الجمهورية الجزائرية الديمقراطية الشعبية

People's Democratic Republic of Algeria

Ministry of High Education and Scientific Research

Ibn khaldoun university Tiaret

Nature and life sciences Faculty

End of studies dissertation

In view of obtaining the Master's degree

Field: nutrition and agro-food technology

Speciality: Precision Agriculture

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Theme

Crop Soil Mapping Using Machine Learning In Tiaret Region

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College Year : 2022/2023

Acknowledgments

First and foremost, we thank "ALLAH," the Almighty, for granting us faith, courage, and guiding us in the completion of this work.

We express our gratitude to our parents, brothers, sisters, friends, and companions who have supported us morally, spiritually, and materially, and have assisted, advised, and encouraged us, their support is deeply appreciated.

We express our deep appreciation to our supervisor, Mr. Bouacha Mohamed Islam and Mr. Omar Safa, doctors and professors at the Faculty of Natural and Life Sciences, Ibn Khaldoun University of Tiaret, who have accompanied us throughout this academic journey for their guidance, valuable advice, as well as their encouragement and trust.

Dedication

We dedicate this humble work as a proof of respect, gratitude, and appreciation to:

Our dear parents,Who have patience with us, guided us on our ways, Who have never ceased to encourage and advise us. They have been of great help throughout our journey, thanks to their love, dedication, understanding, and unwavering support. We can never truly express how we feel towards them, both in terms of their moral and material support.

Our brothers and sisters, For their indulgence towards us, their support and care, we express the deepest affection we feel towards them.

Our friends and colleagues, For their companionship and the good times we have shared together, it was a fun and memorable experience in life.

Table Of Contents

Acknowledgments
Dedication
Abstract
List Of Figures
List Of Tables
List Of Abbreviations

Introduction……………………………………………………………………………… 01

Chapter I: Cereal Crops In Algeria

I.1 General Context ………………………………………………………………… 05
I.2 Current state of cereal production in Algeria………………………………………… 06
I.3 Challenges Facing Cereal Production In Algeria…………………………………… 08
I.3.1 Water Scarcity……………………………………………………………………… 08
I.3.2 Climate Change…………………………………………………………………… 09
I.3.3 Soil Degradation…………………………………………………………………… 10
I.3.4 Inadequate Agricultural Policies…………………………………………………… 10
I.3.5 Limited Infrastructure……………………………………………………………… 10
I.4 Improving Cereal Production In Algeria……………………………………………… 10
I.4.1 Expansion Of Agricultural Research And Development…………………………… 10
I.4.2 Sustainable And New Farming Practices…………………………………………… 11
I.4.3 Developing The Value Chain For Cereal Crops…………………………………… 11
I.5 The Saharan Agriculture In Algeria………………………………………………… 11
I.5.1 Cereals Production In Sahara……………………………………………………… 12

Chapter II Agriculture Soils In Algeria

II.1 Soil Classes In Algeria……………………………………………………………… 15
II.2 Soil Types In Algeria ……………………………………………………………… 17
II.2.1 The Northern Tell Atlas Zone……………………………………………………. 17
II.2.2 The High Plateaus Zone…………………………………………………………. 17
II.2.3 The Saharan Atlas Zone…………………………………………………………… 17
II.2.4 The Saharan Zone ……………………………………………………………….. 18
II.3 Cereal Soils In Algeria……………………………………………………………….. 18
II.4 Soil Quality…………………………………………………………………………… 19
II.5 The Main Cereals Soils Characteristics………………………………………………. 19
II.5.1 Organic Matter……………………………………………………………………… 19
II.5.3 Soil Texture………………………………………………………………………… 20
II.5.4 PH……………………………………………………………………………………… 20
II.5.5 Water Holding Capacity…………………………………………………………… 20
II.5.6 CaCO3 (Calcium carbonate)………………………………………………………… 20

II.5.7 Nutrient Availability …………………………………………………………………20
II.5.8 Salinity………………………………………………………………………………. 21
II.5.9 Cation Exchange Capacity (CEC)……………………………………………………21
II.6 Soil Fertility…………………………………………………………………………….21
II.6.1 Types Of Fertilisers And Their Impacts On Soil Fertility ………………………….. 22
II.7 Soil Variability In Cereal Crop Fields………………………………………….…..….23
II.8 Factors That Affect Soil Variability………………………………………………….. 23
II.8.1 Parent Material……………………………………………………………………….24
II.8.2 Topography ………………………………………………………………………….. 24
II.8.3 Vegetation…………………………………………………………………………… 24
II.8.4 Land use ……………………………………………………………………….   24
II.8.5 Climate……………………………………………………………………………..   25

Chapter III: Digital Soil Mapping

III.1 Into Digital Soil Mapping………………………………………………………… 30
III.1.1 Montpelier workshop……………………………………………………………….. 31
III.1.2 USDA and DSM…………………………………………………………………….32
III.2 Soil Mapping Concepts and Principles………………………………………………..33
III.2.1 Sampling ……………………………………………………………………………33
III.2.2 Spatial variability……………………………………………………………………33
III.2.3 Data Sources……………………………………………………………………….. 34
III.2.4 Data processing and analysis methods………………………………………………35
III.3 Spatial Data Analysis Techniques…………………………………………………… 36
III.3.1 Geostatistics…………………………………………………………………………36
III.3.2 Remote Sensing……………………………………………………………………. 36
III.3.3 Machine Learning………………………………………………………………….. 37
III.3.4 Soil Properties Prediction Methods………………………………………………… 37
III.5 Future Directions and Challenges…………………………………………..…………38
III.6 Soil mapping in Algeria……………………………………………………………… 39

Chapter IV: Study Area

IV.1 Situation……………………………………………………………………………. 42
IV.2 Landscape………………………………………………………………………….. 43
IV.3 Water Sources……………………………………………………………………… 45
IV.4 Soils……………………………………………………………………………….. 46
IV.5 Climate…………………………………………………………………………….. 48

Chapter V: Methodology

Objective……………………………………………………………………………… 51
V.1 Data collection………………………………………………………………………..51
V.1.1 Sampling……………………………………………………………………………51
V.1.2 Soil Laboratory Analysis……………………………………………………..….54
V.1.2.1 Physico-Chemical Analysis…………………………………………………………54

V.1.2.2 Laboratory Data Processing ………………………………………………………….. 59
V.1.3 Geoprocessing Tools and Data……………………………………………………….. 59
V.1.3.1 Sentinel-2………………………………………………………………………… 59
V.1.3.2 Google Earth Engine (GEE)……………………………………………………… 60
V.1.3.3. Google Colaboratory…………………………………………………………. 62
V.1.3.4. QGIS (Quantum Geographic Information System).. 63
V.2 Model Building……………………………………………………………………. 63
V.2.1 Import Libraries……………………………………………………………………. 63
V.2.2 Data upload and Identification……………………………………………………. 63
V2.3 Correlation matrix………………………………………………………………….. 63
V.2.4 Multi linear regression (MLR)…………………………………………………… 63
V.2.5 Intercept and Model Coefficient……………………... 64
V.2.6 Model Training……………………………………………...................................... 64
V.2.7 Prediction………………………………………………………………………… 64

Chapter VI: Results and discussion

VI.1 Laboratory Test Results…………………………………………………………….68
VI.2 Data Collection Maps…………………………………………………………… .68
VI.3 Correlation.………………………………………………………………………..70
VI.4 Model Evaluation………………………………………………………………… 71
VI.4.1 Intercept and Coefficients……………………………………………………… 71
VI.4.2 Linear Assumption………………………………………………………………72
V.2.8 R squared (R2)…………………………………………………………………72
VI.3 NPK Maps…………………………………………………………………. …..73

Chapter VII: Conclusion

Conclusion………………………………………………………………………………78

Reference List

List Of Figures

Figure 01: Production/Yield quantities of Cereals n.e.c. in World (1994 - 2021)............... 05
Figure 02: Cereal production in Algeria from 1961 to 2021…………………………… 06
Figure 03: Crop production in Algeria 2021 (Webmaster 1)... 07
Figure 04: Algeria cereals cultivation area……………………………………………… 06
Figure 05: Map of the climatic zones of Algeria………………………………………… 09
Figure 06: El Menia, Algeria farms sample (Webmaster 2).. 12
Figure 07: J.H.Durand Soils Of Algeria 1936 From Fao Database……………………… 15
Figure 08: Parent material and mineral resources of Algeria (Webmaster 3).................... 26
Figure 09: Algeria Vegetation Land Cover map………………………………………….. 27
Figure 10: Major biogeographical and bioclimatic regions of Algeria…………………… 28
Figure 11: The general framework of digital soil mapping……………………………… 31
Figure 12: Tiaret Province Location……………………………………………………… 43
Figure 13: Tiaret Province Altimetry………………………………………………………44
Figure 14: Tiaret Land-Cover…………………………………………………………… 45
Figure 15: Tiaret water sources map……………………………………………………… 46
Figure 16: Tiaret Lithology map………………………………………………………….. 47
Figure 17: Ombrothermic Chart of Tiaret (2022)... 48
Figure 18: Climate chart of Tiaret………………………………………………………… 49
Figure 19: photos from the sampling sites…………………………………………………52
Figure 20: Samples Location in the study area…………………………………………… 53
Figure 21: Soil moisture by drying technique (B.omar)..54
Figure 22: NPK Measurements (B.omar)... 55
Figure 23: PH measurement (B.omar)... 56
Figure 24: Organic carbon/matter analysis (B.omar)... 57
Figure 25: EC measurement (B.omar)... 57
Figure 26: TL measurement using the Bernard-calcimeter (B.omar)................................ 58
Figure 27: Active-limestone titration (B.omar)..59
Figure 28: GEE code Snippets…………………………………………………………… 61
Figure 29: Google Collaboratory Welcome page………………………………………… 62
Figure 30: model initiative code…………………………………………………………... 65
Figure 31: GEE data collections calculated maps for Tiaret……………………………… 69
Figure 32: correlation matrix of the variables…….. 71
Figure 33: Linear assumption of the model……………………………………………….. 72
Figure 34: Nitrogen (N) IDW interpolated char…………………………………………... 74
Figure 35: Phosphorus (P) IDW interpolated chart……………………………………….. 75
Figure 36: Potassium (K) IDW interpolated chart………………………………………… 76

List of Tables

Table 1: Predictions for a digital map of the world on the basis of current rate of progress …39
Table 2: Laboratory Test Descriptive statistics ……………………….……………………68
Table 3: NPK Model interception and coefficients …………………………..………………71
Table 4: R^2 of the model ………………………………………………………………..….73

List Of Abbreviations

ANN: Artificial Neural Network

ASGA: Algerian Geological Services Agency

BI: Brightness Index

BRT: Boosted Regression Tree

CSV: Comma Separated Values

DA: Discriminant Analysis

DTM: Decision Tree Modeling

DSM: Digital Soil Mapping

ESA: European Space Agency

FAO: Food and Agriculture Organization

GBM: Gradient Boosting Machine

GEE: Google Earth Engine

GIS: Geographic Information System

GLM: Generalised Linear Model

H%: Soil Humidity

IDW: Inverse Distance Weighted

IK: Indicator Kriging

K: Potassium

k-NN: k-Nearest Neighbors

MLP: Multi-Layer Perceptron

MLR: Multi Linear Regression

N: Nitrogen

NB: Naive Bayes

NDMI: Normalised Difference Moisture Index

NDVI: Normalised Difference Vegetation Index

NRCS: Natural Resources Conservation Service

NPK: Nitrogen Phosphorus Potassium

PCA: Principal Component Analysis

P: Phosphorus

QGIS: Quantum Geographic Information System

RF: Random Forest

SVM: Support Vector Machine

SQ: Soil Quality

USDA: United States Department of Agriculture

WSS: Web Soil Survey

X: Independent Variable

Y: Dependent Variables

Abstract

Soil is a main key for land use management, in agriculture soil management is an important factor that determines production, it is fundamental to know the soil quality in order to advance in any agricultural practice. Soil properties are affected by land use practices and climatic factors. In order to collect and determine the right soil data a soil mapping is unavoidable, however, there are many mapping techniques that aren't always accurate or representable of the instantaneous situation.

Digital soil mapping is a suitable approach as a decision support, based on weighted factors to approach the real soil properties using different geostatistics, remote sensing, machine learning models and other digital tools to estimate the unavailable data.

In this study we perform a Multi linear regression model in python based on 113 sampling points where we predict the (N P K) values based on the laboratory analysis data, we used 5 covariates in the model NDVI, NDMI, BI, Slope and Texture, the predicted values where near to the real NPK values with an R-square at approximately 0.2.

Keywords: Digital soil mapping, machine learning, MLR, NPK, soil properties prediction, Tiaret

ملخص

التربة هي المفتاح الرئيسي لإدارة استخدام الأراضي، في الزراعة إدارة التربة عامل مهم يحدد الإنتاجية، ومن الأساسي معرفة جودة التربة من أجل التقدم في أي ممارسة زراعية. تتأثر خصائص التربة بممارسات استخدام الأراضي وعوامل المناخ. في جمع وتحديد البيانات الصحيحة للتربة رسم خرائط التربة لا مفر منه، ومع ذلك هناك العديد من تقنيات التوثيق التي لا تكون دقيقة أو تمثل الوضع الحالي دائمًا.

