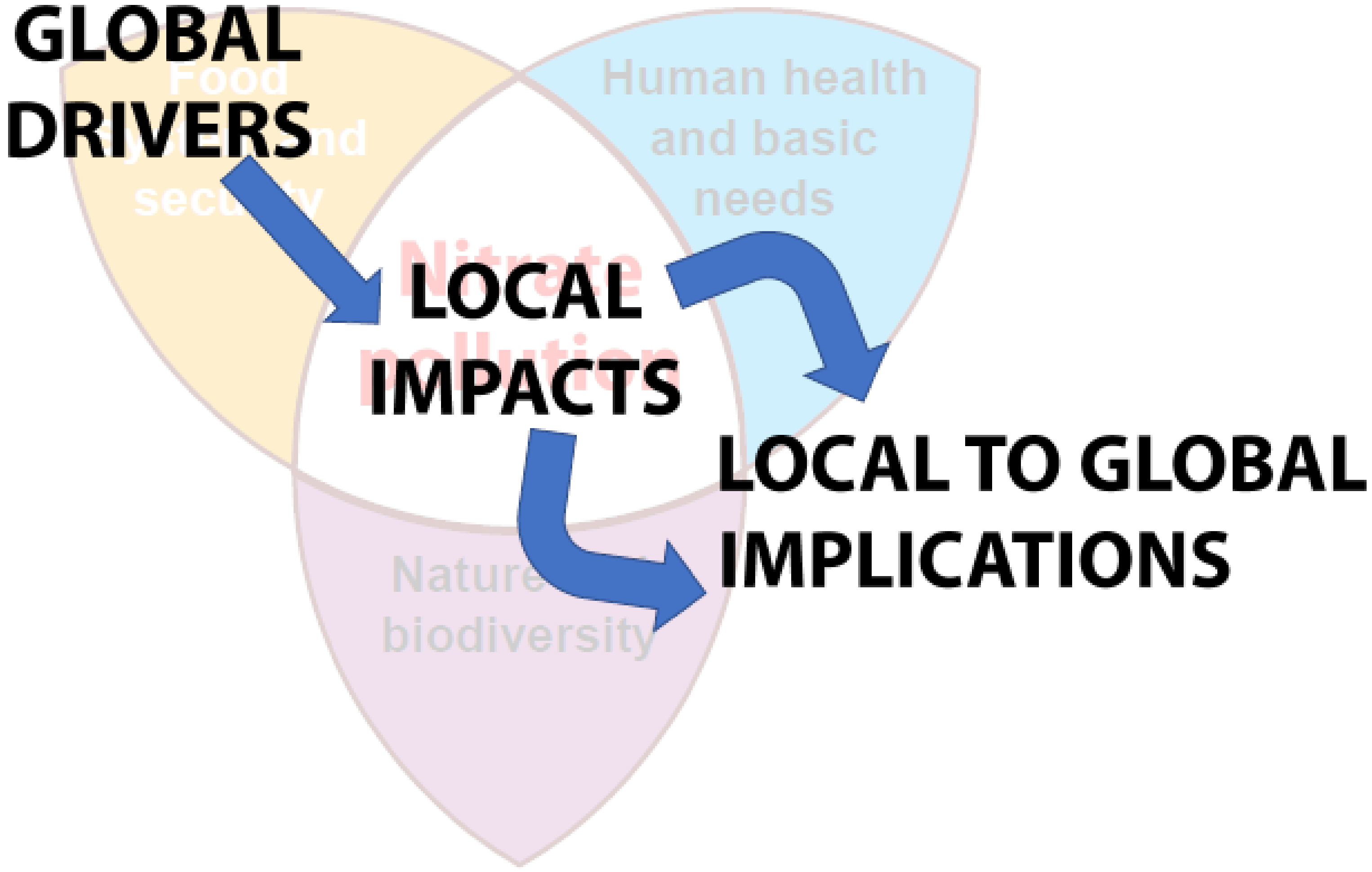
Source: https://doi.org/10.1051/asees/2014004

- ✓ Groundwater is a major important resource for drinking water in Burkina Faso
- ✓ Groundwater nitrate pollution is an environmental concern, as reported in many African cities

Groundwater Vulnerability Assessment



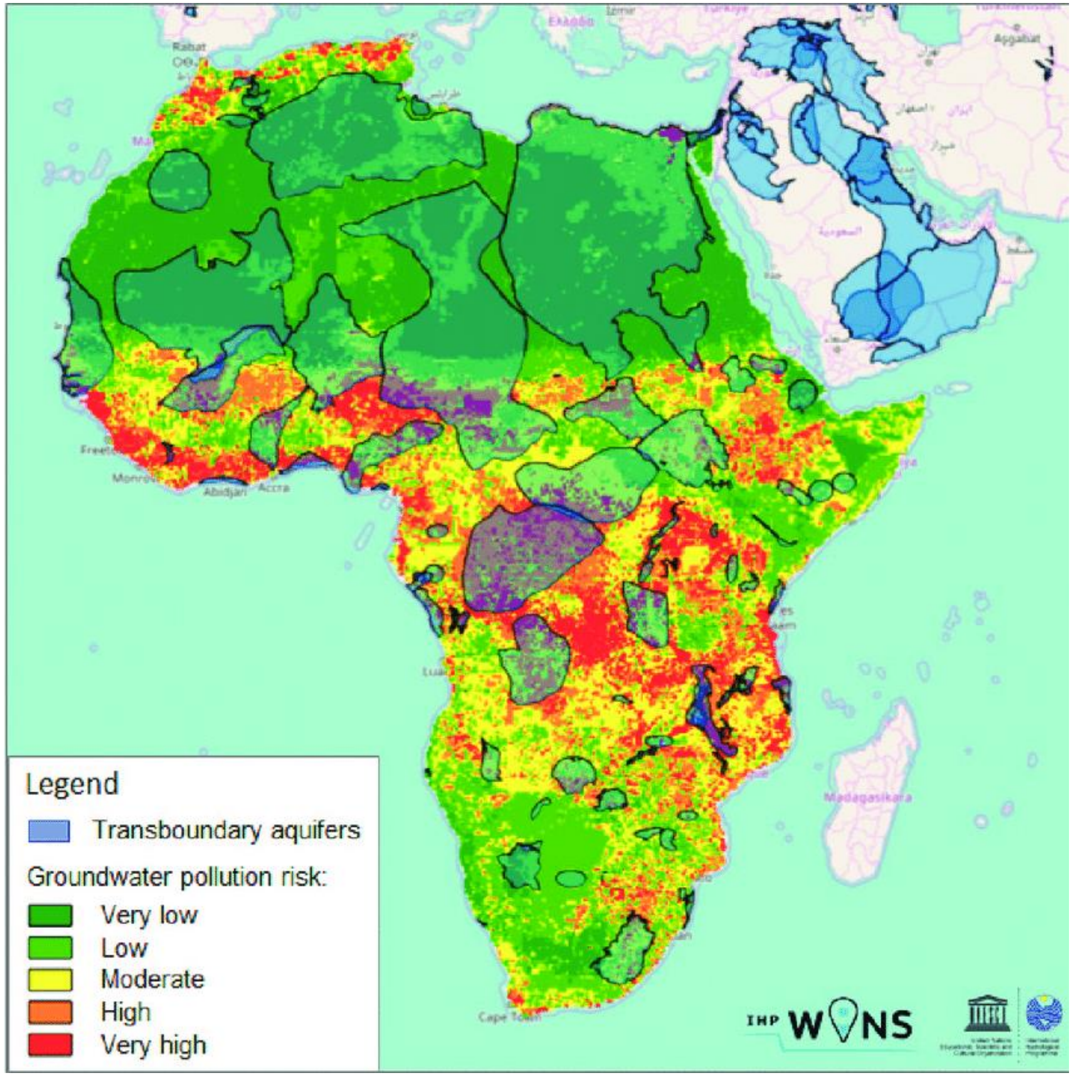
Global-to-local-to-global challenges



IN WATER QUALITY

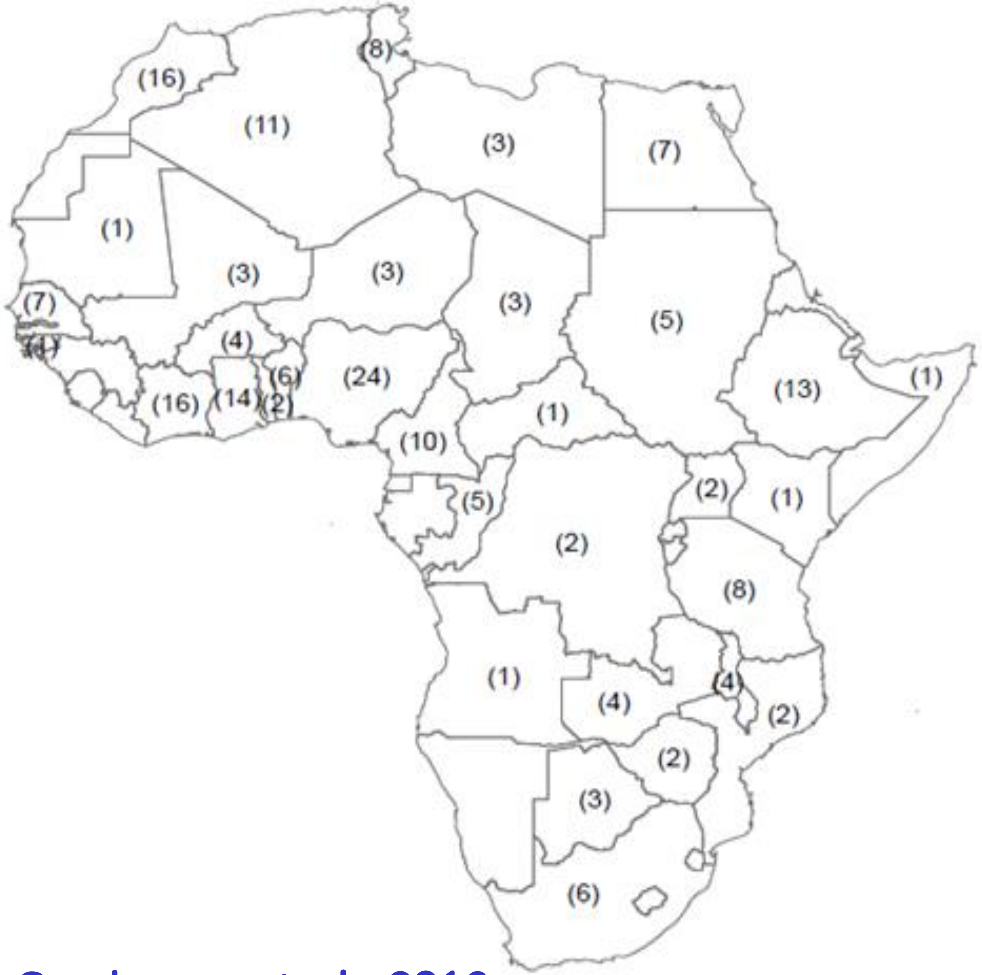
Schmitt et al., 2022 at AGU

Transboundary aquifers and groundwater pollution risk in Africa



Ouedraogo et al. (2018)

