Machine Learning techniques using multi-sensor data for groundwater potential estimation

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Outline

- ❑ Objective
- ❑ Groundwater Potential maps: Machine learning application
    - Study area
    - Explanatory variables : a focus on Remote Sensing Products
    - Borehole database
    - Performance evaluation
    - Groundwater Potential maps
- ❑ Main findings
- ❑ Conclusion

Objectives

ResEau PROJECT - Chad

- ❑ To improve the country's **resilience** to the effects of **climate change**
- ❑ To support the **water resources management** for planning the exploitation of the aquifers

WHAT'S THE GAP?

- ❑ Limited knowledge of **groundwater** and **surface resources**
- ❑ **High borehole failure rates**

HOW TO SOLVE IT?

- ❑ **Groundwater potential mapping (GPM)** and reliable predictions using Machine Learning (ML) techniques

Groundwater Potential Mapping (GPM) - 1/2

WHAT’S THE RESULT?

GPM as the **likelihood** of borehole success (finding water)

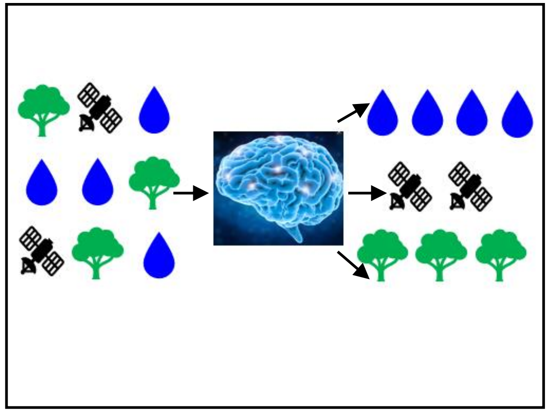
Groundwater Potential Mapping (GPM) - 2/2

Traditional GPM: based on expert judgement techniques

WHY MACHINE LEARNING?

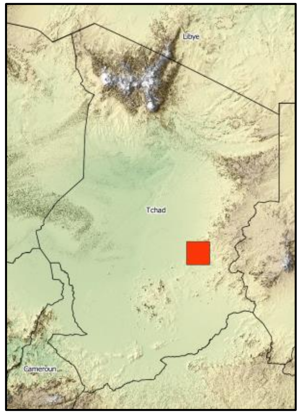
Machine Learning GPM:

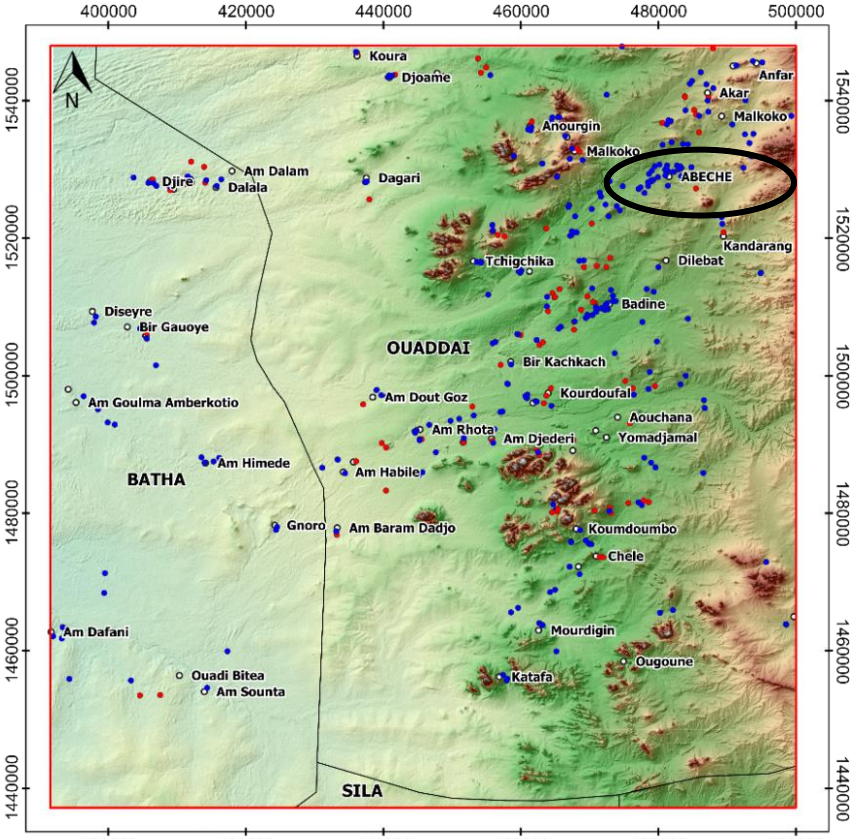
- To find **complex associations** between explanatory variables
- To use several **satellite - products** (first attempt)
- To show how **seasonal fluctuations** derived from **satellite-based products** can enhance map outcomes