استخدام الخرائط الرقمية للتربة هو اختيار مناسب لدعم اتخاذ القرارات، بناءً على عوامل مرجحة لاستعراض الخصائص الفعلية للتربة باستخدام إحصاءات مكانية مختلفة، واستشعار عن بُعد، ونماذج التعلم الآلي وغيرها من الأدوات الرقمية لتقدير البيانات الغير متاحة.

في هذه الدراسة، أجرينا نموذج الانحدار الخطي المتعدد في لغة Python استنادًا إلى 113 نقطة عينة حيث نتوقع قيم (N P K) بناءً على بيانات تحليل المختبر، استخدمنا 5 متغيرات في النموذج (NDVI, NDMI, BI, Slope, Texture) وكانت القيم الناتجة قريبة من القيم الأصلية مع معامل R-square بحوالي 0.2.

كلمات مفتاحية:

خرائط التربية الرقمية, تعلم الآلة, NPK, MLR, توقع خصائص التربة, تيارت

INTRODUCTION

The world population is increasing dramatically which has affected several domains in between food production, among the solutions for food supplies is agricultural intensification, however its practices are not sustainable that leads to environmental problems such as soil degradation (FAO 2015). In fact soil degradation is a limiting factor to food production, in Africa cereal losses are estimated at about 280 million tons yearly from 105 million hectares which can be avoided by managing soil erosion (ELD Initiative & UNEP, 2015).

Farmers all over the world are looking for high quality yields with high economic returns, they gained field experience through years of practice but they lack the scientific knowledge of mechanisms behind it to interact and make better decisions. In addition crops are affected by growth conditions such as nutrients and water deficiency, soil compaction, weather etc…, many limiting factors are directly or indirectly related to soil, here comes precision agriculture as a leading science in food production by achieving high yields with low resources consumption while preserving the environment. One of the main objectives of precision agriculture is soil quality assessment, using satellite technology and data science (Boca & al. 2015).

Arid and semi arid regions of the north african region are among the very poorly covered regions with quality soil data, unfortunately they are the most affected with land degradation and land management issues (Pereira & al. 2017).

In a global scope researchers worked on soil quality assessment using digital soil mapping, Behrens & al. (2018) introduced a new method using mixed scales of terrain features with deep learning, resulting in improved performance. Meier & al. (2018) tested machine learning algorithms for soil mapping in a mountainous tropical region in Brazil using morphometric maps and climatic maps. Zhang & al. (2020) tested a 3D regression kriging method using laboratory analysis and a cubist spectral model to predict soil properties at different depths in a specific field. Zare & al. (2021) studied the performance of an ECe soil sensor for mapping soil salinity in Iran and found that regression co-kriging was the best method. Zhou & al. (2021) studied the performance of different satellite sensors and machine learning techniques for predicting soil organic carbon and carbon-to-nitrogen ratio in Switzerland, finding that remote sensing variables were the best predictors. Kebonye & al. (2022) demonstrated a new methodology in digital soil mapping visualisation, emphasising the association between mapped soil variables and pH as a soil quality indicator.

The main objective of our study is to create a crop soil map of the Tiaret region using the most adapted and advanced machine learning techniques and remote sensing data where we use soil samples from chosen regions to estimate the soil quality.
In this document we discuss the methodology of creating an agriculture soils properties map of the Tiaret region using artificial intelligence, we introduce cereal crops in Algeria in a general perspective, their soils and the current situation of agriculture, afterwards we identify the study area and methodology used to conduct the research, we finish by demonstrating the results of this research and the conclusion.

CHAPTER I
Cereal Crops In Algeria

I.1 General Context

Cereal farming plays a crucial role in the economic development of areas, production, and yields in Algeria. According to the Food and Agriculture Organization (FAO) in 2020, the state of cereal crops has a significant impact on the economy. Global grain markets are expected to experience record production in the 2020-21 season, although stocks are projected to increase only slightly. The FAO's forecast for world grain trade in 2021-2022 indicates that trade levels are at an all-time high, representing a 0.8% increase from the previous year (FAO 2021).

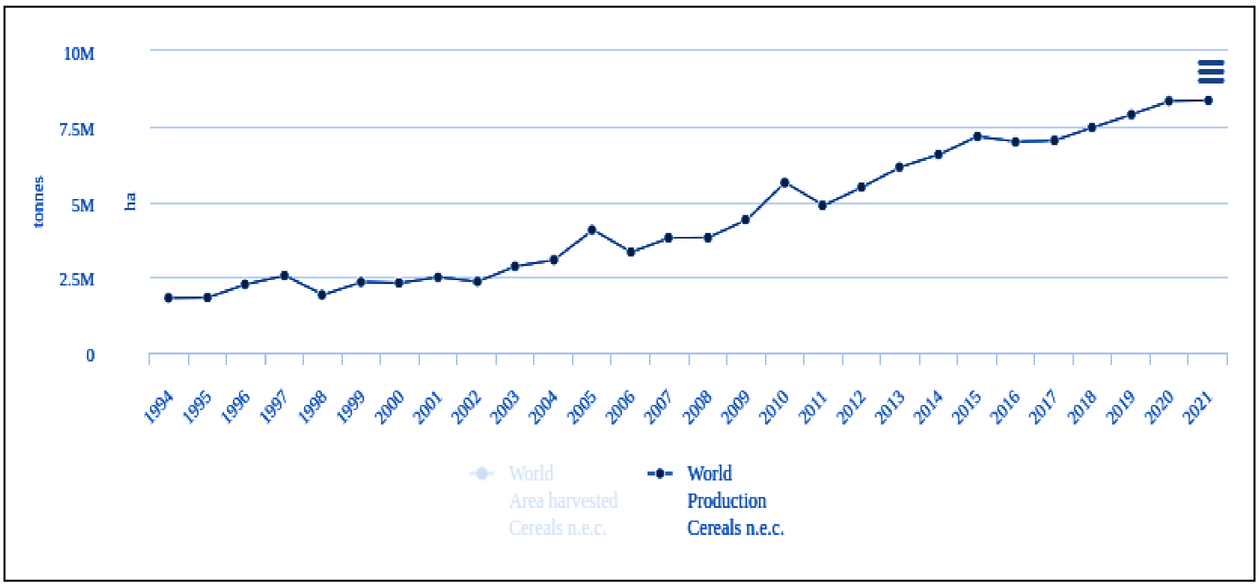

Figure 01: Production/Yield quantities of Cereals n.e.c. in World (1994 - 2021)

In 2021, global cereal production is expected to increase by 1.1%, reaching 2800 million tonnes, despite drought conditions (FAO 2021). In Algeria, cereals are essential, and their consumption is rising due to population growth. Unfortunately, most cereals are imported, and the gap between supply and demand is growing. This means that Algeria is heavily dependent on foreign countries for its food, particularly cereals, which is worrying for the cereal industry. The country's specific climate, rainfall deficits, and land supply make things even more complicated. However, according to a model developed for the grain sector in Algeria, there is still hope to improve the performance of the cereal industry (Chaban & Boussard. 2012). The results of the model suggest that Algeria has the potential to develop its own cereal crops and reduce its reliance on imports.In conclusion, although Algeria faces significant challenges in its cereal industry, it is possible to improve the situation. By developing its own cereal crops, Algeria can reduce its dependence on foreign imports and ensure that its growing population has access to the vital resources it needs.

I.2 Current state of cereal production in Algeria

Cereals are essential in Algeria, especially wheat forming the basis of the country's food consumption including bread, pasta, couscous, and patties. Unfortunately, Algeria heavily relies on importing cereals, and in 2020, the country produced only 5.6 million tonnes, which is below the record level achieved in 2019 by about 8 percent. Compared to other countries, this is considered low, and Algeria's import requirement for mostly common wheat is about 7.9 million tonnes annually, representing about 70 percent of its domestic usage (FAOSTAT 2021).

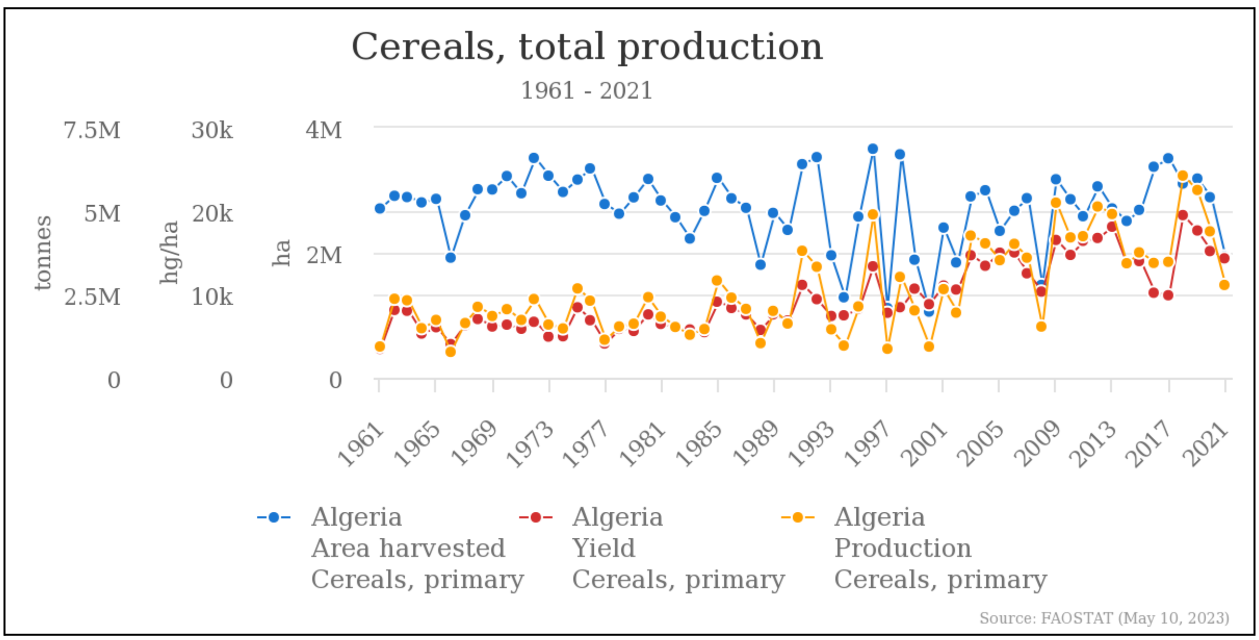

Figure 02: Cereal production in Algeria from 1961 to 2021

After Potatoes, cereals play a crucial role in crop production in Algeria, covering a significant portion of agricultural land use at almost 80%, it's cultivated on almost all farms, figure (3) shows the 2021 Algeria crop production. The national cereal area in Algeria spans over

43,968,653 hectares, with over two-thirds of the area located within the country. Barley, durum, and soft wheat are the most widely cultivated cereals, accounting for 97.60% of the total area, followed by oats at 2%, and other cereals like sorghum, triticale, and maize at 0.4% (MADR 2019). Virtually all highland regions in semi-arid and sub-humid areas, the Great Inland Coastal, and Sub-Coastal Plains are used for cereal production (Figure 04).

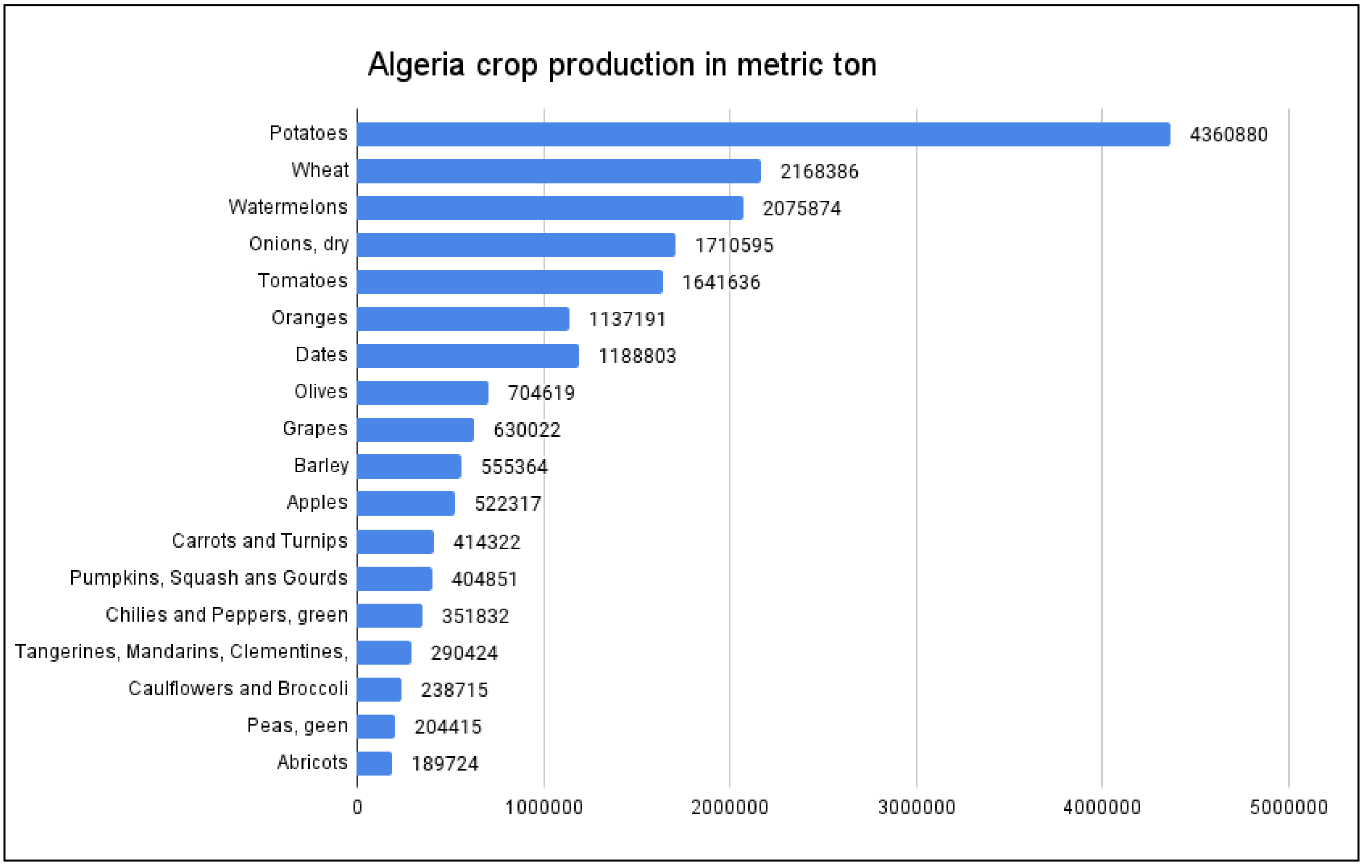

Figure 03: Crop production in Algeria 2021 (Webmaster 1)