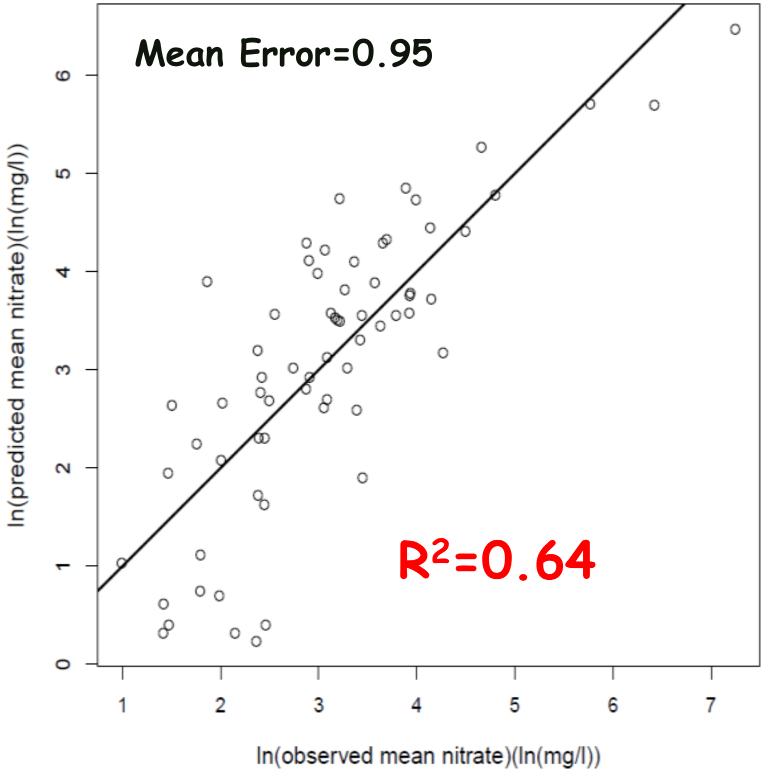
Spatial distribution of nitrate studies identified across Africa



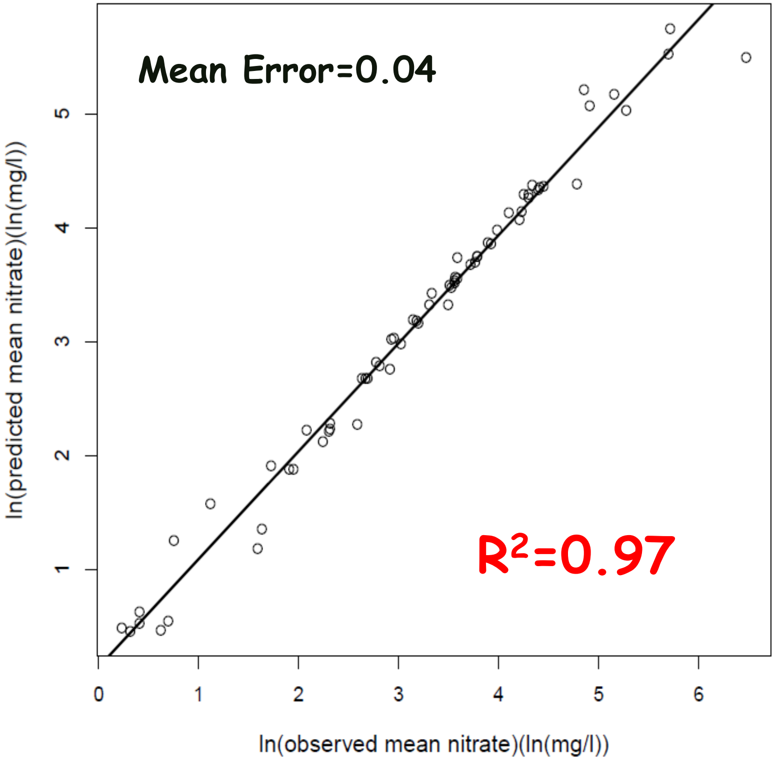
Ouedraogo et al. 2018

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)

Previous example of machine learning (Ouedraogo et al. 2018) at continental scale of Africa

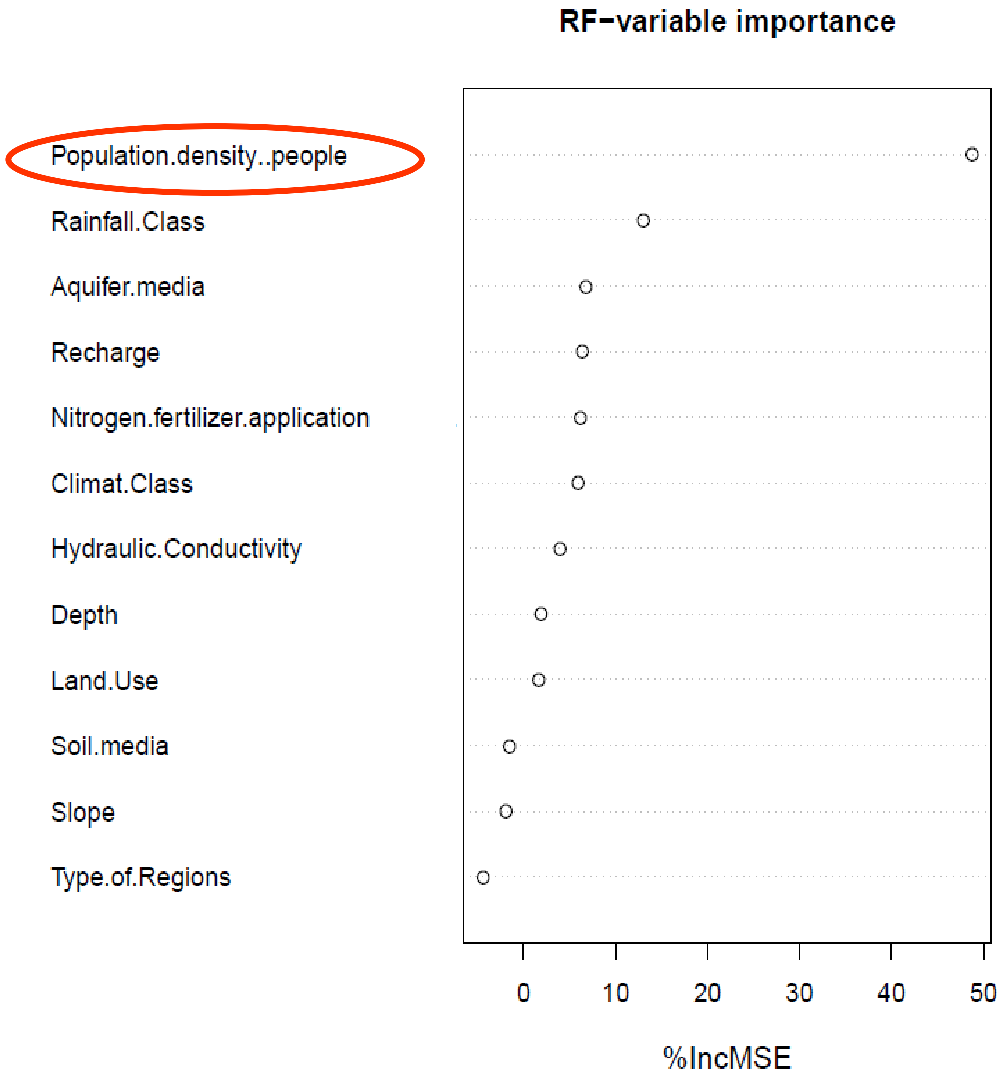


Multiple Linear Regression



Random Forest Regression

Variable importance in Random Forest (RF) model



The most important variable identified in RF model was the **population density**. This is most likely related to the lack of sanitation in major parts of the African continent and development of small-scale farming systems in peri-urban environments.

Machine Learning technique is a tool to support for groundwater protection and management.

1st Case: Mouhoun basin study:

General objective: To improve knowledge on the state of surface water and groundwater quality at the Mouhoun basin scale, supporting the monitoring of the implementation of the UN Sustainable Development Goals agenda for Burkina Faso.

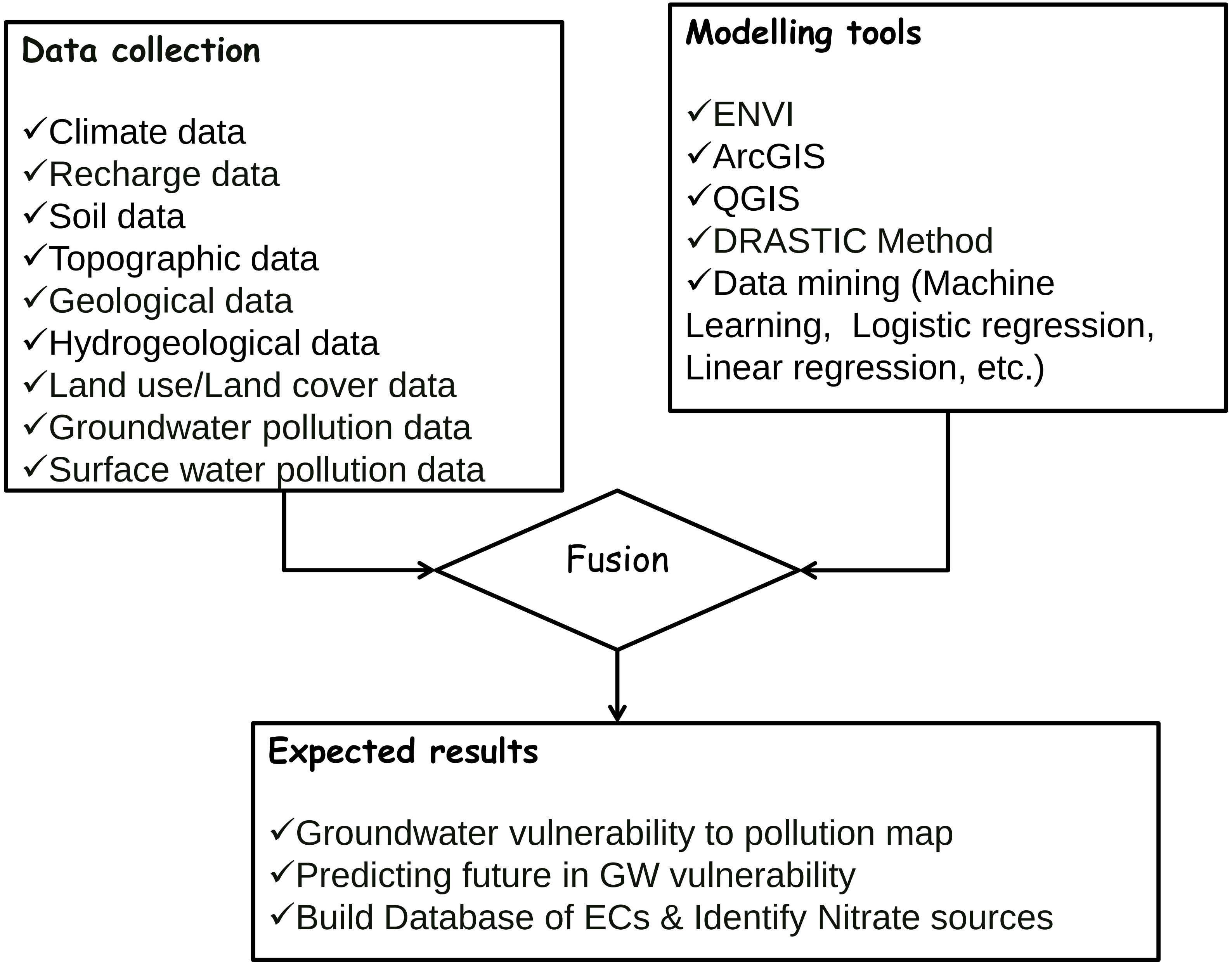
Specific objectives:

SO1. To collect and analyse new and existing, rainfall, topography, geology and hydrogeology data of the Mouhoun basin area;

SO2. To develop a machine learning model for mapping groundwater vulnerability to pollution in terms of public available generic data (remote sensing data, generic physical attributes data);

SO3. To predict future change in groundwater vulnerability of the Mouhoun basin.