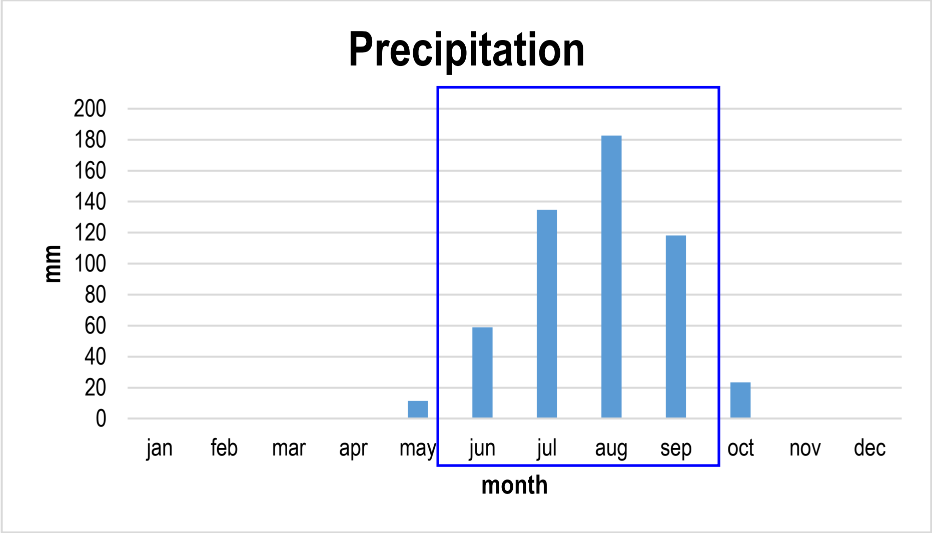
Collaboration with University of Madrid

Study area





Area = 12000 km^2	Water points	Elevation [m a.s.l.]
Geological setting: Crystalline rocks and unconsolidated sediments	● Water	850
Seasonal river network	● No Water	400



Satellite imagery
Multiple sensors and **multitemporal analysis**

Fieldwork: hydrogeological/geological data collection

Generation of GPM

Explanatory variables :
a focus on Remote Sensing Products

- Martinez-Santos (2019) collected the **most frequent** explanatory variables in literature for GPM
- Presence or absence of groundwater can be **inferred from surface features**
- This study adds **several satellite-products**