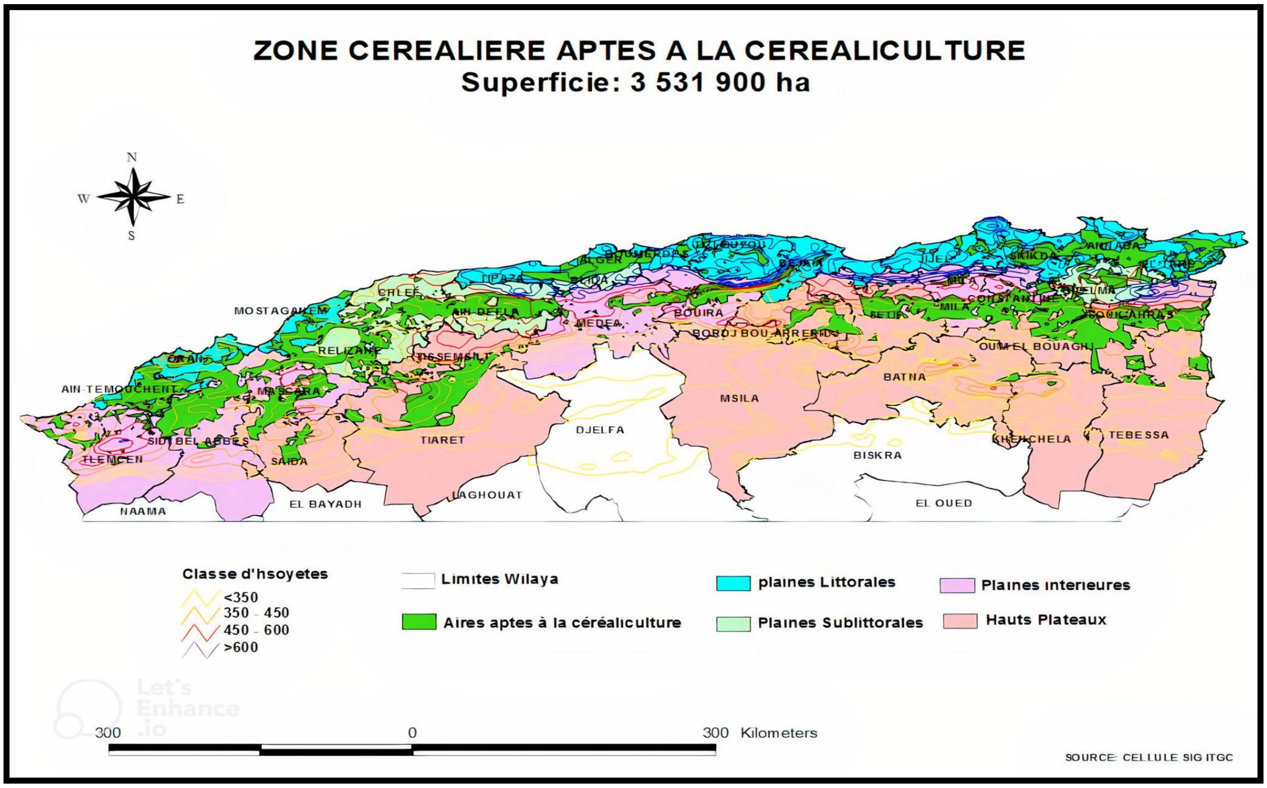

Figure 04: Algeria cereals cultivation area

I.3 Challenges Facing Cereal Production In Algeria

Algeria has a useful agricultural area of 8.5 million ha, but with a lot of low quality soils and sloping surface, The main constraint in the Algerian agriculture lies in water resources and their randomness, especially since the volume of losses due to leakage from the distribution network amounts to 30% (Omari and al, 2012), and other challenges including, climate change, soil degradation, and inadequate agricultural policies.

I.3.1 Water Scarcity

Algeria is a semi-arid country with limited water resources, and water scarcity is becoming increasingly severe due to climate change and population growth. According to a study by

(Touitou & al. 2018) water scarcity is a major constraint on cereal production in Algeria, and there is a need for better water management practices to increase water use efficiency and reduce water waste.

I.3.2 Climate Change

Algeria is experiencing the adverse effects of climate change, including drought, heatwaves, and floods, which are affecting cereal production. According to (Gaaloul & al. 2020) climate change is projected to reduce cereal yields in Algeria by up to 30% by 2050. Additionally, the study found that climate change will result in an increase in pests and diseases which will further reduce cereal production.

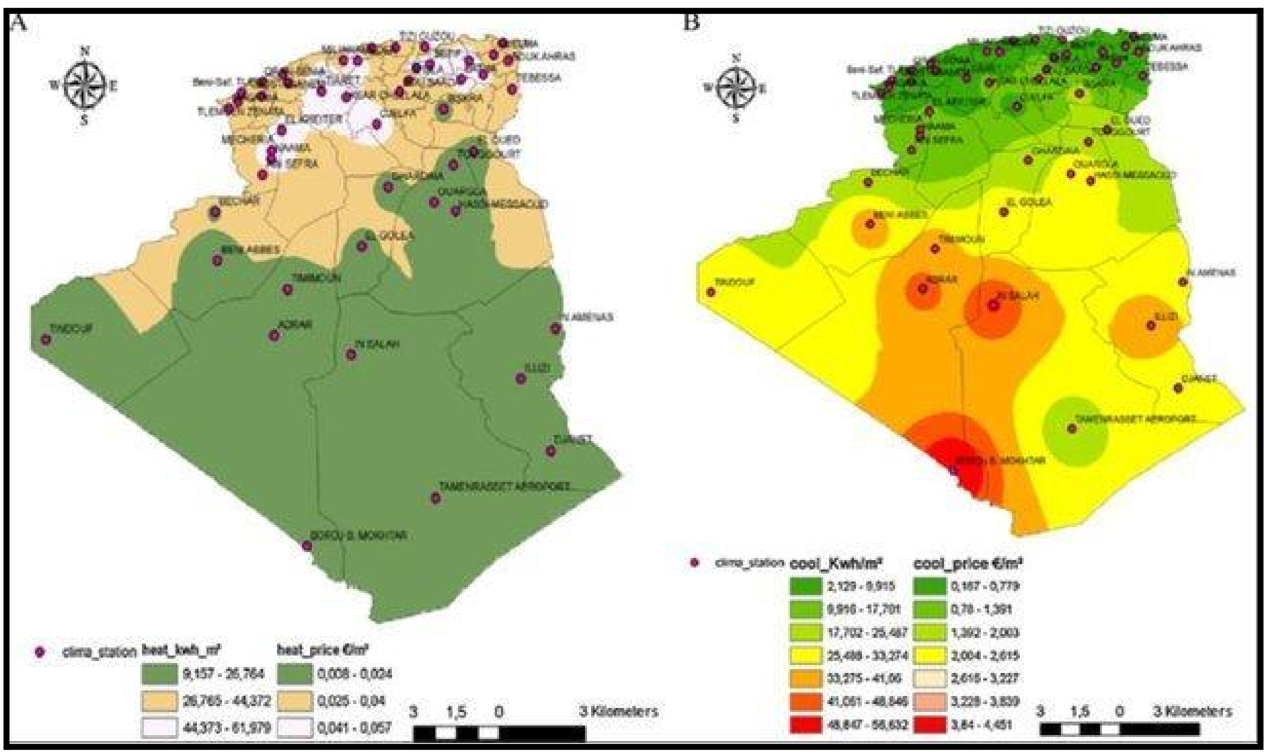

Figure 05: Map of the climatic zones of Algeria(Mezouari & al. 2020)

I.3.3 Soil Degradation

The overuse of fertilisers and pesticides as well as poor farming practices has led to soil degradation and a decline in soil fertility. This resulted in a reduction in cereal yields and increased production costs, according to Gomiero (2019) there is a need for sustainable farming practices to improve soil health and increase cereal yields.

I.3.4 Inadequate Agricultural Policies

The Algerian government's agricultural policies have been criticised for being inadequate and not providing enough support to cereal farmers. According to the FAO (2018) report, there is a need for the Algerian government to develop more supportive policies for cereal production, including providing better access to credit, improving infrastructure, and increasing investment in research and development, and also implementing new aspects and supplying farmers with new technologies.

I.3.5 Limited Infrastructure

Algeria's agricultural infrastructure, including irrigation systems, storage facilities, and transportation networks, is often inadequate or outdated. This limits the productivity and profitability of cereal production (MADR 2019).

I.4 Improving Cereal Production In Algeria

Improving cereal farming in Algeria requires a multifaceted approach that addresses the various challenges facing the agricultural sector.

I.4.1 Expansion Of Agricultural Research And Development

Investing in agricultural research and development could help to develop new varieties of cereal crops that are better adapted to the Algerian climate and soil conditions. According to a report by the National Agricultural Research Systems (Zebakh & al. 2022) there is a need for increased investment in agricultural research and development in Algeria. They suggest that collaboration between universities, research institutions, and farmers could help to develop new cereal varieties that are better adapted to local conditions.

I.4.2 Sustainable And New Farming Practices

Promoting sustainable farming practices such as precision agriculture practices that have a specialised equipment, software, and IT services. The approach incorporates getting to continuous information about the conditions of the crops, soil and ambient air, alongside other significant data, for example, hyper-local weather predictions, labour costs and equipment availability. Predictive analytics software utilises the information to furnish farmers with guidance and directions about crop rotation, optimal planting times, harvesting times and soil management (Annie B. 2010).

I.4.3 Developing The Value Chain For Cereal Crops

Including improving marketing channels and supporting agribusinesses, can help to create more opportunities for farmers and increase the profitability of cereal farming in Algeria(FAO 2018).

I.5 The Saharan Agriculture In Algeria

Saharan agriculture in Algeria refers to agricultural activities carried out in the vast desert regions of the country, including the Sahara Desert. It is an important sector for the economy of the country and plays a crucial role in the livelihoods of the local population.

Despite the harsh climatic conditions and limited availability of water, Saharan agriculture in Algeria has been developing over the years, thanks to the introduction of modern irrigation techniques, the use of drought-resistant crops, and the establishment of specialised research and development institutions.

The main crops cultivated in the region include date palms, olives, almonds, figs, and citrus fruits and in the last few years cereals (Hadied & al. 2012). Figure (5) a satellite image of a part from El-Menia Algeria that shows a few farms in the desert.

Figure 6: El Menia, Algeria farms sample (Webmaster 2)

I.5.1 Cereals Production In Sahara

Algerian Sahara is an arid region, but it has significant potential for cereal production.

From an economic aspect, cereal production in Algerian Sahara can have a positive impact on the local economy as it can create job opportunities and contribute to the growth of the agricultural sector. In a recent analysis, it was determined that Africa could produce two to three times more cereals and grains, which would add 20 percent to the continent's current output of cereals and grains (FAO 2021).

From an ecological aspect, cereal production can have both positive and negative impacts. On the positive side, cereal crops can help prevent soil erosion and improve soil fertility. Additionally, the use of drought-resistant varieties and efficient irrigation systems can help conserve water resources. On the negative side, if not managed properly, cereal production can lead to soil degradation, loss of biodiversity, and depletion of water resources. Studies have been conducted to evaluate the agronomic performance of cereal crops in the region. One such study evaluated the growth development, grain yield, and grain quality characteristics of seven cereal crops in the region and found that some varieties performed better than others (Koull & al, 2022).

Overall, cereals are an important agricultural product in Algeria, providing food for both humans and animals, and contributing significantly to the country's economy. Algeria does not have the physical opportunities and weather conditions to support food demand in cereals even with an important progress in the agricultural sector. The country will stay structurally in deficit for a long time for cereals. It is nevertheless possible to improve the current performance of the sector by working on soil management and get to know more about the fertility and implement technologies in the agricultural sector (Chaban & al. 2012).

CHAPTER II

Agriculture Soil In Algeria

Soils are a vital natural resource that plays a critical role in sustaining agricultural production and ensuring food security. For a long time farmers in Algeria have been dealing with soils, soil has been especially related to its fertility, irrigation and drainage, liming of acid soils and extension of agriculture to new lands . J.H. Durand made important research work on the soils of Algeria and their classification. Durand recognised the great importance of red soils and classified them separately, He also established a map of Algerian soils at the scale 1:500,000 and a map of red soils and crusts (Benchetrit M. 1956).