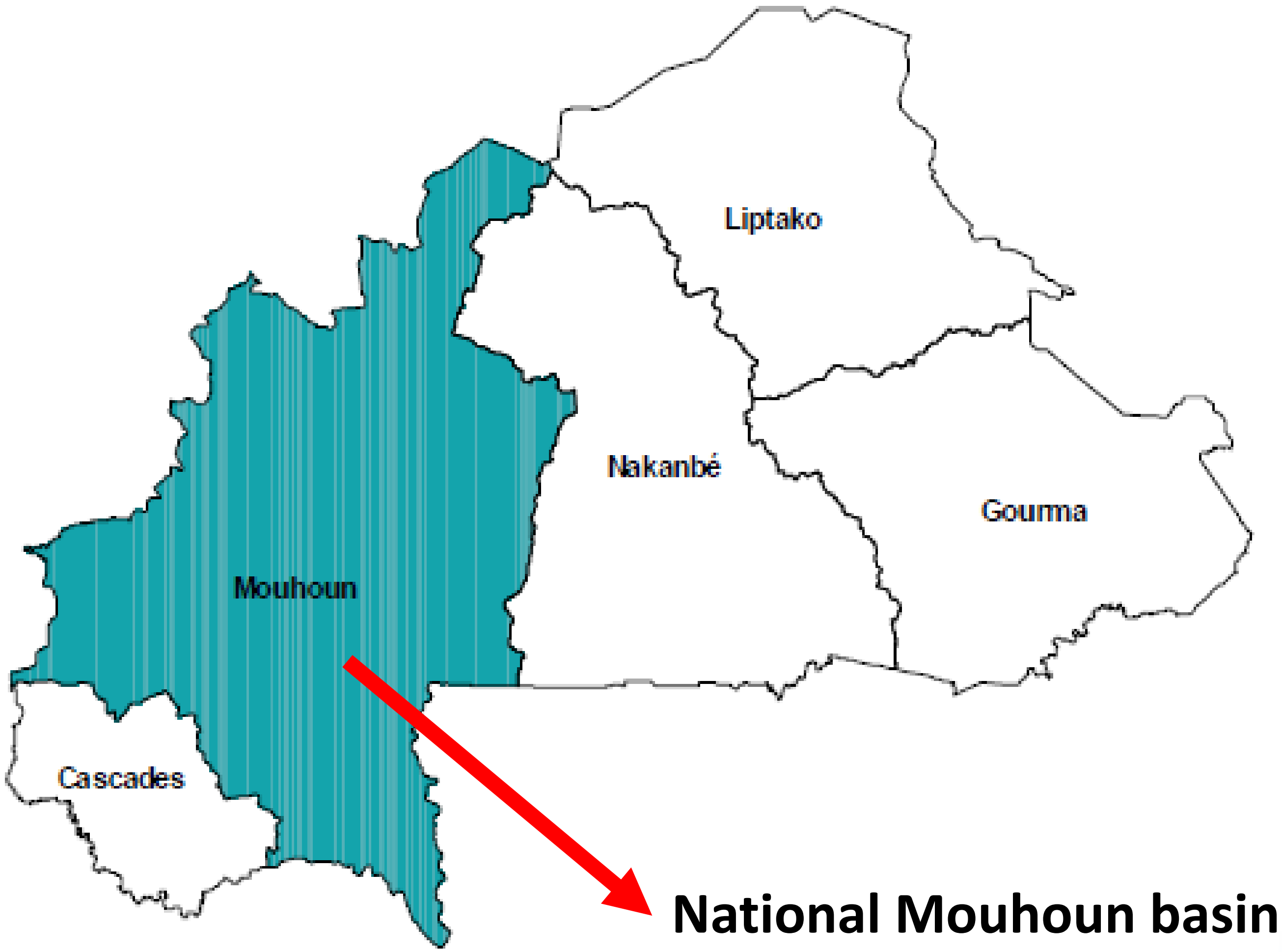
General Methodology of the study



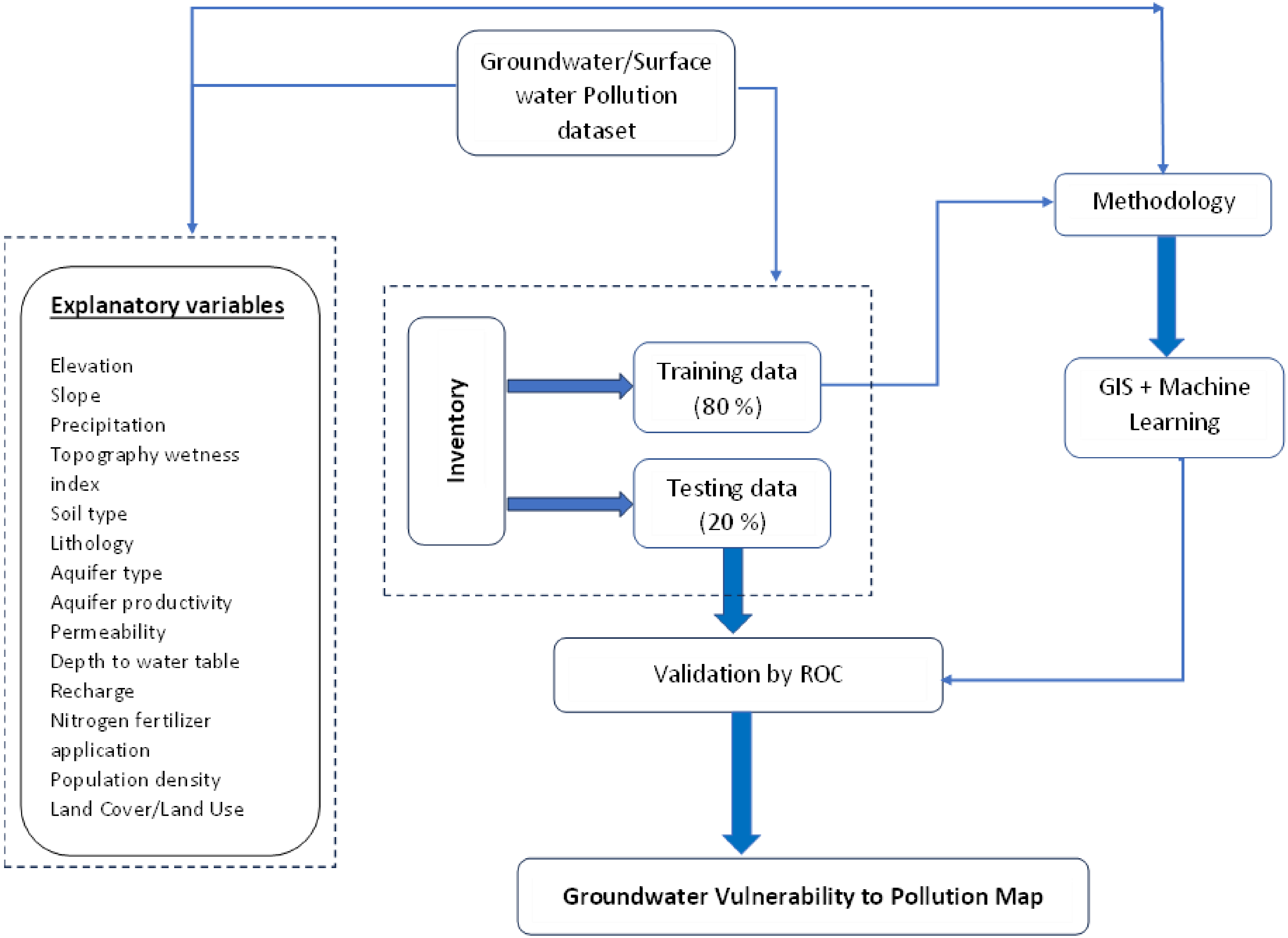
1st case of study : National Mouhoun basin in Burkina Faso

As main features on space, we can note the following:

- **Area: 91 203 km²**
- 33 % of the country territory
- Number of dams: 358
- Number of modern water points: 16723
- Population: about 4,826,687 inhabitants in 2006.



Methodology: Data and mapping groundwater pollution procedures



Spatial distribution of historical data nitrate (2017-2019)