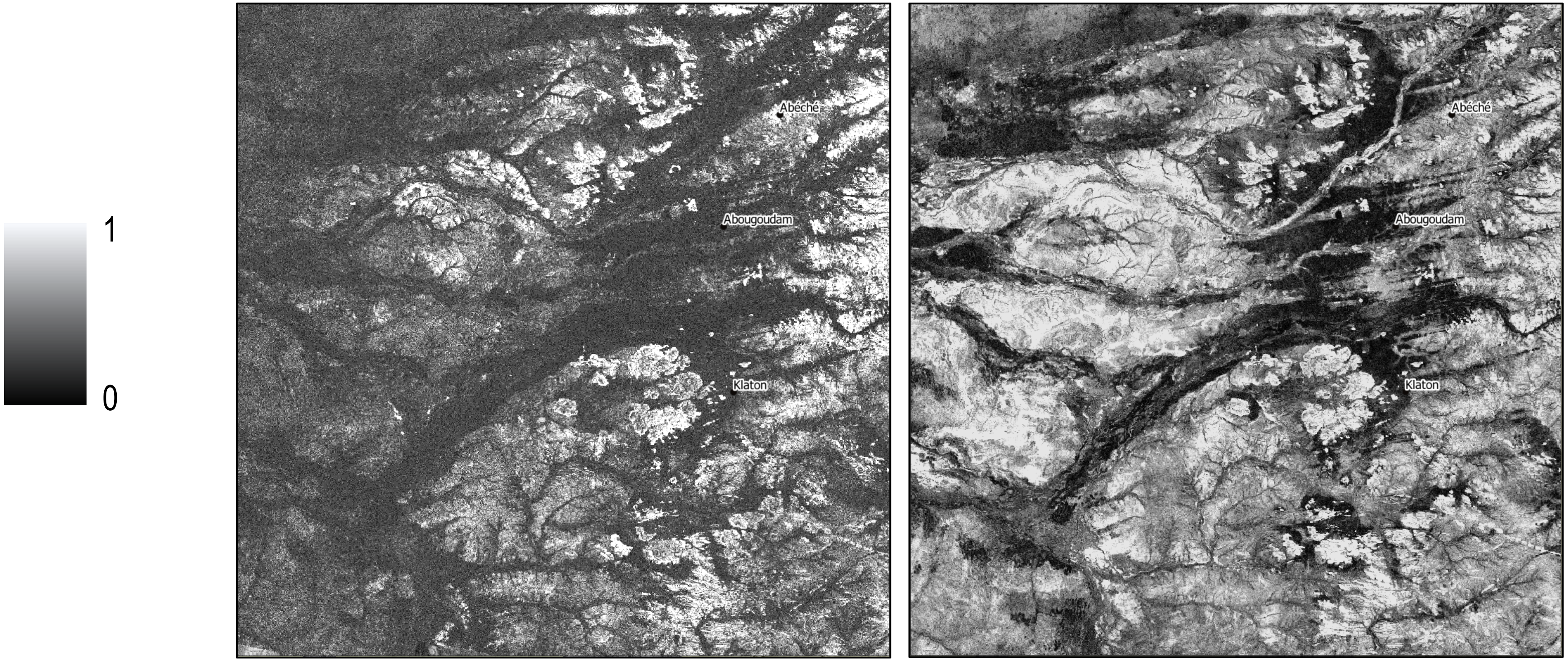
Seasonal and static products

Name/shorthand	Description	Source	
COH Dry min	Minimum value of coherence dry season	Sentinel-1	Seasonal variation
COH Wet min	Minimum value of coherence wet season		
Min COH difference	Difference between COH Dry min and COH Wet min		
VV Dry mean	Mean value of VV intensity dry season		
VV Wet mean	Mean value of VV intensity wet season		
Mean VV difference	Difference between VV Dry mean and VV Wet mean		
NDVI Dry	NDVI at end of the dry season	Sentinel-2	
NDVI Wet	NDVI at end of the wet season		
NDVI max	Maximum value of NDVI wet season		
Land cover dry	Land cover (end of the dry season)	Sentinel-1/-2 Landsat-8	
Land cover wet	Land cover (end of the wet season)		
Precipitation	Cumulated Precipitation wet season 2017 and 2018	MSG	
Evapotranspiration	Cumulated Evapotranspiration wet season 2017 and 2018		
Lithology	Geological domains per rock type	Landsat-8	

Name/shorthand	Description	Source	
Drainage density	Length of channels per unit area	AW3D-WorldDEM	Topographic control of surface run off and infiltration
Distance permanent channels	Distance to channels classified as permanent due to permanent seasonal regime		
1000 Fault	Fault density with a 1000 m radius		
2000 Fault	Fault density with a 2000 m radius		
Fracture density 100 m	Fracture density with a 100 m radius		
Fracture density 250 m	Fracture density with a 250 m radius		
Fracture density 50 m	Fracture density with a 50 m radius		
Distance ephemeral channels	Distance to channels classified as ephemeral due to their seasonal regime		
Geomorphology	Landform		
Stream Power Index	Describe potential flow erosion at the given point of the topographic surface		
Elevation	Topographic elevation		
Aspect	Direction of the slope		
Slope	Slope		
Topographic wetness index	Steady state wetness index. Quantifies topographic control on surface hydrology.		
Saturated thickness	Difference between hydraulic heads and basement depth	Field data	Subsoil Info 3D
Hydraulic head	Interpolated hydraulic heads from field measurements (January-February 2020)		
Basement Depth	Interpolation of the geophysics and borehole data	Field data	