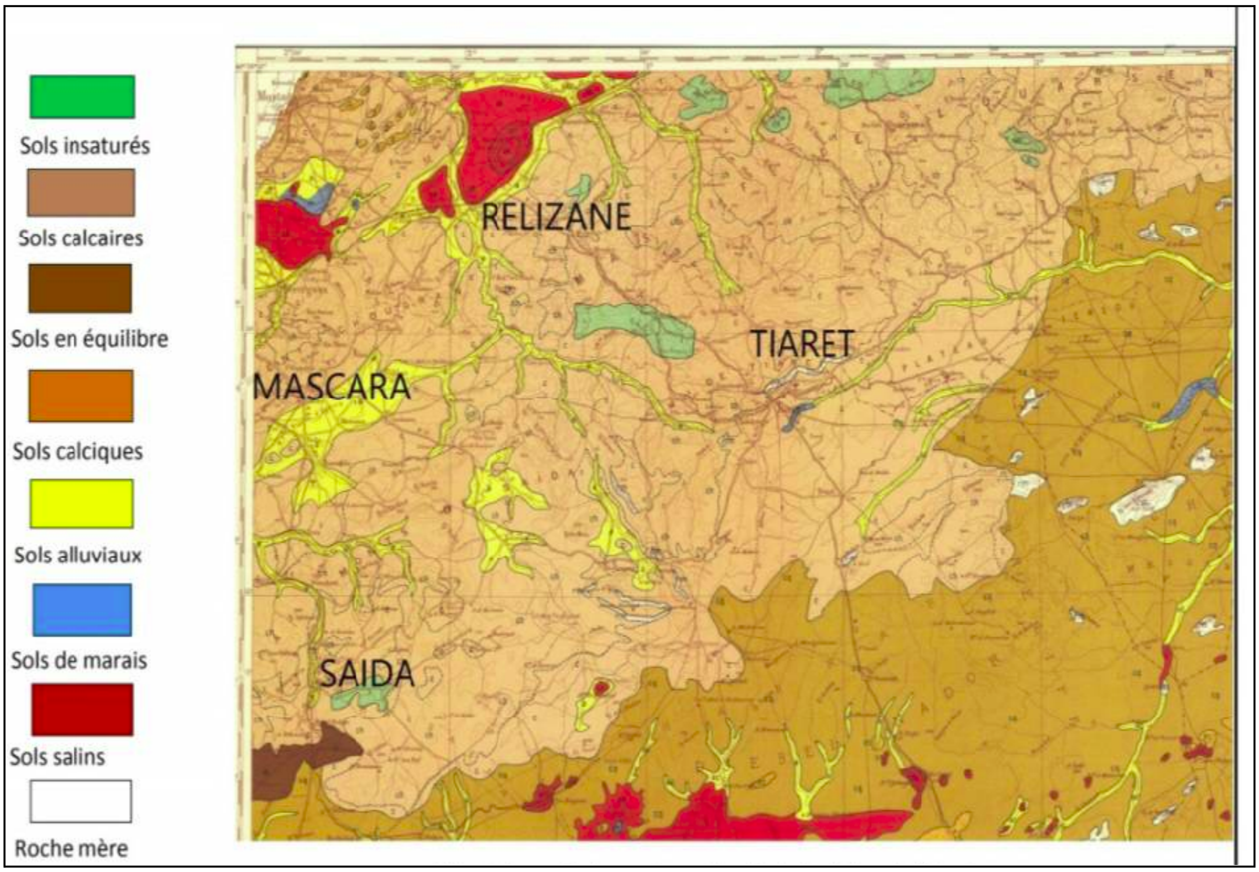

Figure 07: J.H.Durand Soils Of Algeria 1936 From Fao Database

II.1 Soil Classes In Algeria

According to Ramadan M. (2001) soils in Algeria were divided in 5 classes classified by category according to their suitability for agriculture, considered to be suitable on the basis of their chemical, physical and physico-chemical properties (geomorphology, topography, climate, etc).

Class 1: This class includes deep soils, of medium to fine texture, well structured and well drained. Topography is regular and slope is irrelevant. These soils have priority for agricultural development since they do not present major problems or constraints for the cultivation of crops. They are suitable for all the crops grown in Algeria.

Class 2: The soils of this class are generally deep or moderately deep, of medium to fine texture and well structured up to an average soil depth. There may be an impermeable layer (50-60 cm depth) that may cause the formation of a perched water table after introducing irrigation. Topography is regular or slightly undulated with low slopes. These soils are suitable for major crops, however they possess some restrictions for some of them. They are more specifically favourable to industrial crops. Some minor land management interventions are necessary (stone removal or surface land levelling).

Class 3: This class includes deep or moderately deep soils of medium, fine or very fine texture. Soils are generally well structured down to a given depth and then can exhibit salinity or water logging problems once the presence of the water table reaches approximately 1-metre depth. Topography is regular or moderately undulated and slope can be as high as 5 percent. These soils should be used for rotational crops. Major reclamation problems are drainage and desalination to be corrected before implementing irrigation projects.

Class 4: The soils of this class have a high variability in soil depth. They are coarse to fine textured and possess poor structure properties. The presence of inclusions within these classes can be also high. Often soils could be salty or waterlogged with the presence of the water table at shallow depth. Topography is regular or undulated and the slope can reach up to 10 percent. This zone is often heterogeneous, with limited suitability for irrigation, therefore, they should not be included in major land reclamation projects that require drainage, desalination, and land levelling improvements for instance. Alternatively, dry farming is more recommended.

Class 5: This category characterised by: urban area, oueds-beds, swamps, high steep slope, mountain or uneven area, very high salinity and waterlogging problems, presence of crusts (calcareous or gypseous) at shallow depth, etc. Major land reclamation works to be carried out for this class are land levelling, stone removal, desalination, drainage, deep ploughing, and establishment of wind breaks.

II.2 Soil Types In Algeria

Algeria has a diverse range of soil types that are influenced by its climate, geography, and vegetation. The country can be broadly divided into four soil zones, each with its unique characteristics.

II.2.1 The Northern Tell Atlas Zone

This region comprises the northern coastal plains and foothills of the Atlas Mountains. The soils in this region are mostly alluvial and loamy red soils, with a high clay content and good water retention capacity, mostly the red mediterranean soils. These soils are well-suited for cultivation, and the area is one of the most fertile regions in Algeria (Fedoroff N. 1999).

II.2.2 The High Plateaus Zone

This region lies in the central part of Algeria and comprises high plateaus and mountains. The soils in this region are mostly brown calcareous and calcimagnesic soils, with low organic matter content and high levels of salinity. However, some areas have a deep loamy soil with good water-holding capacity (vertisols) making them suitable for agriculture (Dellal A. & al. 1989).

II.2.3 The Saharan Atlas Zone

This region lies south of the Tell Atlas and includes the Saharan Atlas Mountains and adjacent plateaus. The soils in this region are typically shallow and rocky, with low water-holding capacity. However, some areas have deep sandy soil with good drainage, which makes them suitable for growing crops like wheat, barley, and olives (Belaroui K. 2013).

II.2.4 The Saharan Zone

This region is located south of the Saharan Atlas and is characterised by vast expanses of sandy and stony desert, The soils in this region are mostly sandy with low fertility and low water-holding capacity including Haplic Petric Gypsisols, Gleyic Solonchaks and Haplic Gypsisols, making agriculture challenging. However, there are some oases in this region where agriculture is possible due to the presence of groundwater (Assami T. & al. 2019).

II.3 Cereal Soils In Algeria

Algeria has a diverse in geography and climate so cereal crops can divers in many parts of the country in 1989 a study has been done on isotopic techniques for the suitability of phosphate element for cereal crops by “Jean Claude Fardeau”, he choose 5 cereal soil types that found in algeria:

- Vertisols can be suitable for cereals if managed properly. Their high clay content can help retain moisture during dry periods and a high cation exchange capacity (CEC) , which can be beneficial for cereal crops.
- Red Mediterranean soils found in regions with a Mediterranean climate and have high clay content and low organic matter. While these soils can support cereal cultivation, their low water-holding capacity and susceptibility to erosion make them challenging to manage (Khiari & al. 2020).
- Brun calcareous soils have high levels of calcium carbonate, can have a positive impact on soil pH but can limit the availability of certain nutrients.
- Calcimagnesic soils are found in various regions of Algeria and have unique properties that impact their suitability for cereal cultivation, which are characterised by high levels of calcium and magnesium, have a high CEC and can support the growth of cereal crops (Cumhur 2010).
- Saline soils can pose a challenge to cereal cultivation due to their high salt content. so, with proper management practices such as using salt-tolerant crops and implementing

appropriate irrigation techniques, the negative effects of soil salinity can be mitigated (Saidi 2012).

II.4 Soil Quality

The term "Soil Quality" (SQ) refers to the assessment of the condition of soil, whether it is in a good or bad state. The concept of SQ gained prominence in the 1970s and further attention in the mid-1980s as concerns about sustainable farming practices grew among the public. Throughout the years, various definitions of SQ have been debated, including the following current and theoretical definition: SQ is the soil's capacity to sustain biological productivity, maintain or improve water and air quality, and support human, plant, and animal health (Bünemann & al. 2018).

Although the concept of SQ is broad and complex, this definition emphasises the significance of soil functions and their connection to ecosystem services. When SQ is compromised, it often indicates that the soil is susceptible to erosion, contamination, compaction, sealing, loss of biodiversity, salinization, flooding, landslides, and/or a decline in soil organic matter (SOM) (European Commission 2002). Therefore, the pursuit of SQ is crucial to ensure the long-term sustainability of agricultural or natural ecosystems and land management.

II.5 The Main Cereals Soils Characteristics

The characteristics of the soil in which cereal crops are grown have a significant impact on their growth, yield, and overall quality including: organic matter, soil texture, pH, water holding capacity, $CaCO_3$, nutrient availability, salinity, and cation exchange capacity.

II.5.1 Organic Matter

Organic matter plays a crucial role in maintaining soil fertility and structure. It provides a source of nutrients for the cereal crops, improves water retention, and enhances soil aggregation. For optimal cereal production, soil organic matter should be maintained at 2-6% of the total soil composition (Wood S. & al. 2018)

II.5.2 Soil Texture

Soil texture refers to the relative proportion of sand, silt, and clay particles in the soil. Cereal crops generally prefer loam and sandy loam soils with a balance of these particles. A well-balanced soil texture ensures good water infiltration, aeration, and root penetration, all of which contribute to healthy plant growth (Poeplau C. & al. 2017).

II.5.3 PH

Soil pH is a measure of acidity or alkalinity in the soil. The ideal pH range for cereal crops is between 6.0 and 7.5. Soil pH affects nutrient availability, microbial activity, and root development. Soils with a pH outside the optimal range may require amendments such as lime (to raise pH) or sulphur (to lower pH) to create a more suitable environment for cereal growth (Mahler R. 2008).

II.5.4 Water Holding Capacity

Water holding capacity is the ability of the soil to retain water for plant use. Cereal crops require adequate moisture for optimum growth and yield. Loam and clay soils generally have higher water holding capacities compared to sandy soils. Improving soil structure (e.g., through the addition of organic matter) can enhance the water capacity of the soil (Boyle & al. 1989).

II.5.5 CaCO3 (Calcium carbonate)

Calcium carbonate is a naturally occurring compound found in some soils, which can affect the availability of certain nutrients, particularly phosphorus. High levels of $CaCO_3$ may cause phosphorus to become less available to plants, leading to phosphorus deficiency in cereal crops. In such cases, phosphorus fertilisation may be necessary (Brownrigg S. & al. 2022).

II.5.6 Nutrient Availability

The availability of essential nutrients such as nitrogen (N), phosphorus (P), and potassium (K) is critical for cereal crops. Soil tests can help determine nutrient levels and guide fertilisation strategies. Properly balanced fertilisation is necessary to optimise crop growth and yield, while minimising environmental impacts (Luna & al. 2019).

II.5.7 Salinity

High salinity can negatively affect cereal crop growth and yield by impairing water uptake, nutrient availability, and metabolic processes. Cereal crops generally have low to moderate salt tolerance, with wheat and barley being more salt-tolerant than corn and rice. Strategies to manage soil salinity include using salt-tolerant crop varieties, improving drainage, and applying appropriate irrigation practices.

II.5.8 Cation Exchange Capacity (CEC)

CEC is a measure of the soil's ability to hold and exchange positively charged ions (cations) such as calcium ($Ca2+$), magnesium ($Mg2+$), potassium ($K+$), and ammonium ($NH4+$). A higher CEC indicates a greater capacity to hold nutrients and resist changes in pH. Soils with high organic matter and clay content typically have greater CEC. Maintaining an adequate CEC is important for ensuring sufficient nutrient availability for cereal crops (Luna et al. 2019).

II.6 Soil Fertility

Soil fertility is the ability of soil to sustain plant growth and optimise crop yield. It is essential for ensuring food security and maintaining healthy ecosystems. Soil fertility is influenced by various factors, including nutrient availability, soil structure, and microbial activity. Nutrient sources that contribute to soil fertility include chemical and mineral fertilisers, organic fertilisers such as livestock manures and composts, and sources of recycled nutrients (IAEA 2016).