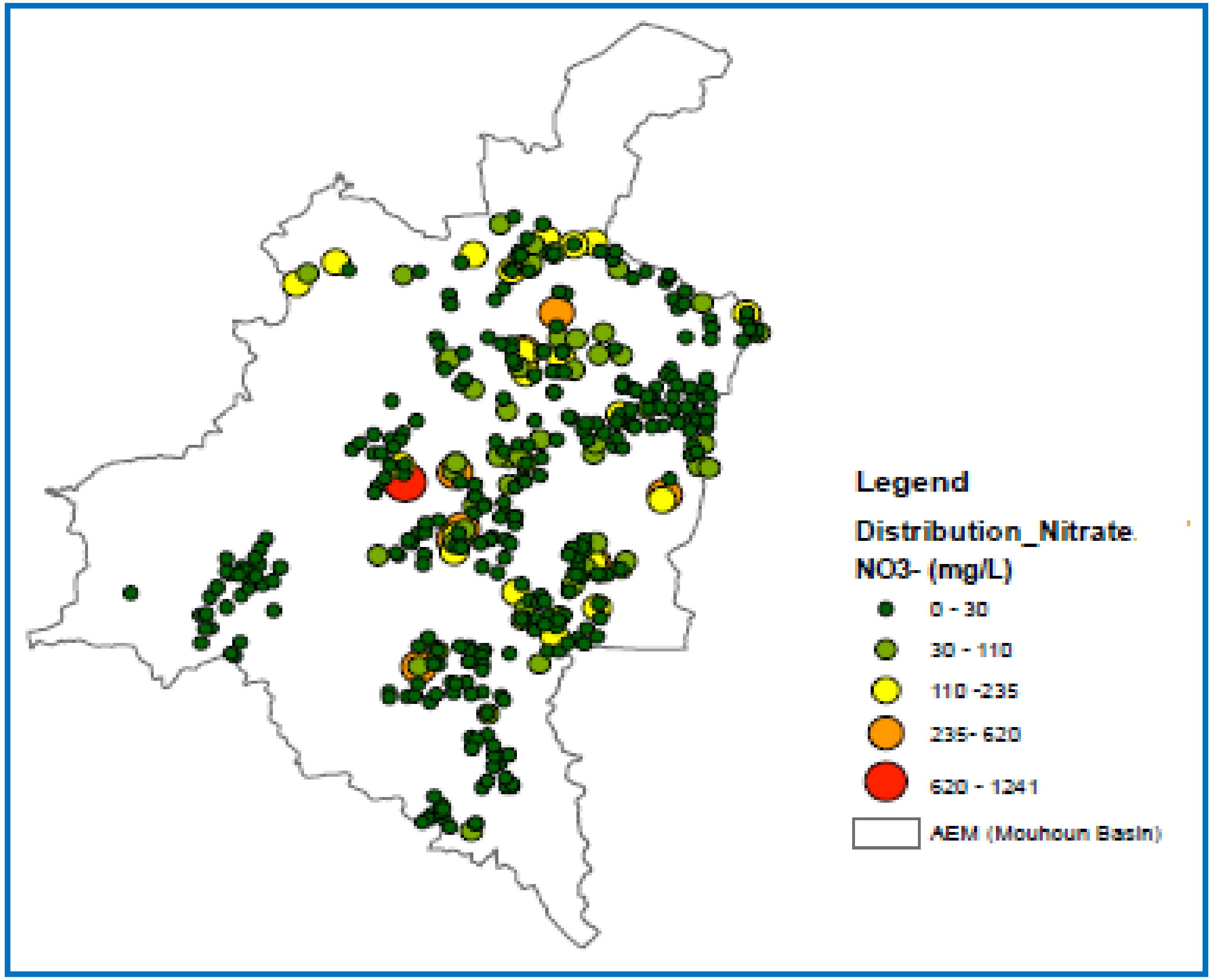
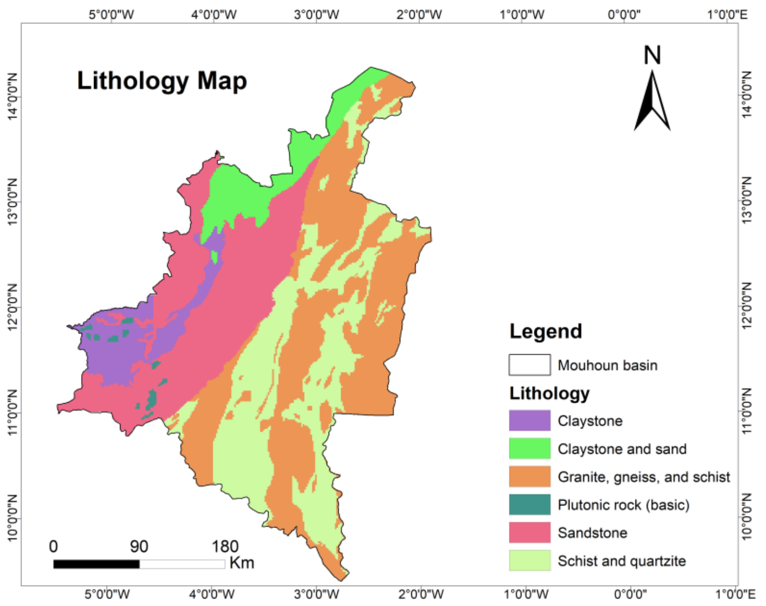
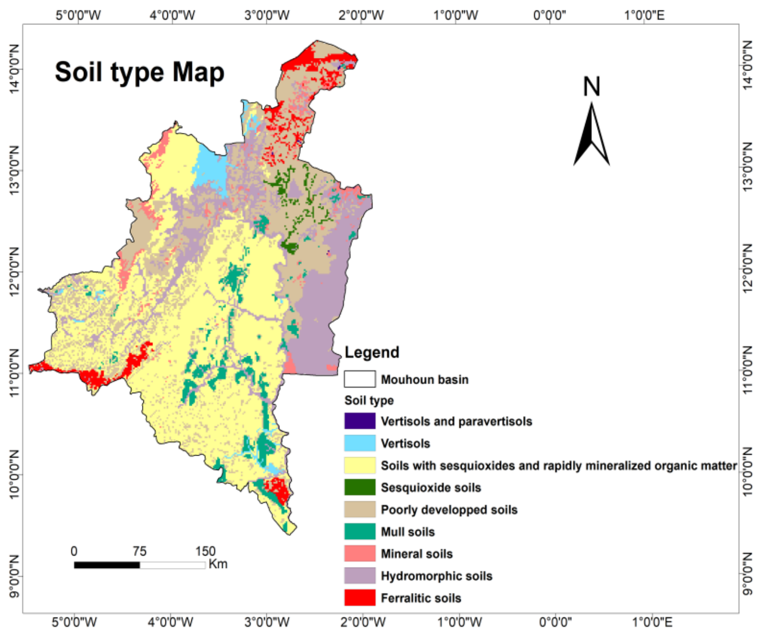


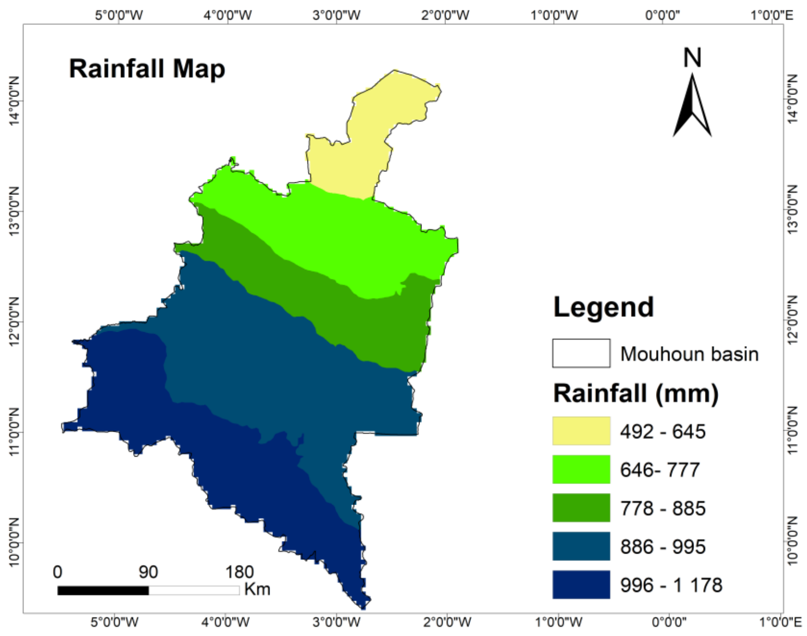
Fig. Distribution map of nitrate in the Mouhoun basin

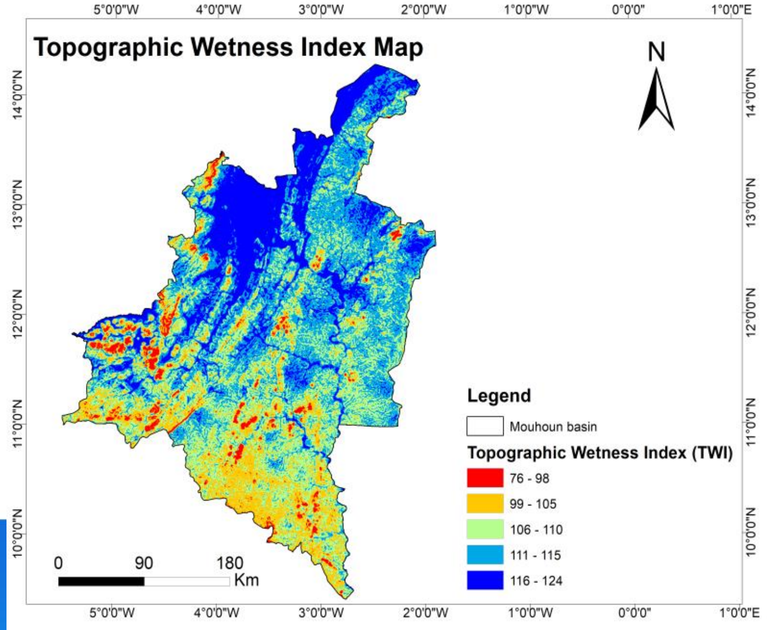
This dataset will be used to develop Machine Learning modelling !!!

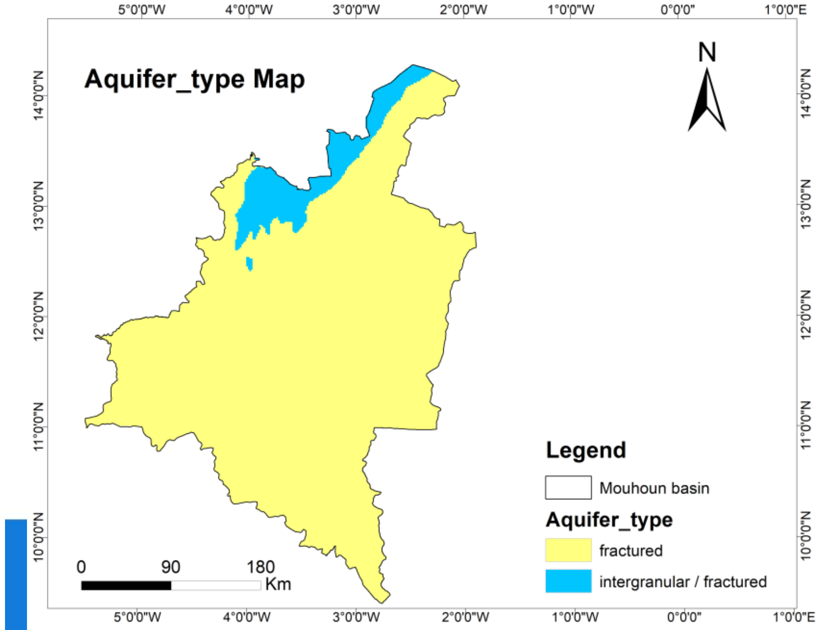
Data acquisition and processing: Explanatory variables (1/3)