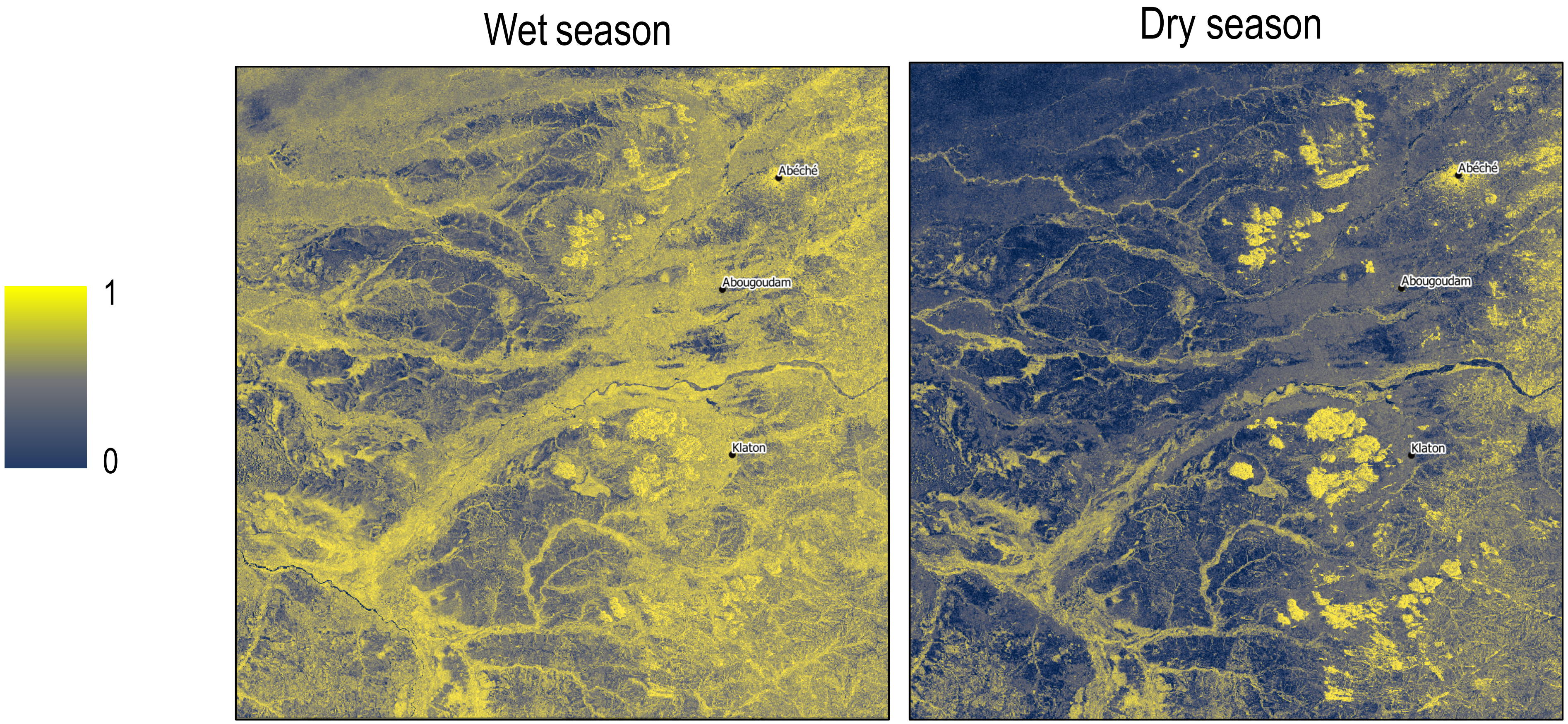
Seasonal variation: Coherence

Wet season | Dry season

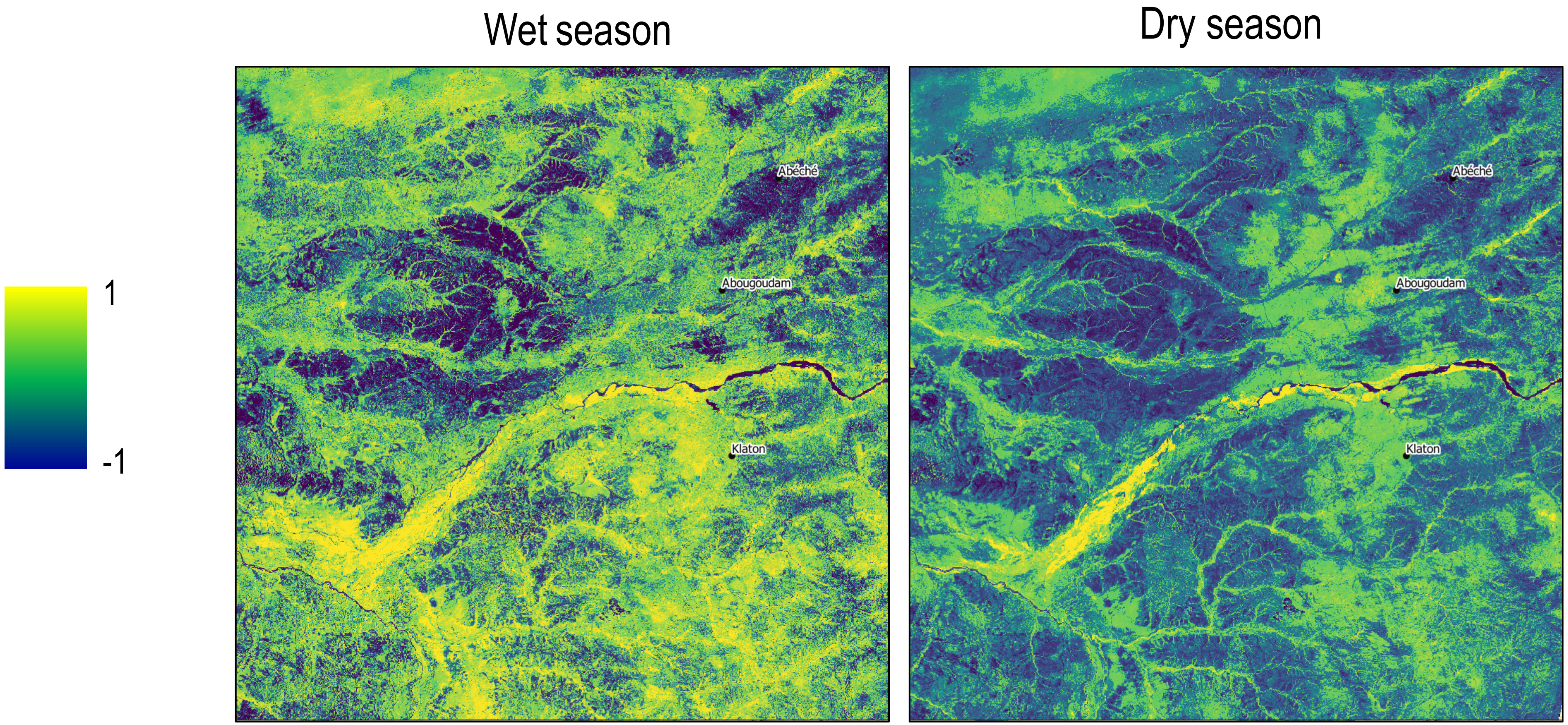


Minimum Coherence value

Seasonal variation: Intensity



Seasonal variation: NDVI



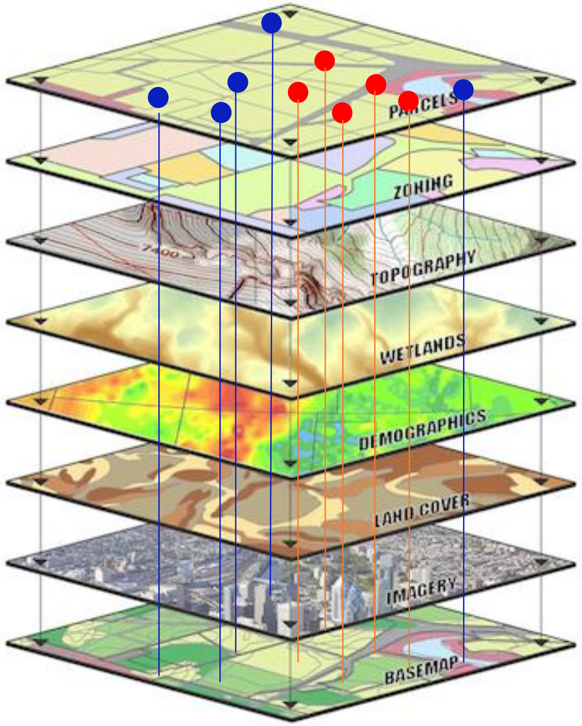
Borehole database

Positive

enough water to supply a manual hand pump on a permanent basis