II.6.1 Types Of Fertilisers And Their Impacts On Soil Fertility

Organic fertilisers

Compost and manure improve soil quality and physical and chemical properties Organic fertilisers, compared to inorganic fertilisers, maintain soil quality, increase soil organic matter, as well as improve soil physical and chemical properties through the decomposition of its substances . Organic matter enhances soil nutrients, plant growth regulators, and biodiversity . Thus, an integrated nutrient management system is required to maintain soil quality as well as to obtain high yield and preferred grain quality. Hence, there is an urgent need to apply numerous sources of organic fertilisers as a substitute to reduce the utilisation rate of inorganic fertilisers (Kakar & al. 2020).

Inorganic Fertilisers (NPK)

Nitrogen, phosphorus, and potassium, can improve crop yield but can also have negative impacts on soil fertility if overused,regarding the application of NPK fertilisers and their impact on soil fertility. According to a study by Krasilnikov et al. (2022), the imbalanced use of chemical fertilisers, including NPK fertilisers, can lead to changes in soil pH, increased pests attack, acidification, and soil crust formation, which ultimately results in a decrease in soil fertility and crop yields. Therefore, the balanced and sustainable use of NPK fertilisers is crucial to maintain soil fertility and improve crop yields . Another study by Dong & al. (2012) found that the application of organic matter (OM) and NPK fertilisers resulted in a significant increase in soil organic carbon (SOC), total nitrogen (TN), carbon-to-nitrogen (C/N) ratios, available nitrogen (AN), and available phosphorus (AP) contents relative to the other fertilisation treatments. This study highlights the importance of combining NPK fertilisers with OM to improve soil fertility and crop productivity.

To enhance soil fertility, farmers often utilise organic amendments such as manure or compost. Additionally, they may apply chemical fertilisers to supplement the soil's nutrient levels (Donn & al. 2014).

II.7 Soil Variability In Cereal Crop Fields

Soil variability can have a significant impact on cereal crop growth and yield. Different soil types, textures, and structures can affect water retention, nutrient availability, and root penetration, all of which can influence crop growth and development.

In addition to soil type, variability in soil pH, organic matter content, and nutrient levels can also impact cereal crop growth and yield. To address soil variability, farmers may use a variety of techniques such as soil testing, targeted fertilisation, and crop rotation to optimise soil conditions for their specific crops and growing conditions (Dellal & Moumene. 1989)

II.8 Factors That Affect Soil Variability

Cereal crops such as wheat, maize, rice, and barley are grown in a wide range of soil types, ranging from sandy soils to heavy clay soils. Soil variability can affect the physical, chemical, and biological properties of the soil, which in turn can impact the availability of water and nutrients for plant growth (Earl R. & al. 2003).

Soil formation is influenced by various geological and geographical factors. These factors contribute to the diversity of soil types found across the country, some of the key elements that influence soil formation are : parent material, climate, relief and topography, vegetation and biological activity, time and human activities (Sitayeb et al. 2018). Understanding the geological and geographical factors is essential for assessing soil quality, fertility, and suitability for different agricultural practices (Liu Y. & al. 2013). It also helps inform soil conservation and management strategies to ensure sustainable use of agricultural soils in Algeria.

II.8.1 Parent Material

The physical and chemical properties of parent material have a major influence on the properties of the soil that forms from it. This is because parent material provides the initial source of nutrients, minerals, and organic matter for the soil. As a result, soils formed from different parent materials can have very different properties, such as texture, pH, nutrient content, and water-holding capacity (Ito R. & al. 2022). This variability in soil properties can have a significant impact on plant growth and ecosystem function, figure (8) represents the chart of parent material and mineral resources of Algeria made by the Algerian industrie ministry (Ministère de l’industrie et des mines before) and the Algerian Geological Services Agency (ASGA).

II.8.2 Topography

Topography is also an important factor that affects soil variability in cereal crops. For instance, steep slopes can lead to soil erosion, affecting soil structure and nutrient availability. On the other hand, flat topography can lead to water stagnation, affecting soil aeration and nutrient availability (Singh G. & al. 2021).

II.8.3 Vegetation

In a study by (Durán J. & al. 2022) they concluded that reductions in plant cover, such as those caused by desertification, increases in aridity, or deforestation, are likely to increase the spatial variability of multiple soil organisms and that such changes are likely to negatively impact ecosystem functioning across global biomes, figure (9) shows Algeria vegetation cover.

II.8.4 Land use

Land use also can affect soil variability in cereal crops like crop rotation includes mostly cereals and intermittently potatoes and legumes, it can lead to variations in soil nutrient availability and soil organic matter content, which can increase cereal crop productivity (Chahal & a., 2021).

Cereal soils play a crucial role in the monitoring and management of soil health and productivity over time. By periodically updating soil maps and monitoring changes in soil properties, such as nutrient depletion, soil erosion, or compaction, farmers can implement appropriate soil conservation and management strategies. This is where digital soil mapping becomes instrumental (Godwin R. & al. 2003).

II.8.5 Climate

Climate is an important factor that affects soil variability in cereal crops. Changes in temperature and rainfall patterns can significantly affect the growth and productivity of cereal crops. For example, drought conditions can lead to reduced soil moisture content, affecting the availability of water and nutrients for cereal crops. Similarly, heavy rainfall can lead to soil erosion and nutrient loss, affecting soil fertility and cereal crop productivity (Qiao L. & al. 2022), figure (10) a chart by (Amrani et al. 2019) demonstrates the bioclimate in Algeria.

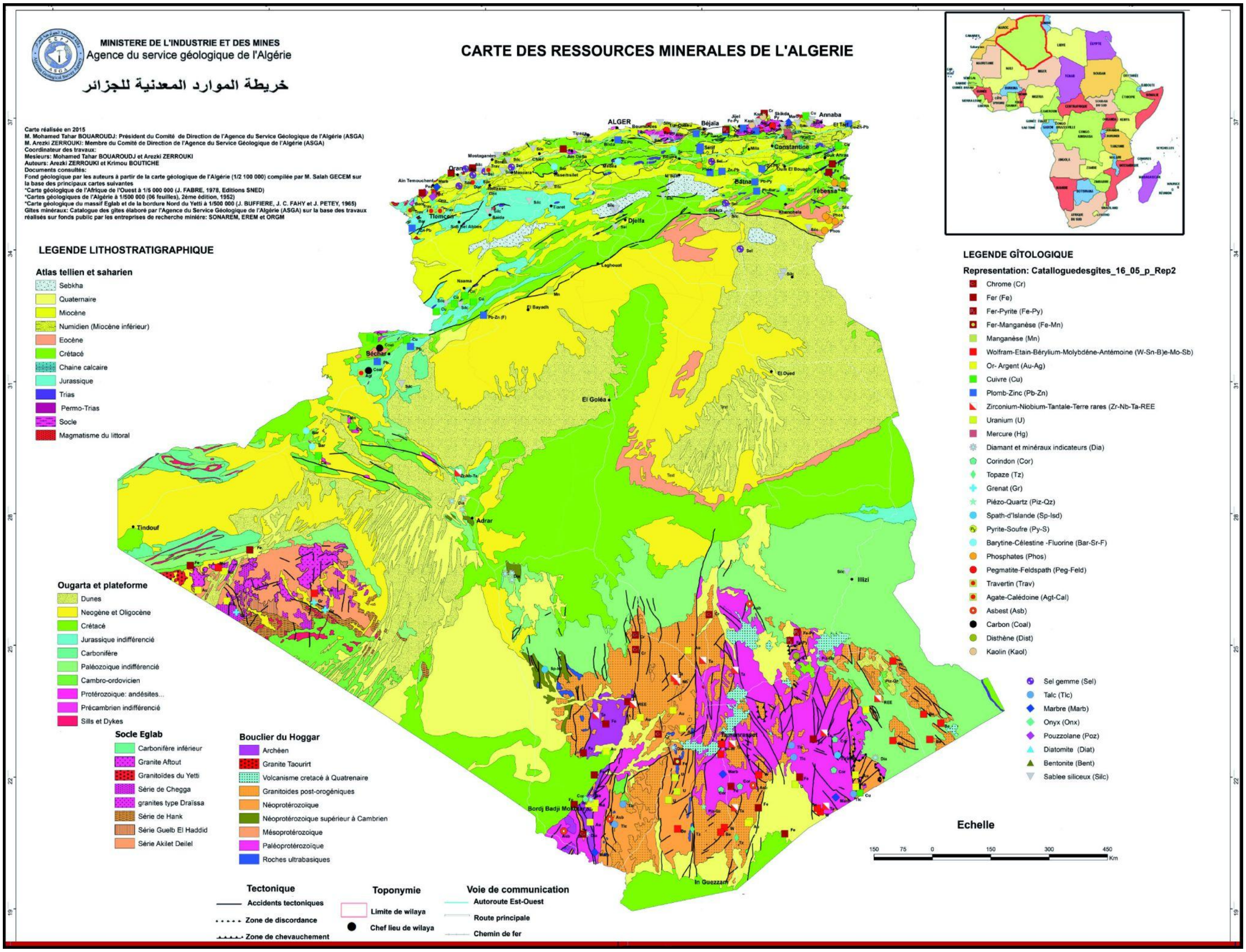

Figure 08: Parent material and mineral resources of Algeria (Webmaster 3)