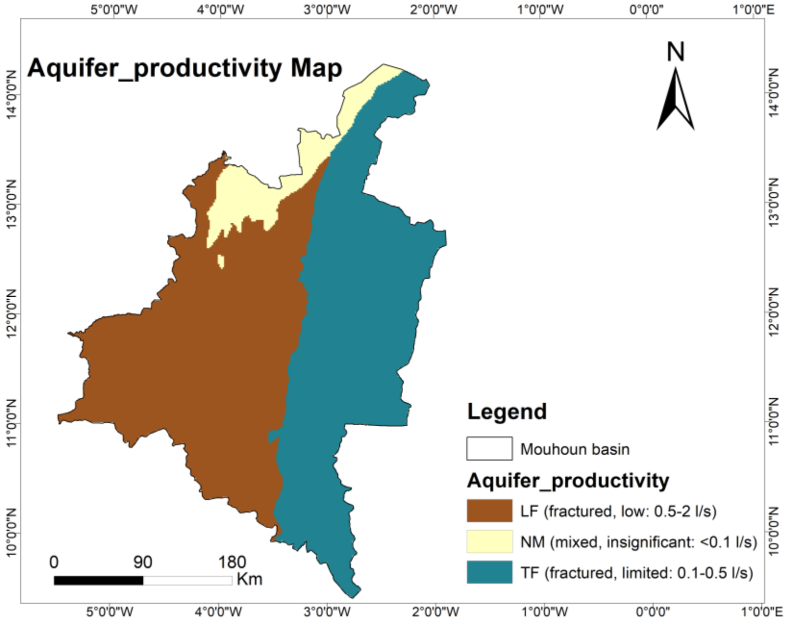




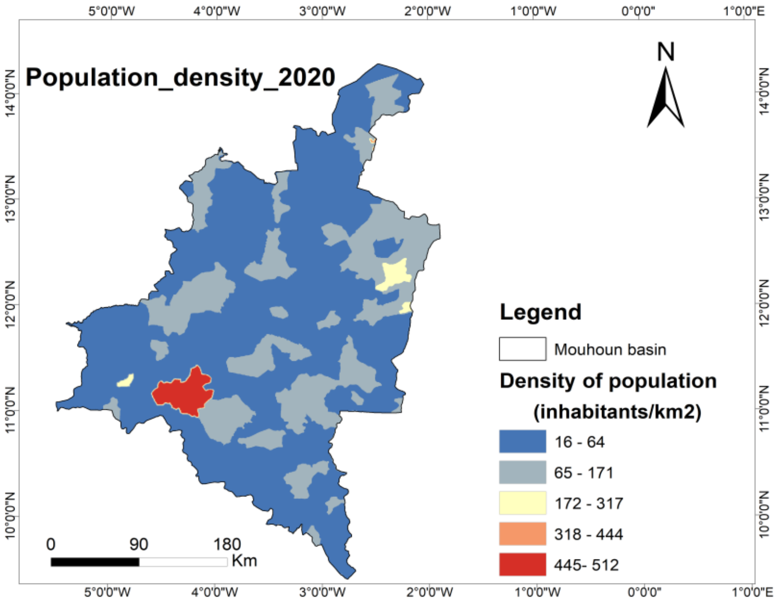


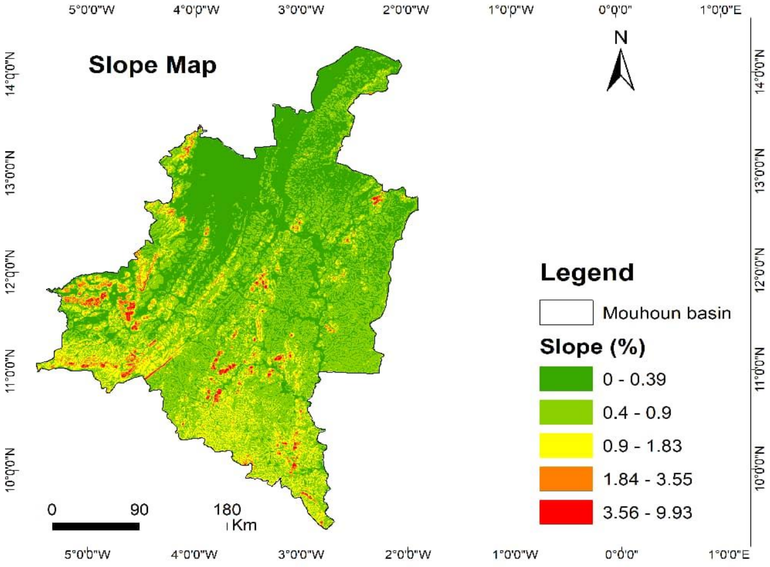


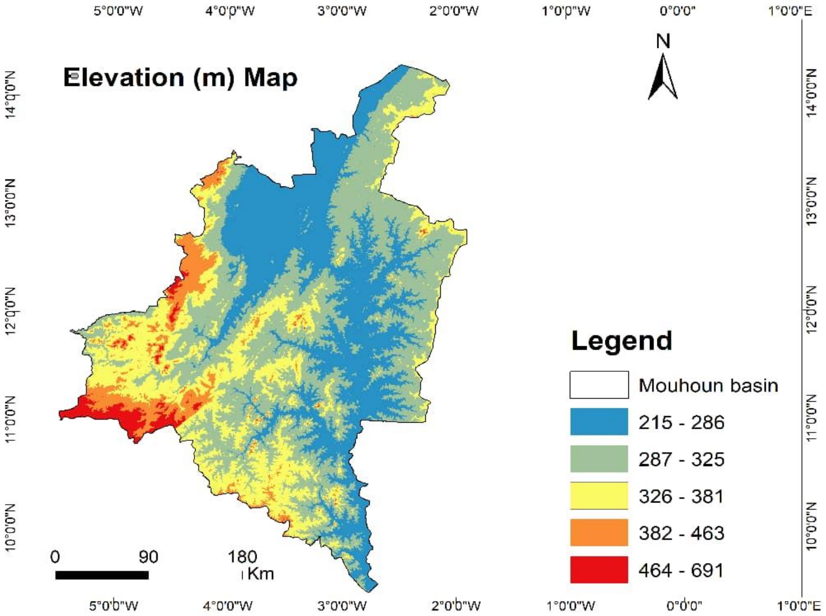


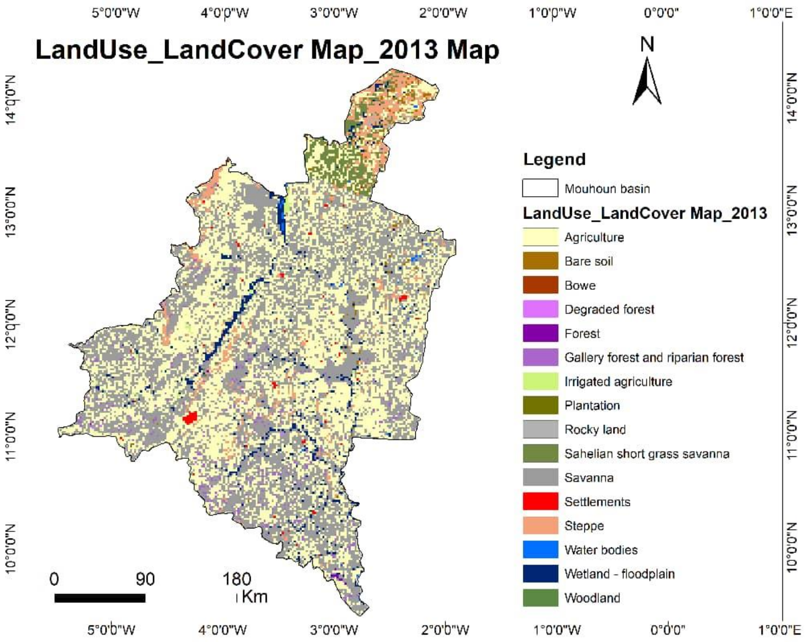


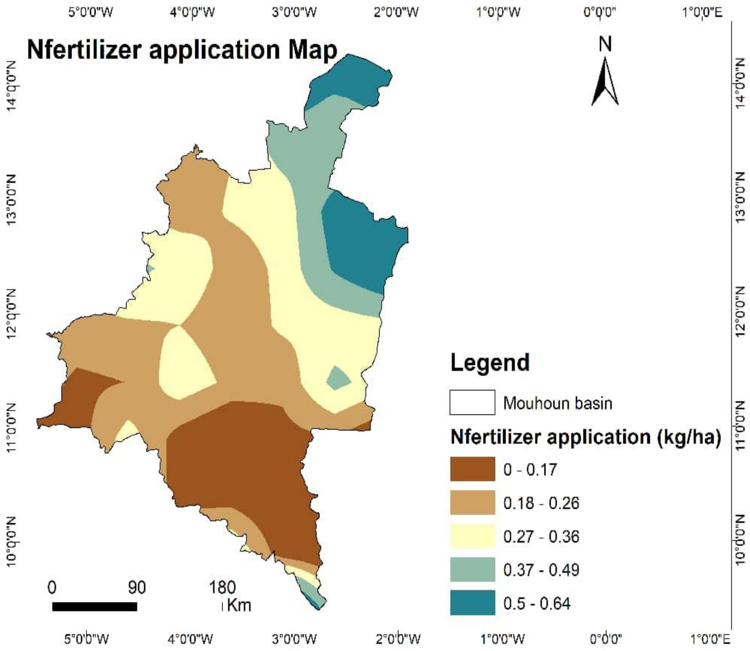
Data acquisition and processing: Explanatory variables (2/3)

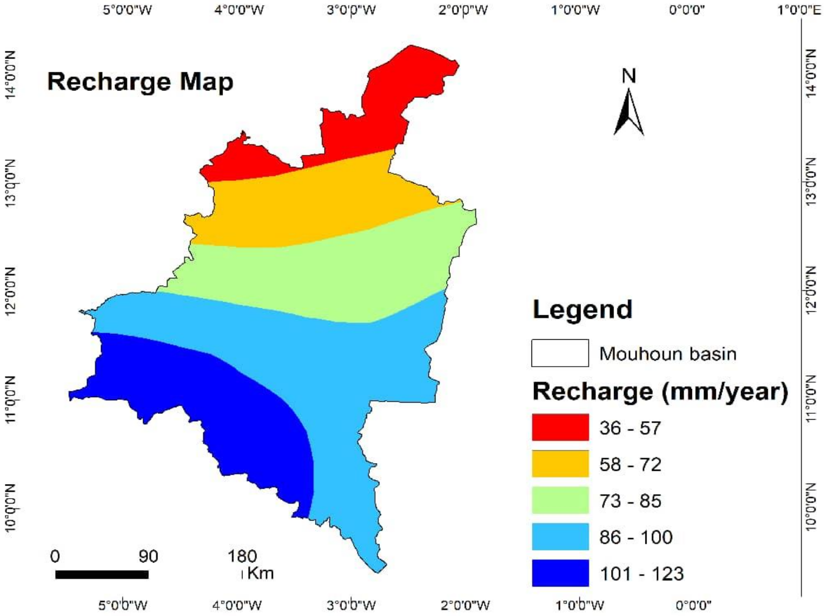




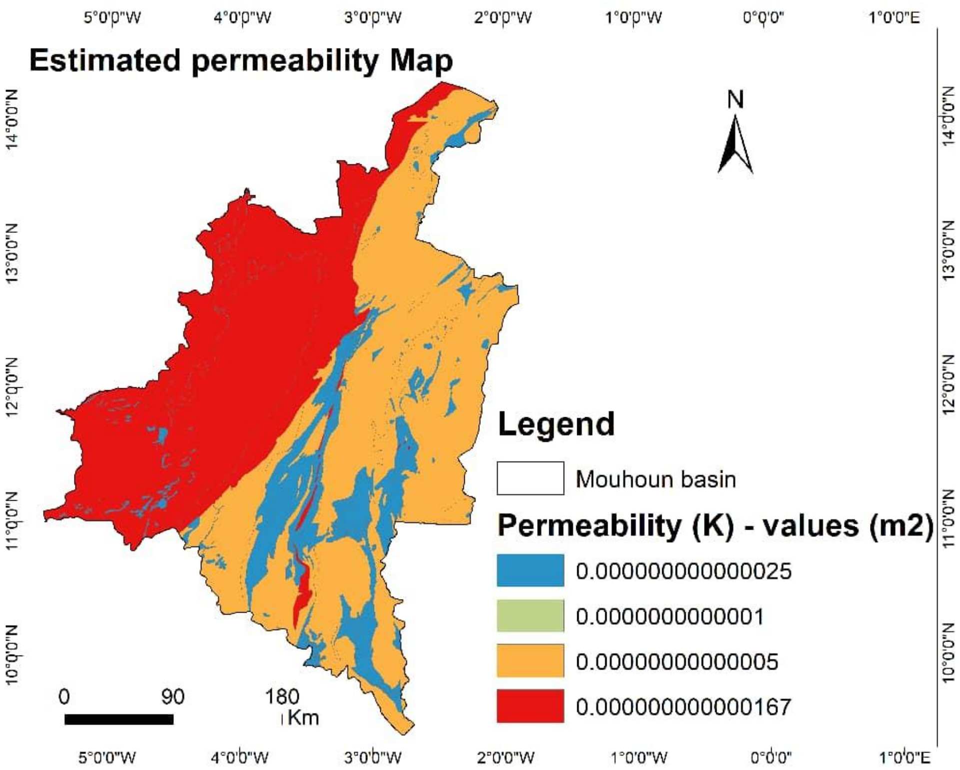








Data acquisition and processing: Explanatory variables (3/3)



Depth to groundwater Level !!!