Negative

failed to find groundwater drilling (additional points on outcrops)



488 boreholes/wells
74.7% positive
25.3% negative

train (70%) and **test** (30%)

MACHINE LEARNING

MLMapper 2.0 code*

Tests on several classifiers

SELECTED

Random Forest (RFC)
Extra-tree classifiers (ETC)

**SciKit-Learn 0.24.1 toolbox*

Performance evaluation

NO strong direct **correlations** among explanatory variables (collinearity >0.60) were observed (Dormann et al. 2013)

METRICS

- AUC score= 0.87- 0.90
- Test score= 0.84
- Balanced score= 0.83-0.84

The algorithms are able to distinguish POSITIVE and NEGATIVE classes

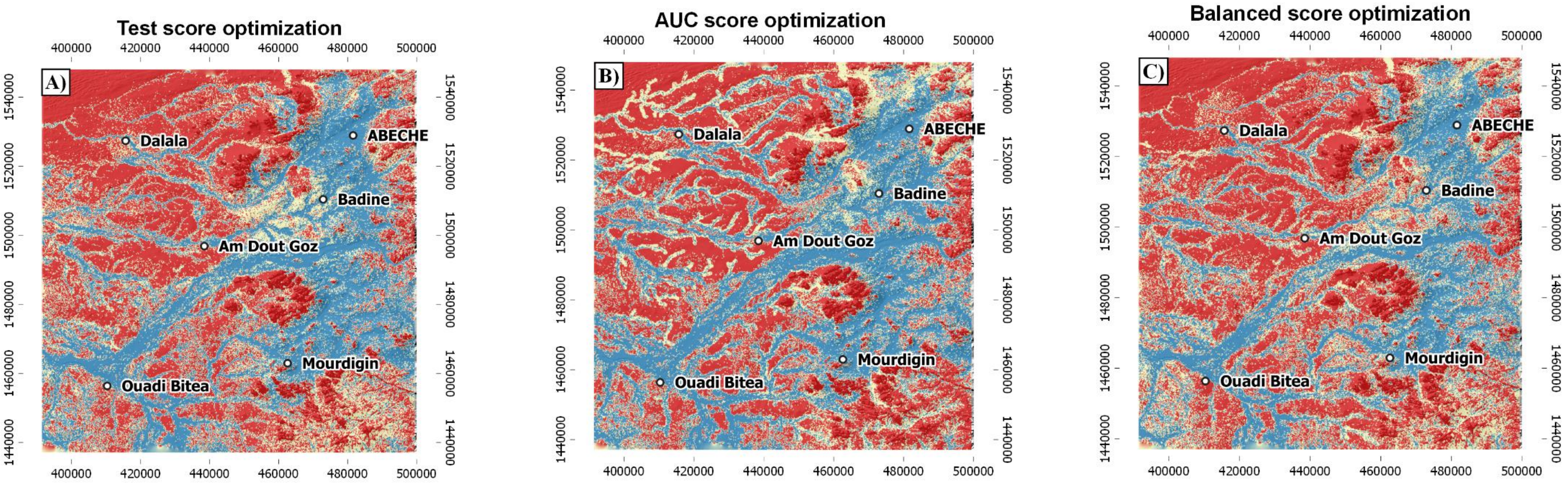
HOW MANY VARIABLE AND **WHICH VARIABLES** ARE IMPORTANT?