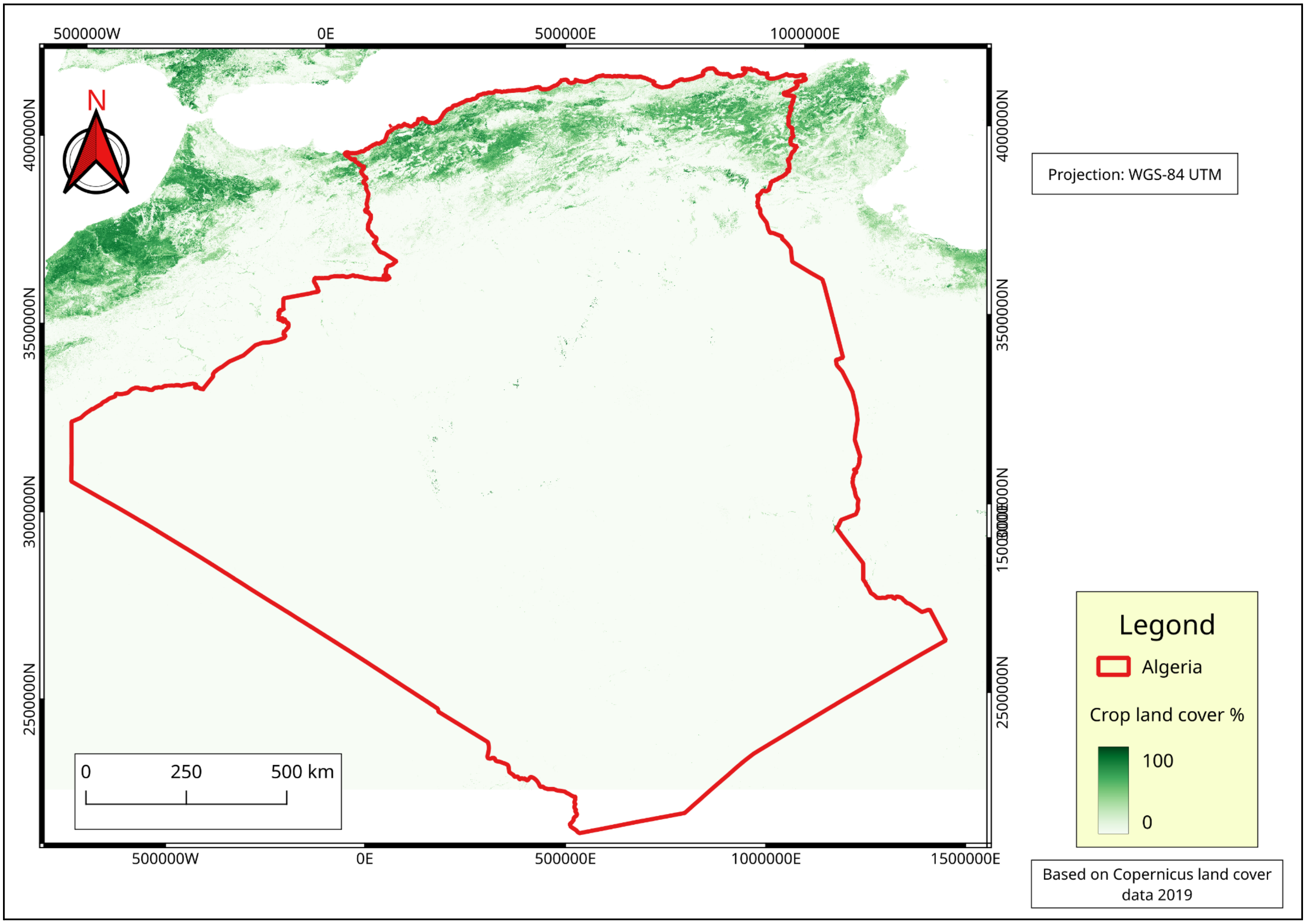

Figure 09: Algeria Vegetation Land Cover map

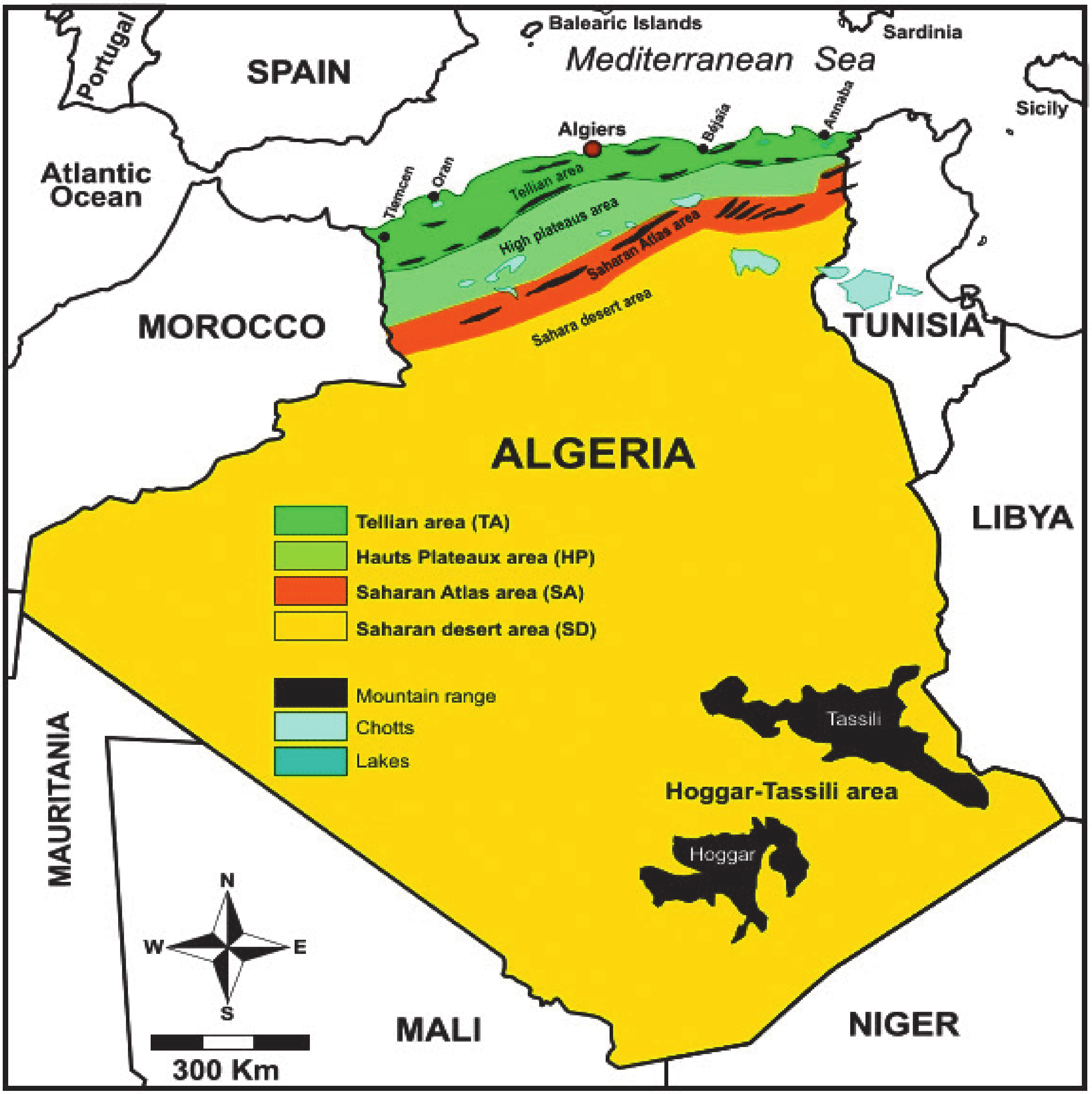

Figure 10: Major biogeographical and bioclimatic regions of Algeria (Amrani et al. 2019)

CHAPTER III

Digital Soil Mapping

III.1 Into Digital Soil Mapping

Lagacherie and McBratney (2007) defined digital soil mapping as "the creation and population of spatial soil information systems by numerical models inferring the spatial and temporal variations of soil types and soil properties from soil observation and knowledge and from related environmental variables". While Grunwald (2010) describes dsm as " a discipline linking field, laboratory, and proximal soil observations with quantitative methods to infer on spatial patterns of soils across various spatial and temporal scales".

In the past, soil mapping has typically been conducted using conventional methods, such as field surveys and laboratory analyses. Conventional soil mapping involves physically sampling soils and analysing their properties in the laboratory, followed by interpretation of the results and creation of maps (Kairis & al. 2020). While this approach has been successful in producing detailed soil maps, it is time-consuming, labour-intensive, and expensive (Kempen & al. 2012). With the advent of digital technologies, a new approach to soil mapping has emerged known as digital soil mapping (DSM). DSM involves the use of spatially referenced environmental data, such as topography, geology, vegetation, and climate, to create digital maps of soil properties (Boettinger, 2010). DSM can use a variety of methods, such as statistical modelling, machine learning, and remote sensing, to predict soil properties and produce soil maps (Yuzugullu & al, 2020).

DSM offers several advantages over conventional soil mapping. It is less labour-intensive and time-consuming, and can provide more accurate and detailed maps of soil properties (Zeraatpisheh & al. 2017). DSM can also incorporate a wide range of environmental data, making it a powerful tool for understanding soil variability and its relationship to environmental factors (Roecker & Thompson. 2010).

(Zhang & al. 2017) suggested A general framework of DSM and its main components presented in figure (11).

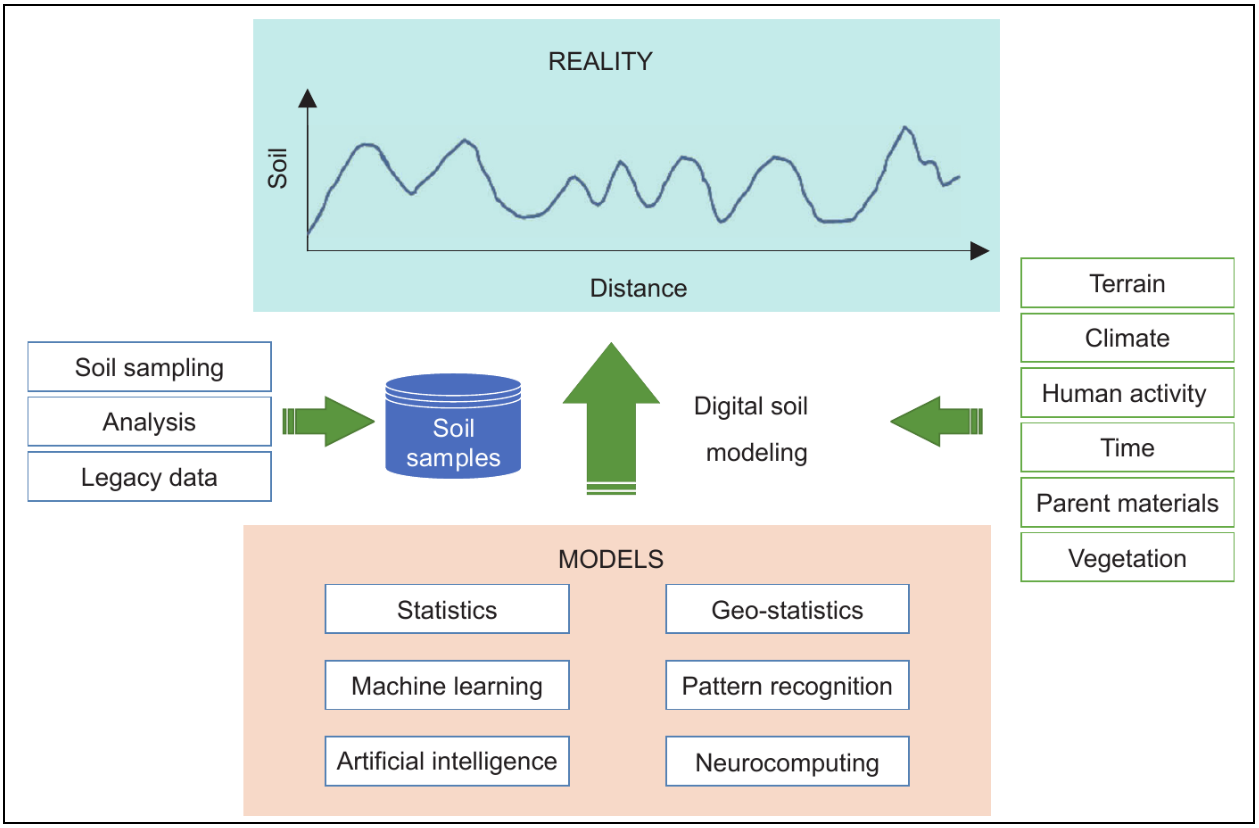

Figure 11: The general framework of digital soil mapping (Zhang & al. 2017).

III.1.1 Montpelier workshop

The Montpellier Workshop on Digital Soil Mapping (DSM) was a conference held in Montpellier, France in 2004, titled “Digital soil mapping: An introductory perspective” which brought together experts in the field of soil science, geography, statistics, and computer science to discuss and develop new methods and applications for DSM. The workshop resulted in the publication of a set of guidelines for the practice of DSM, which has since become a seminal work in the field. The guidelines are titled "Digital Soil Mapping with Limited Data" and were published in the Geoderma journal in 2003. The Montpellier Workshop played a key role in advancing the development of DSM and establishing it as a recognized discipline in soil science and geospatial analysis. The Montpellier Workshop also helped to promote the use of advanced technologies, such as remote sensing and geostatistics, in digital soil mapping and provided a forum for researchers and practitioners to share their experiences and insights on the use of these technologies and to identify gaps and challenges that need to be addressed in future research (Lagacherie. 2008).

III.1.2 USDA and DSM

USDA Natural Resources Conservation Service (NRCS) has a webpage on digital soil mapping, which provides information on the methodology and applications of DSM. The webpage describes DSM as "the use of geographic information systems, spatial statistics, and other digital tools and data to create accurate and detailed maps of soil properties and characteristics across a landscape" (Webmaster 4).

The National Cooperative Soil Survey generates soil data and information, which is made available through the Web Soil Survey (WSS), a system operated by the USDA Natural Resources Conservation Service (NRCS). WSS grants access to the largest natural resource information system globally and offers online soil maps and data for over 95 percent of the counties in the United States (Webmaster 5).

(Webmaster 6) provides documentation including "Digital Soil Mapping Job Aides Composite" which is a document that provides guidance and resources for creating digital soil maps. It covers the importance of digital soil mapping in modern soil science and provides an overview of the methods and technologies used. The document also includes a comprehensive list of software and tools, guidance on data collection and processing, and the essential steps involved in creating accurate digital soil maps. It is a valuable resource for soil scientists, land managers, and GIS professionals who want to create reliable digital soil maps by emphasising the importance of data quality and processing (Webmaster 7).

III.2 Soil Mapping Concepts and Principles

III.2.1 Sampling

Sampling is crucial for gathering data that can be used to estimate statistical parameters or predict properties over an area. In order to optimise the sampling process for soil and other materials at the Earth's surface, prior information at various locations is utilised (Bui et al, 2006). However, financial and resource constraints can limit the sampling process, making it important to develop efficient sampling strategies. This is particularly important for practical applications such as soil surveying for mapping and establishing sites for monitoring networks (Minasny & McBratney, 2006).

In a complex terrain and diverse soils (mountainous) prior knowledge of the soil properties and the terrain is important as it is for geostatistical analysis in designing the survey, the selection of survey methods, including the choice of sample density, sample type, and sample size (Thomas & al, 2012).

There are four main categories of soil sampling designs, which include comprehensive sampling, supplemental sampling, verification sampling, and monitoring sampling (Huang et al. 2020. The sampling design for digital soil mapping depends on factors like project area, modelling objectives, desired precision, soil variability, and cost. It must be random and feasible within time, budget, and staff limitations (Soil Science Division Staff. 2017).

III.2.2 Spatial variability

Soil properties vary in space due to differences in climate, topography, vegetation, parent material, and land use (Mishra & Riley, 2012)

Vegetation influences spatial variability in soil properties through root exudates, litter inputs, and nutrient cycling. Parent material, or the underlying rock or sediment from which soils form, can also create spatial variability in soil properties due to differences in mineralogy, texture, and nutrient content (Rodríguez & al, 2009)

Climate is a primary driver of spatial variability in soil properties, with factors such as temperature, precipitation, and evapotranspiration affecting soil moisture and nutrient availability. Topography also plays a crucial role in spatial variability, as it affects soil moisture and nutrient retention (Keshavarzi, 2021), as well as erosion and deposition of soil particles (Teuling & al. 2007).
Several methods are used to characterise and quantify spatial variability in DSM. Geostatistics is a commonly used method that models spatial autocorrelation and estimates prediction uncertainty. Variogram analysis is a tool used in geostatistics to describe the spatial structure of a soil property and estimate the spatial dependence of soil properties (Mcbratney & Pringle. 1999). Understanding spatial variability is essential in developing accurate and reliable DSM models that can produce high-resolution soil maps for various applications, such as land-use planning, precision agriculture, and environmental management (Turetta & al. 2008).

III.2.3 Data Sources

Data sources are a critical concept in DSM as they provide the information needed to create soil maps. DSM relies on multiple data sources to capture the variability of soil properties across landscapes, including both traditional and emerging sources of data (Lagacherie 2008).