Work is progress, despite some technical problems !!

Groundwater nitrate Vulnerability map obtained using Random Forest

2nd Case of study: Kou watershed for isotope and ECs analysis

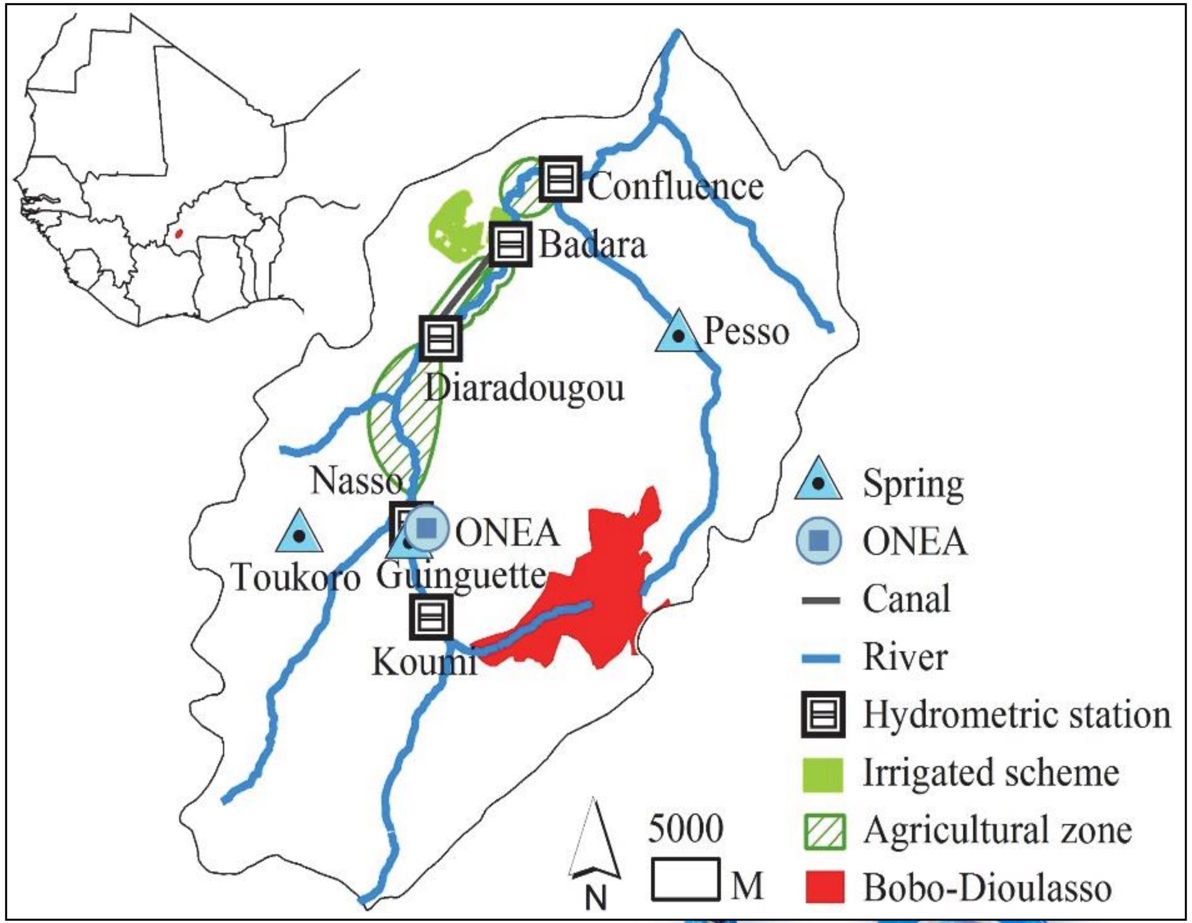
- Collaboration with General Directorate of Water Resources (Direction Générale des Ressources en Eau/Burkina Faso)

- Study area for **isotope sampling** and **emerging contaminants sampling**

The Kou watershed is one of several regional watersheds that make up the national Mouhoun river basin:

Kou surface area: **1800 km²**

CRP F32010



Sustainable surface water/groundwater management in Kou watershed located in National Mouhoun basin

Understanding of the nitrate contamination process

Identifiyng contamination sources

Outlook for Kou case of study: Methodology (1/2)

How ???:

- ✓ Sampling and Emerging Contaminants (ECs) and also meta-analysis;
- ✓ Physical and chemical analysis and isotope tracer analysis;
- ✓ Modelling isotope with non-linear Machine Learning algorithm.

Expected results:

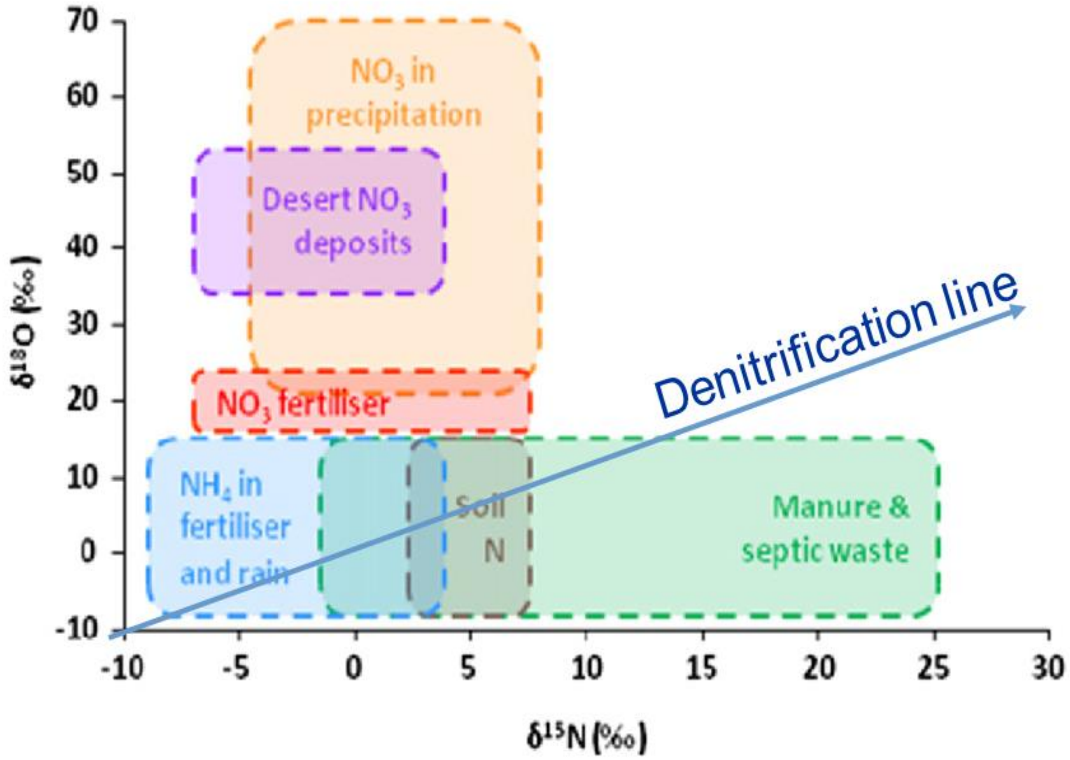
- ✓ Quantify the contribution of different anthropogenic activities on groundwater/surface water quality degradation in **Kou watershed;**
- ✓ Improve understanding of pollutants pathways, e.g. anthropogenic/natural recharge,

Outlook for Kou case study: Methodology of Data processing

- Sampling of representative nitrate pollution sources;
- Determination of physical-chemical parameters: in situ measurement of pH, electrical conductivity (EC), water temperature, dissolved O2, lab: major ions;
- Analysis for water isotopes (^{2}H and ^{18}O of H_2O) and nitrate isotopes (^{15}N and ^{18}O of NO3-) @ Lab. of Université de Corse Pascal Paoli/ France;

- Select water samples for CECs analysis !!!

Kendall and McDonnell (1997)



Kou case study: Monitoring Locations

- Sampling campaigns: 2022 - 2023: **Forty-eight (48)** groundwater and surface water sources has been sampled across Kou watershed for isotope and also, ECs are be planned to collect.

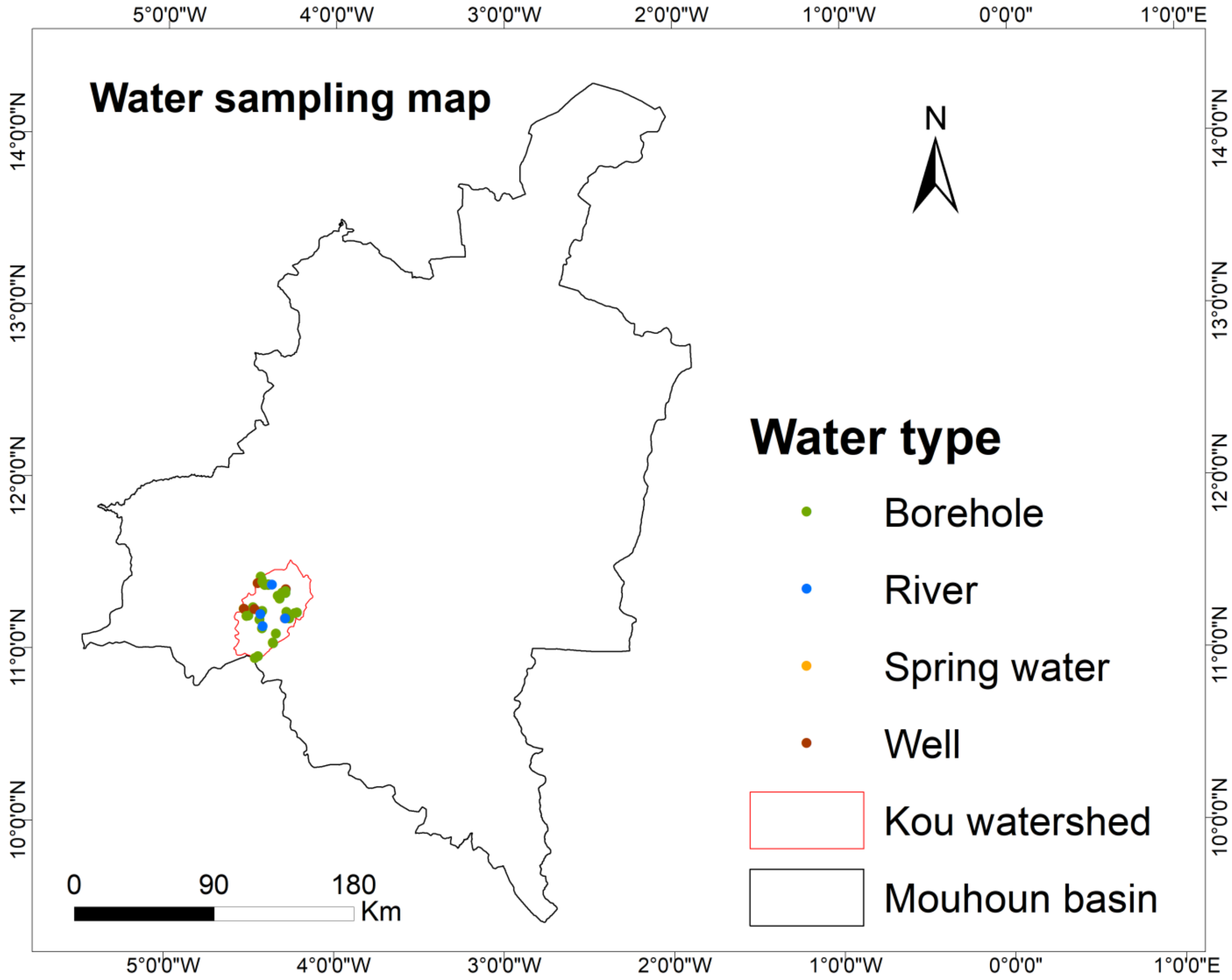
Project	Sample code	City	Latitude	Longitude	Water type	Groundwater type	pH	EC (uS/cm)
CRP F32010	GW01	BAMA	11.31138889	-4.335555556	Groundwater	Borehole	5.65	16.5
CRP F32010	GW02	BAMA	11.33	-4.310277778	Groundwater	Borehole	5.55	15.1
CRP F32010	GW03	BAMA	11.34944444	-4.288611111	Groundwater	Well	3.8	544
CRP F32010	GW04	BAMA	11.34861111	-4.287777778	Groundwater	Well	4.97	166.4
CRP F32010	GW05	BAMA	11.33944444	-4.289444444	Groundwater	Borehole	4.72	13.5
CRP F32010	GW06	BAMA	11.32833333	-4.290833333	Groundwater	Borehole	4.79	12.7
CRP F32010	GW07	BAMA	11.37472222	-4.391388889	Groundwater	Borehole	4.74	15.5
CRP F32010	GW08	BAMA	11.37722222	-4.390833333	Groundwater	Borehole	3.68	27.5
CRP F32010	GW09	BAMA	11.40666667	-4.430277778	Groundwater	Borehole	3.96	23.5
CRP F32010	GW10	BAMA	11.42194444	-4.436944444	Groundwater	Borehole	6.21	415
CRP F32010	GW13	SAMANDENI	11.38472222	-4.453888889	Groundwater	Well	4.78	126.9
CRP F32010	GW16	BAMA	11.39416667	-4.426388889	Groundwater	Borehole	7.28	454
CRP F32010	GW17	BAMA	11.38333333	-4.42	Groundwater	Borehole	6.62	89
CRP F32010	GW18	BAMA	11.37388889	-4.413055556	Groundwater	Borehole	6.21	95.1
CRP F32010	GW19	BAMA	11.3775	-4.416388889	Groundwater	Borehole	6.37	58.6
CRP F32010	GW21	BAMA	11.29527778	-4.324166667	Groundwater	Borehole	7.09	83.6