11 explanatory variables were found to be important in all cases

- Aspect
- Basement Depth
- **Coherence Dry**
- Evapotranspiration
- Fracture Density 250 m
- Hydraulic Heads
- Lithology
- **NDVI Dry**
- Slope
- Topographic Wetness Index
- **Intensity VV Dry**

Highest probability to predict the groundwater occurrence

Groundwater Potential maps



Agreement map (Groundwater potential)

both algorithms agreed on a negative groundwater potential (0).	Low Potential
disagreement between RFC and ETC outcomes	Medium Potential
both algorithms agreed on a positive groundwater potential	High Potential

Main findings: Seasonal variables

In the **DRY season:**

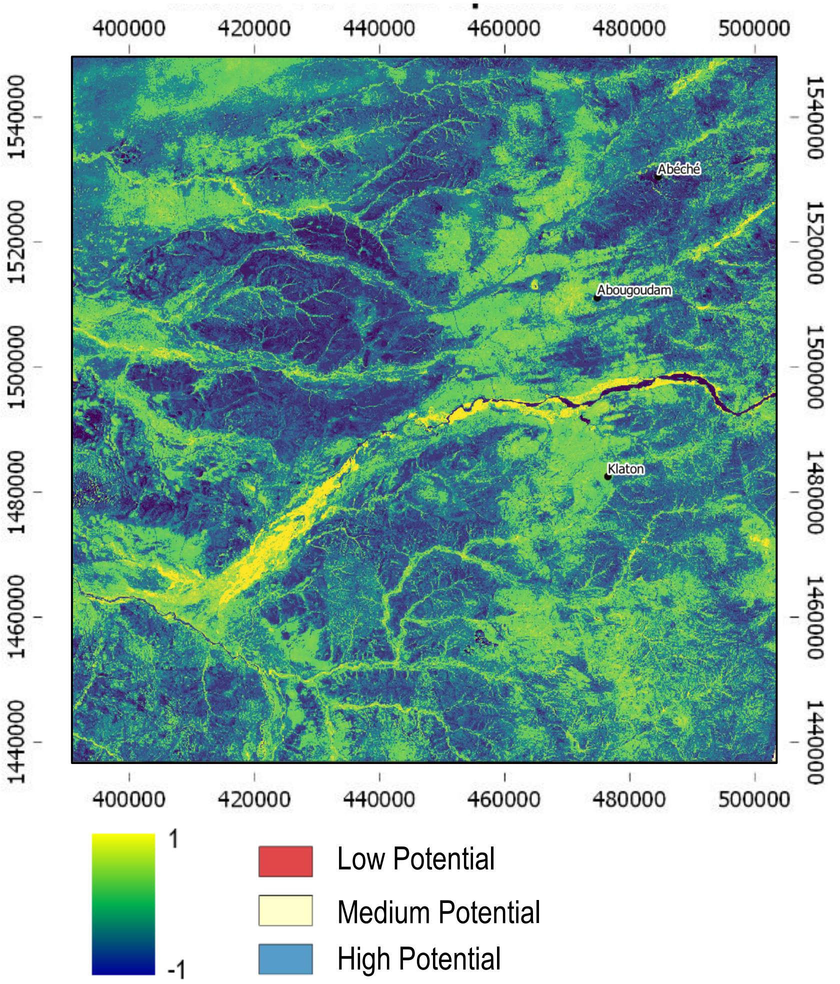
- ❑ products are particularly **significant**
- ❑ **vigorous vegetation** may reflect the
  - permanent surface water
  - irrigation
  - shallow water table