Traditional sources of data for DSM include soil surveys, which provide information on soil characteristics and properties at specific locations, and topographic maps, which provide information on elevation, slope, and aspect. These data sources can be used to create soil-landscape models that predict soil properties at unsampled locations based on relationships with known soil-landscape factors (Soil Science Division Staff, 2017).

Emerging sources of data for DSM include remote sensing, geophysical data, and digital elevation models (DEMs). Remote sensing data, such as satellite imagery, can provide information on vegetation cover, soil moisture, and land use, which can be used to predict soil properties. Geophysical data, such as electrical conductivity and magnetic susceptibility, can provide information on soil properties and subsurface features. DEMs, which provide detailed information on terrain elevation, can be used to derive landscape indices that are related to soil properties (Rossiter 2008).

III.2.4 Data processing and analysis methods

Data analysis is a fundamental principle and concept in Digital Soil Mapping (DSM). It involves the statistical, machine learning, and geostatistical methods used to analyse and interpret soil data (Agyeman & al. 2021). DSM data analysis aims to identify and model the spatial variability of soil properties by integrating multiple sources of information, including remote sensing, digital elevation models, and soil survey data (Minasny & McBratney 2016).

Statistical analysis is used to model the relationships between soil properties and environmental variables. This helps to identify the significant variables that contribute to the spatial variability of soil properties (Sheng & al. 2010). Machine learning methods are used to develop predictive models of soil properties based on the relationships identified by statistical analysis. Geostatistical methods are used to interpolate and extrapolate soil property values across space, accounting for the spatial autocorrelation of soil data (De Sousa Mendes & al. 2020).

Data analysis in DSM is critical to ensure the accuracy and reliability of soil maps and predictions. The choice of data analysis method depends on the availability and quality of data, the scale of analysis, and the specific research question. Data analysis in DSM involves a range of techniques, from simple linear regression models to complex machine learning algorithms. It requires careful consideration of the data sources, processing steps, and validation procedures to ensure the robustness of the results.

III.3 Spatial Data Analysis Techniques

GIS (Geographic Information System) is a powerful tool for spatial data analysis, which has been widely used in digital soil mapping. GIS allows for the integration of various spatial datasets, such as soil surveys, satellite imagery, climate data, topography, and land use/cover, to create a comprehensive and accurate representation of soil distribution and variability in a study area (Weber & al. 2008).

III.3.1 Geostatistics

Geostatistics is an important spatial technique especially in spatial extrapolation of soil data in areas with complex soil patterns, however it requires more computational resources and it's less efficient in terms of processing time. The choice of method should be based on the specific needs and resources available for a given mapping project (Malone & al. 2016).

III.3.2 Remote Sensing

Remote sensing techniques rely on radiation that interacts superficially with soil, rock, and plants, limiting the obtained information to the surface of the soil and vegetation cover (Mulders 1987).

In Maynard & Levi (2017) research considered remote sensing as a useful tool in digital soil mapping, especially hyper-temporal remote sensing in areas with high spatial and temporal variability in soil properties. The study also highlights the importance of understanding the interactions between soil, vegetation, and climate in managing natural resources and mitigating the effects of climate change. Several satellite imageries where used in DSM, Landsat 7 ETM+ (Boettinger & al, 2008), Landsat 8 (Zeng & al, 2020), Aster (Nawar & Buddenbaum 2015), Sentinel-1 and Sentinel-2 (Ma & al 2021), Sentinel-3 (Piccoli & al, 2020), TerraSAR-X and ALOS PALSAR (Elbialy & al. 2014), MODIS (Chen & al. 2019), WorldView-2 (Xu & al. 2022).

III.3.3 Machine Learning

There are different types of machine learning algorithms applied in soil mapping, including regression-based and classification-based approaches. Machine learning has great potential for digital soil mapping, but it is important to carefully consider the data, model, and interpretation of the results (Wadoux & al. 2020).
It is important to understand the strengths and weaknesses of different machine learning methods and their underlying assumptions in order to choose the most appropriate method for a given soil mapping problem. data pre-processing and feature selection play a major role in improving the accuracy and interpretability of the models (Khaledian & Miller 2020). For example Wang & al (2019) used hybrid model random forest with residual kriging to map soil pH efficiently in heterogeneous landscapes.

III.3.4 Soil Properties Prediction Methods

In order to provide soil information in areas where soil data are limited or non-existent several methods have been conducted, basically they are all based on geostatistics and machine learning. Bagheri Bodaghabadi & al (2015) used Artificial Neural Networks (ANNs) for predicting soil properties, including organic matter content and clay content and demonstrated the potential of ANNs as a powerful tool for DSM where soil data are limited and terrain variability is high. In another study Support Vector Machines (SVMs) showed high accuracy in predicting soil classes and interpolating soil properties as a decision support for precision agriculture (Pereira & al, 2022).
Random Forest (RF) also is an excellent algorithm when combined with remote sensing data showed good results in predicting soil texture classes and has the potential to provide valuable information for precision agriculture management, such as soil fertility, water retention, and nutrient availability (Dharumarajan & Hegde 2022). In other researches boosted regression tree (BRT), generalised linear model (GLM), and multiple linear regression (MLR) where tested and showed good performance in predicting pH, EC, clay, silt, sand, and CCE (Mosleh & al. 2016).

Allot of work have been conducted in this field we mention: decision tree modelling (DTM) and indicator kriging (IK) (Greve & al. 2010), Multi-Layer Perceptron (MLP) (Freire 2013), Discriminant Analysis (DA) (Behrens & al. 2010), k-Nearest Neighbors (k-NN) (Heung & al. 2016), Naive Bayes (NB) (Yudhana & al. 2021), Gradient Boosting Machine (GBM) (Hitziger & Ließ 2014).

III.5 Future Directions and Challenges

Digital soil mapping (DSM) has been evolving over the past decades with the emergence of various algorithms and techniques for predicting soil properties (Minasny & McBratney 2016). However, there are still several challenges that need to be addressed in DSM. One of the biggest challenges is the lack of high-quality data, as DSM relies heavily on the availability of spatial data for modelling soil properties. as well as the need for adequate sampling and field validation. In addition, there is a need for more accurate and efficient techniques for feature selection and modelling of soil properties (Hempel & al. 2008). The use of machine learning algorithms, such as support vector machines, neural networks, and random forests, has shown promising results in DSM, but there is still a need for more comparative studies to identify the most suitable algorithms for different soil properties and environmental conditions. Furthermore, more research is needed on the integration of DSM with other disciplines, such as remote sensing, geostatistics, and soil physics, to improve the accuracy and reliability of soil property predictions.

Despite these challenges, the future of DSM is promising. As technology continues to advance, more high-quality data will become available, and more efficient algorithms and techniques will be developed. This will allow for more accurate and reliable predictions of soil properties, which will benefit a range of applications, including precision agriculture, environmental management, and land-use planning. Furthermore, the integration of DSM with other disciplines will enable a better understanding of soil processes and their relationship with the environment.

According to Thompson & al (2020) Soil2026 is a project aiming to provide a comprehensive update of the National Cooperative Soil Survey (NCSS) by 2026, using modern technologies and methods. The authors emphasise the role of digital soil mapping in improving soil data availability and accessibility, and discuss ongoing efforts to improve digital soil mapping techniques, data quality, and interoperability across different agencies and organisations. The article also highlights the potential benefits of digital soil mapping, such as improved land-use planning, precision agriculture, and environmental modelling. Overall, the authors suggest that digital soil mapping will play a critical role in achieving the goals of Soil2026 and improving soil information in the United States.

As reported by Lagacherie & McBratney (2006) one of the future challenges is global mapping scale, the world soil map is composed from different soil systems, however there is a predicted development demonstrated in table (1) below.

Table 1: Predictions for a digital map of the world on the basis of current rate of progress.

Resolution (m)	No. of megapixels	Earliest date
1000	149	2015
100	1490	2027
50	5970	2032
10	14900	2039

III.6 Soil mapping in Algeria

In Algeria, soil data is scarce and often limited to specific regions with small scales. This is particularly true when it comes to large-scale coverage of soil information (Assami & Hamdi-Aïssa 2019). Despite some limited availability of soil data in environmental studies such as erosion, there is generally a lack of comprehensive data on soil characteristics and properties in Algeria. In fact, the available data often relies on remote sensing data rather than direct measurement (Amrouni & al. 2021), which may not accurately reflect soil conditions on the

ground. Overall, the need for more comprehensive and accurate soil data is paramount for sustainable management of soil resources in Algeria (Faraoun & Benabdeli 2010).
The lack of comprehensive soil data in Algeria can be attributed to a number of factors. Traditional soil mapping methods tend to be time-consuming and resource-intensive, limiting their application to small-scale projects. In addition, the exhaustive work involved in soil sampling and analysis often deters researchers from conducting more extensive soil surveys.
As a result, the available soil data in Algeria is often limited in scope and resolution, which can have significant implications for land-use planning, agricultural productivity, and environmental management. To address these challenges, there is a growing need for innovative approaches to soil mapping, such as digital soil mapping, that can provide more accurate and detailed information on soil characteristics at larger scales.

CHAPTER IV
Study Area

IV.1 Situation

Tiaret is an Algerian province located in the northwestern part of the country, situated on a plateau that has an average elevation of 1,200 meters above sea level. It covers an area of approximately 20,673 square kilometers and serves as an intermediary region between the Sahara Desert to the south and the Tell Atlas Mountains to the north. The province is bordered by Tissemsilt and Relizane to the north, Djelfa to the east, Laghouat and El Bayadh to the south, Saïda and Mascara to the west.

The geographical coordinates of the city of Tiaret, the capital of the province, are 35.3804° N, 1.3169° W. Tiaret is situated approximately 250 kilometers southwest of Algiers, the capital city of Algeria. The province's location and coordinates make it an important region in Algeria, connecting the Sahara Desert in the south and the Tell Atlas Mountains in the north. This location has influenced the region's climate, soil types, and landscape, making Tiaret a unique and diverse area with a rich history and culture. Figure (12) represents the situation of the province in the country.

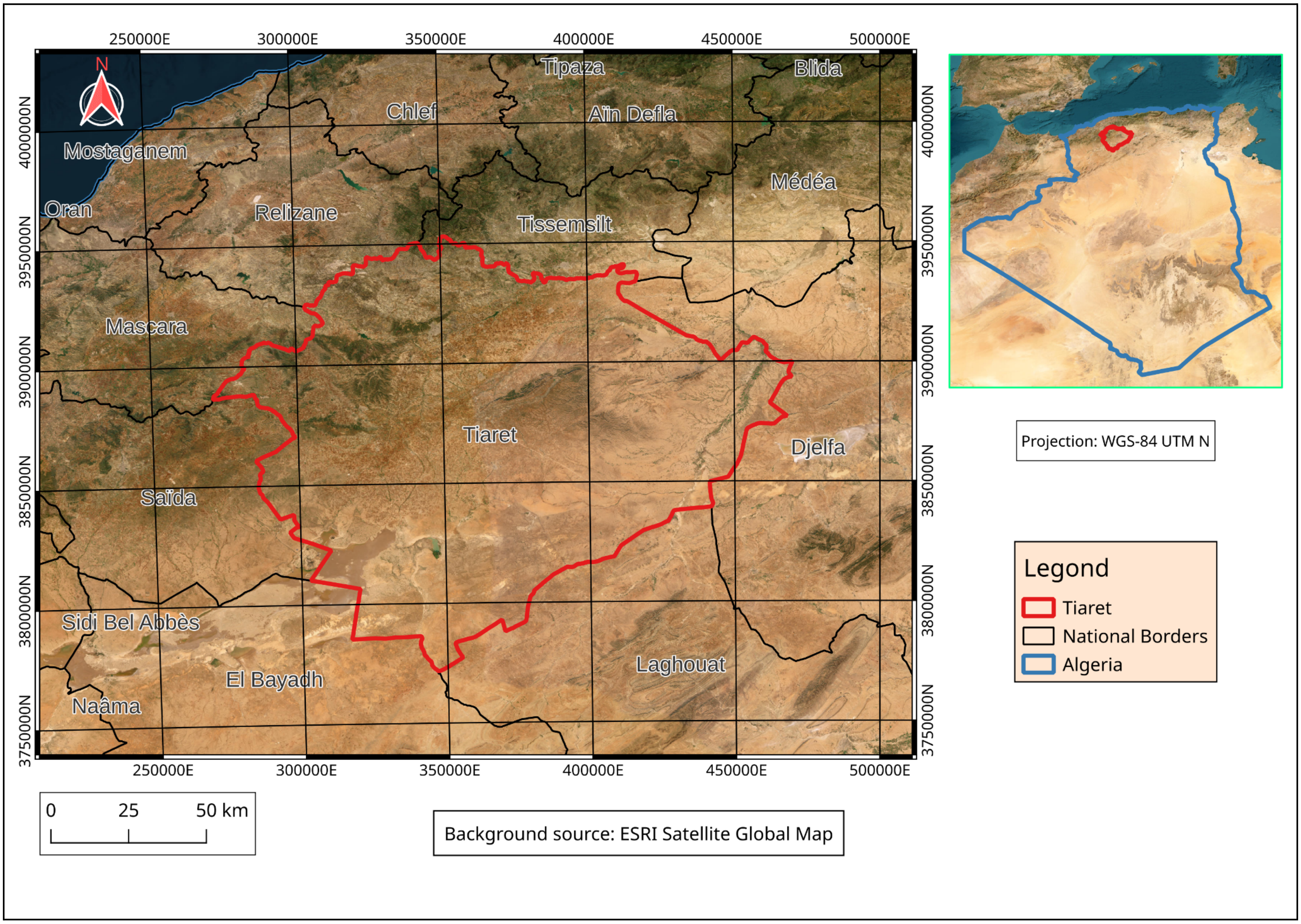

Figure 12: Tiaret Province Location

IV.2 Landscape

The landscape of Tiaret is characterised by hilly and mountainous terrain, with valleys and plains found in the lower areas. The region is dominated by the Atlas Mountains, with the highest peaks Taouaghzout (Frenda) 1524 m and Djebel Chamakh (Nadorah) 1512 m, figure (13) shows the altimetry of Tiaret Province.