Google_Earth_Points

Kou river

Samendéni dam

Figure of water sample collection in Kou watershed

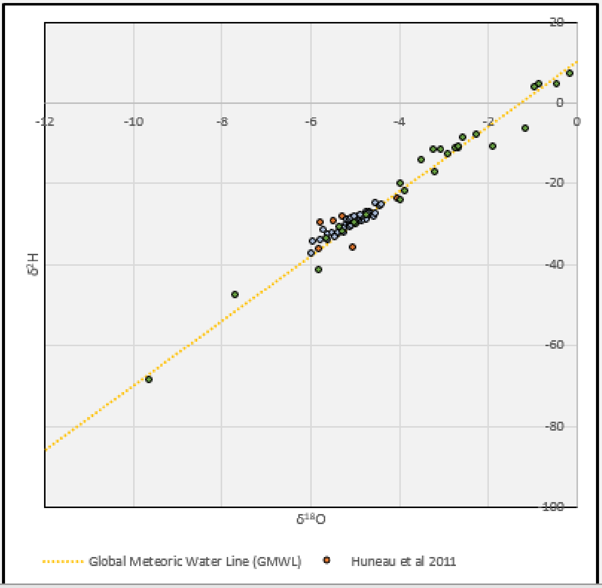


<u>48 samples</u>: groundwater & surface

Kou case study: First results of the isotope analysis

Burkina

Sample Name	Date	H2O [N/cm^3]	Processed Delta 2H	Processed Delta 2H StDev	Processed Delta 18O	Processed Delta 18O StDev	Averaged #	^{2}H excess (d)
GW01		2.82E+16	-29.794166	1.02E+00	-4.970263	8.97E-02	2	9.967938
GW02		2.80E+16	-27.706983	1.48E-02	-4.702281	3.31E-02	2	9.911265
GW03		2.81E+16	-25.059336	1.09E-01	-4.503912	1.97E-02	2	10.971960
GW04		2.90E+16	-32.627647	2.54E-01	-5.361166	1.02E-01	3	10.261681
GW05		2.76E+16	-27.155649	2.66E-01	-4.720684	2.31E-02	3	10.609823
GW06		2.77E+16	-28.261556	3.69E-01	-4.865647	5.74E-02	2	10.663620
GW07		2.76E+16	-28.051546	3.00E-01	-4.660873	1.44E-02	2	9.235438
GW08		2.87E+16	-28.954899	5.34E-01	-4.715945	5.05E-02	2	8.772661
GW09		2.79E+16	-27.233555	2.85E-01	-4.640385	8.33E-03	3	9.889525
GW10		2.78E+16	-28.153345	6.30E-02	-4.904339	1.87E-02	2	11.081367
GW13		2.79E+16	-34.629655	1.46E-02	-5.939738	4.80E-02	2	12.888249
GW16		2.77E+16	-30.464751	2.29E-01	-5.203445	2.66E-02	2	11.162809
GW17		2.75E+16	-29.609616	1.10E+00	-4.833731	1.14E-01	3	9.060232
GW18		2.74E+16	-25.920716	1.02E-01	-4.411488	3.61E-02	2	9.371188
GW19		2.74E+16	-32.635571	1.28E-01	-5.42269	2.55E-02	2	10.745949
GW21		2.74E+16	-32.782857	3.17E-01	-5.607333	5.92E-02	2	12.075807
GW22		2.74E+16	-32.243424	2.12E-01	-5.481893	3.96E-02	3	11.611720
GW23		2.73E+16	-29.031053	2.27E-01	-5.069256	2.60E-02	3	11.522995



Opportunities and Limitations by using Machine Learning tools in hydrology (1/2)

Machine learning can help to protect groundwater quality: Improving modelling and analysis.

It can learn complex patterns, taking into account any nonlinear complex relationship between the predictors and the dependent variables.

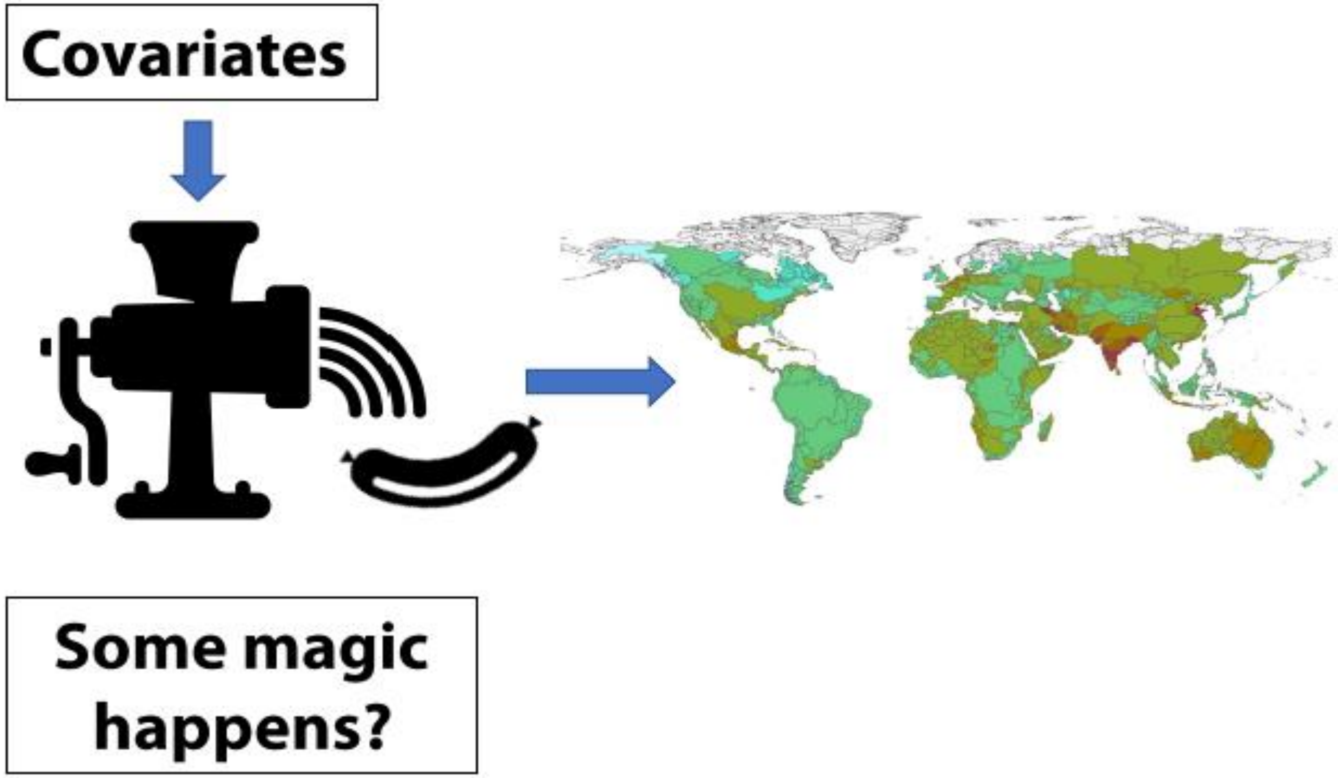
Which covariates are most important to predict observed N??

Interpretable ML to understand drivers and spatial patterns.

The Machine Learning paves the way for creating water quality maps at the Local/regional/continent scale by using isotopic data.