→ **POSITIVE GWP**

In the **WET season:**

- ❑ Higher **infiltration** occurs for areas with
  - Higher Topographic Wetness Index values
  - Lower slope values

NDVI



Main findings: Hydrogeological context

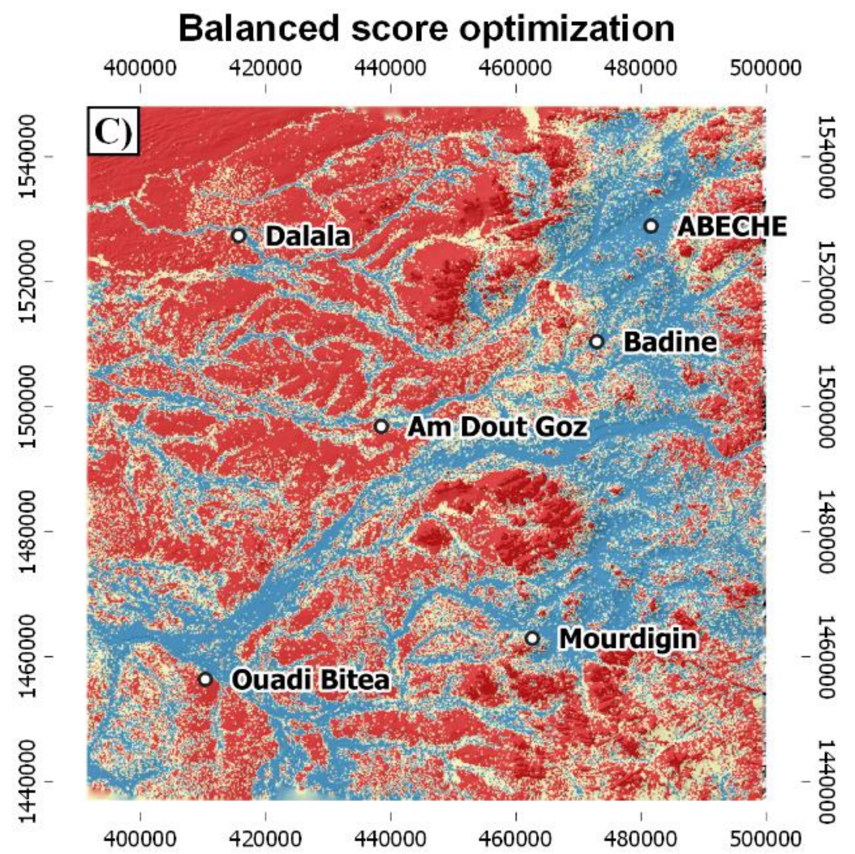
Groundwater Potential maps

High Potential

- ❑ Valleys carved out by **ephemeral streams** (porous conditions)
  → **Wadis** and **piedmonts** as the most productive areas
- ❑ High basement depth (crystalline material): **thick weathered zone**
- ❑ **Abéché**: combination of the wadis and a thicker zone of weathered crystalline basement rocks

Low Potential

- ❑ **basement outcrops** in the east
- ❑ the ***biseau sec*** in the west



LIMITATIONS

- Extensive fieldwork is required
- Low number of wells with flow rate
- Negative borehole have numerous reason

- Machine Learning: **big** data method
- Comparison with expert-based knowledge is missing

Conclusion

- Groundwater is a **crucial resource** in arid regions
- Groundwater potential mapping is an excellent tool for **large-scale groundwater exploration**
- **Satellite-based products** allow to analyze **large** and **remote unsurveyed areas**
- **Seasonal satellite-based products** allow to improve static information
- **Valleys**, **piedmonts** and thick **weathered zone** are the most productive

Reference

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Geocarto International

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Delineation of groundwater potential zones by means of ensemble tree supervised classification methods in the Eastern Lake Chad basin

Gómez-Escalonilla Víctor, Vogt Marie-Louise, Destro Elisa, Isseini Moussa, Origgi Giaime, Djoret Daira, Martínez-Santos Pedro & Holecz Francesco

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