Opportunities and Limitations by using Machine Learning tools in hydrology (2/2)

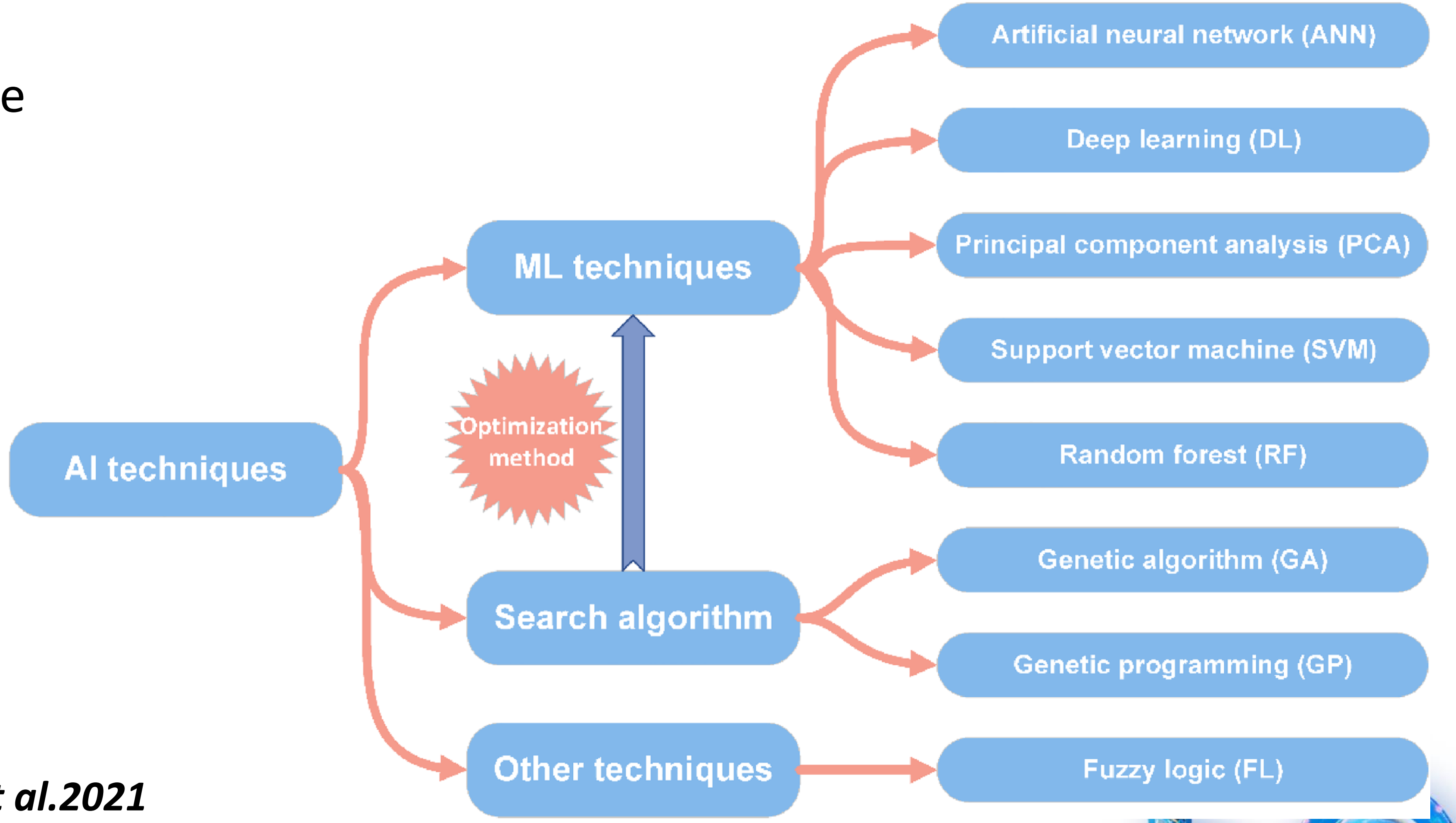
Disadvantage of Random Forests is that the tree structure is in an invisible "black box"/meat grinder.



Classification of AI and ML technologies used in Drinking Water Treatment (DWT)

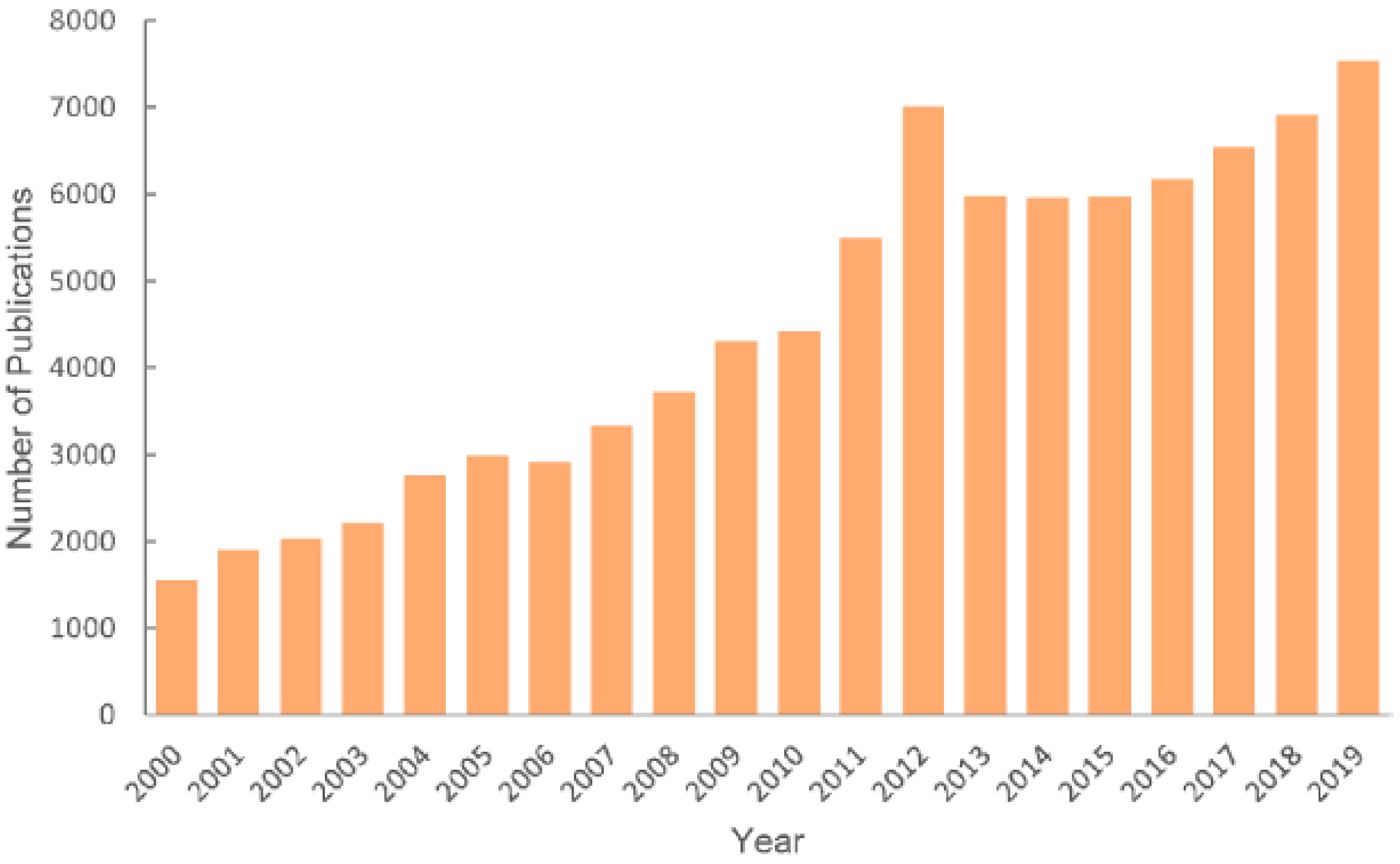
AI: Artificial Intelligence

ML: Machine Learning



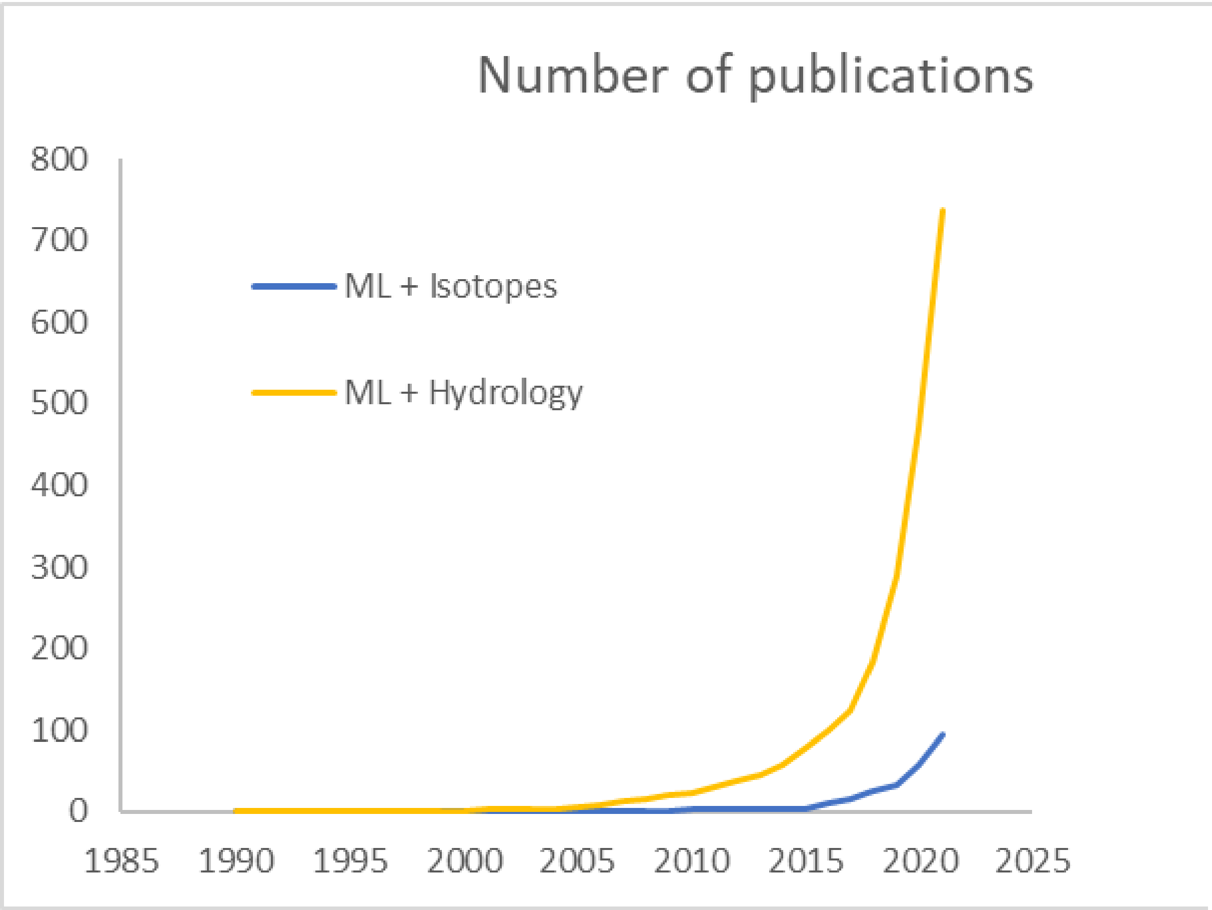
Source: Li et al.2021

The annual number of scientific publications on modelling of Drinking Water Treatment using AI, as obtained from the Google Scholar database.



Source: Li et al.2021

Number of publications in Web of Science on Machine Learning



Harjung et al.2022

Research Article

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Stable isotope and trace element analyses with non-linear machine-learning data analysis improved coffee origin classification and marker selection

Joy Sim,[a*] Cushla Mcgoverin,[b,c] Indrawati Oey,[a,d] Russell Frewe[e] and Biniam Kebede[a*]

Abstract

BACKGROUND: This study investigated the geographical origin classification of green coffee beans from continental to country and regional levels. An innovative approach combined stable isotope and trace element analyses with non-linear machine learning data analysis to improve coffee origin classification and marker selection. Specialty green coffee beans sourced from three continents, eight countries, and 22 regions were analyzed by measuring five isotope ratios ($\delta^{13}C$, $\delta^{15}N$, $\delta^{18}O$, $\delta^{2}H$, and $\delta^{34}S$) and 41 trace elements. Partial least squares discriminant analysis (PLS-DA) was applied to the integrated dataset for origin classification.

Thank you for your attention

Email: ouedraogo.issoufou03@gmail.com