Tiaret is a mix of rural and urban areas, with agriculture playing a significant role in the local economy. The region is known for its fertile soil, which is used to cultivate a variety of crops, including wheat, barley, and vegetables. Additionally, the region is known for its forest cover, figure (14) shows land cover in Tiaret.

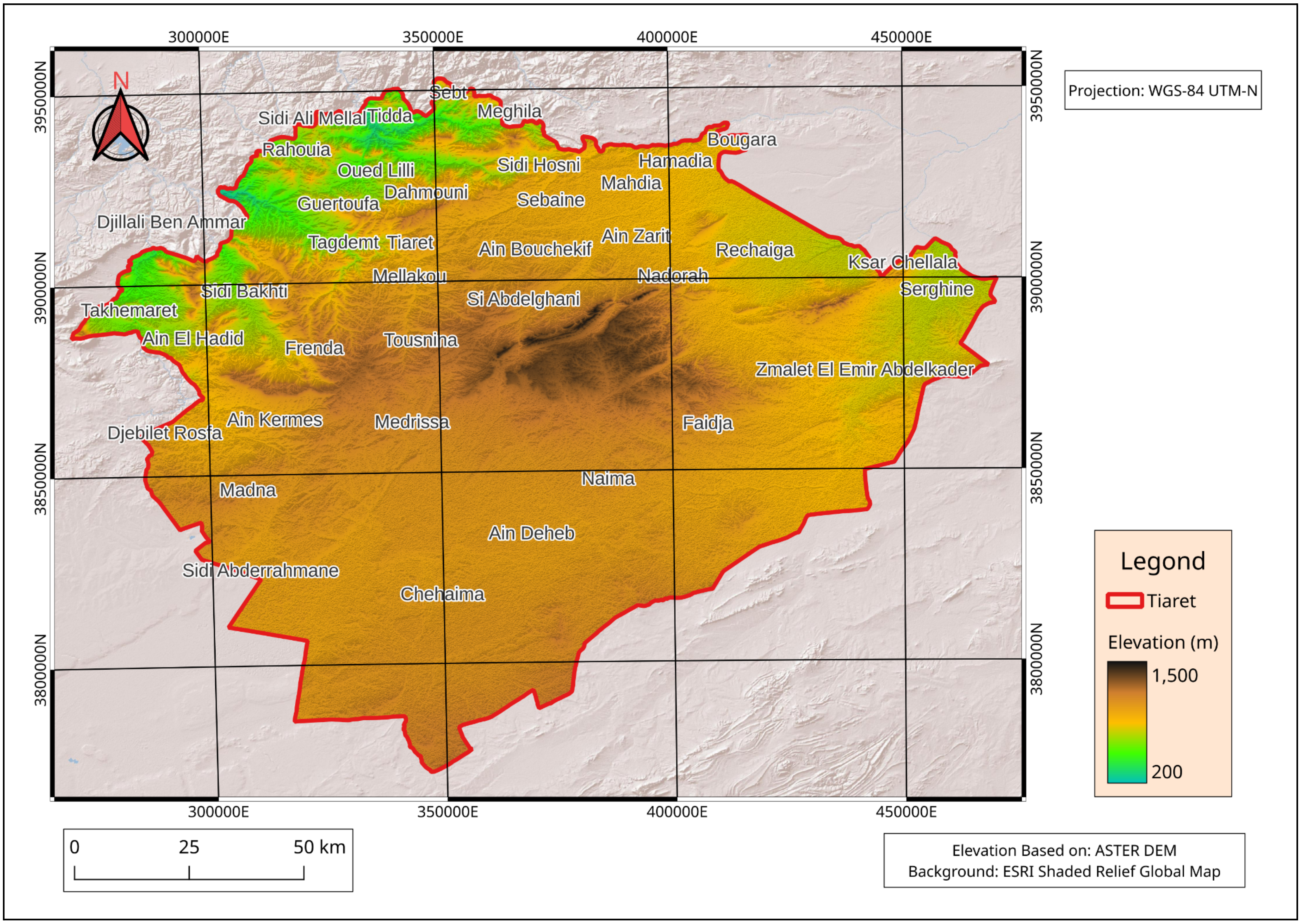

Figure 13: Tiaret Province Altimetry

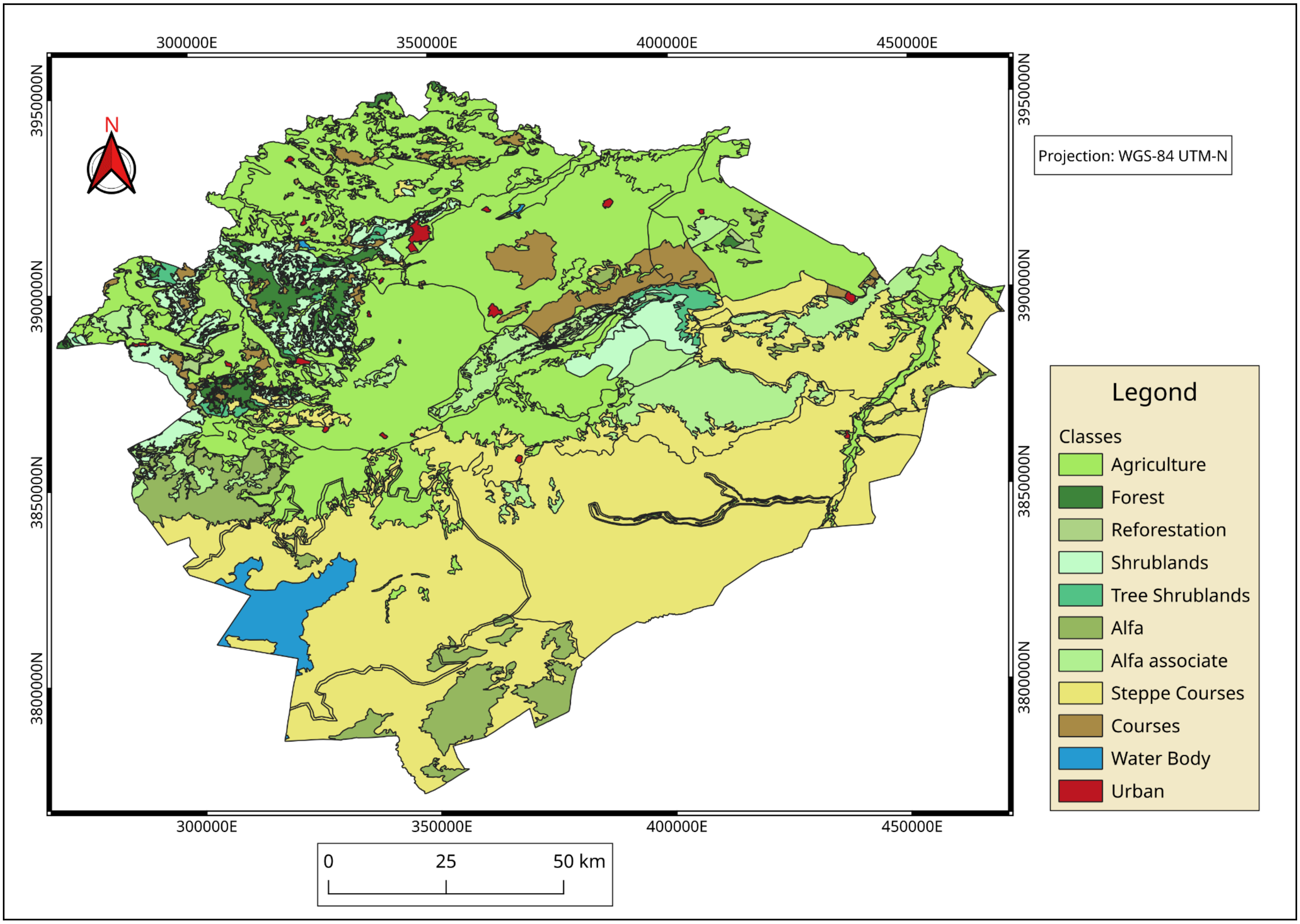

Figure 14: Tiaret Land-Cover

IV.3 Water Sources

The region has several important water sources including rivers and streams, Lakes and Dams for example Bekhada dam (Mechraa-sfa), Dahmouni dam (Dahmouni) and Bougara dam Between Tiaret and Tissemsilt province, also groundwater which provide water for irrigation and support local agriculture and urban life, figure (15) a map of Tiaret water sources and network.

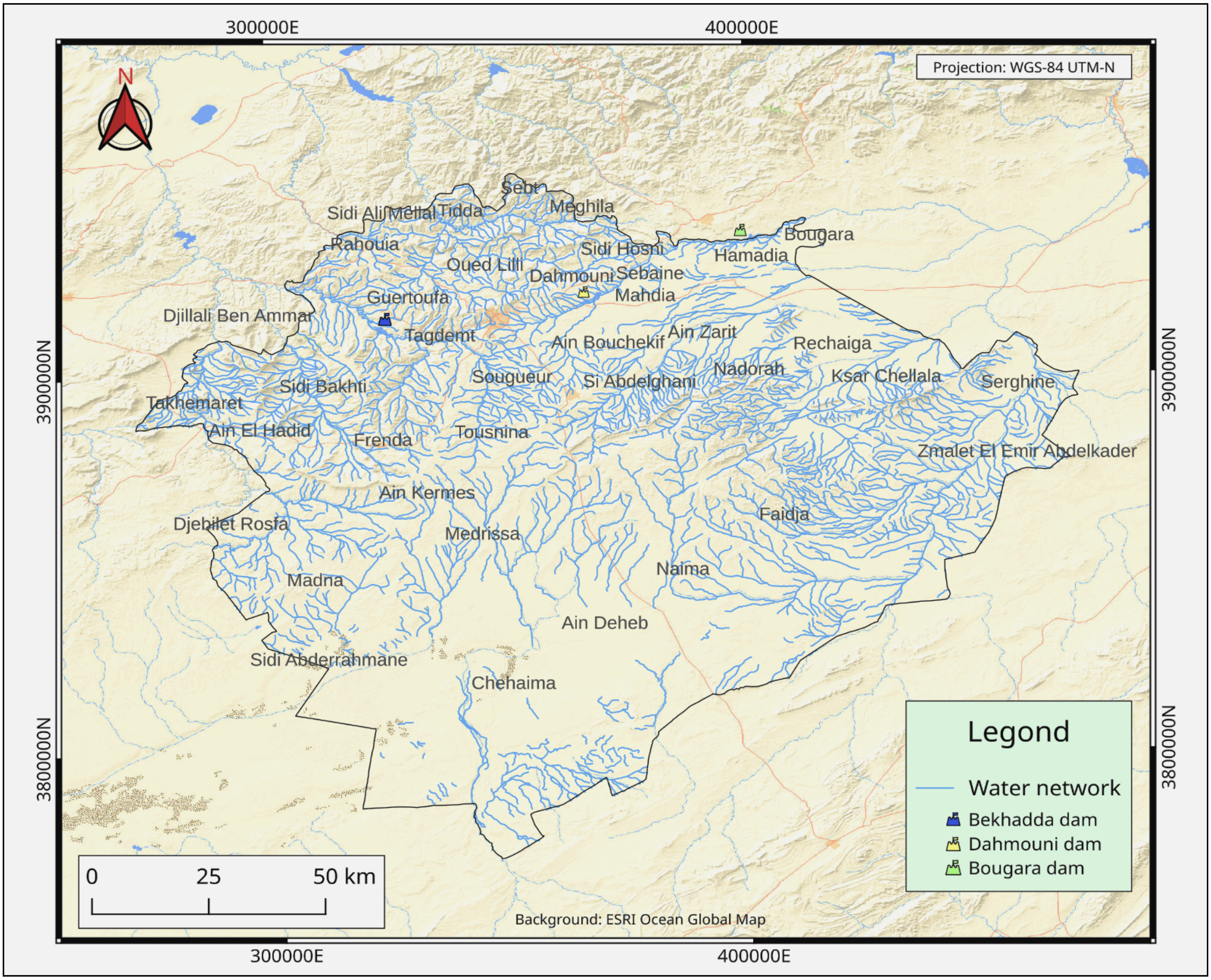

Figure 15: Tiaret water sources map

IV.4 Soils

Tiaret is known for its diverse soil types, which are influenced by various factors, including topography, climate, and vegetation. The region is characterised by several soil types, including

clayey soils, sandy soils, and loamy soils. The dominant soil type in the study area is Vertisols, which are clayey soils that are characterised by high swelling and shrinkage properties.
Tiaret serves as an important intermediary region between the Sahara Desert and the Tell Atlas Mountains, providing a critical connection between the two regions. As such, the region is home to a diverse mix of flora and fauna, with many endemic species found nowhere else in the world, figure(16) shows the soil types in Tiaret.

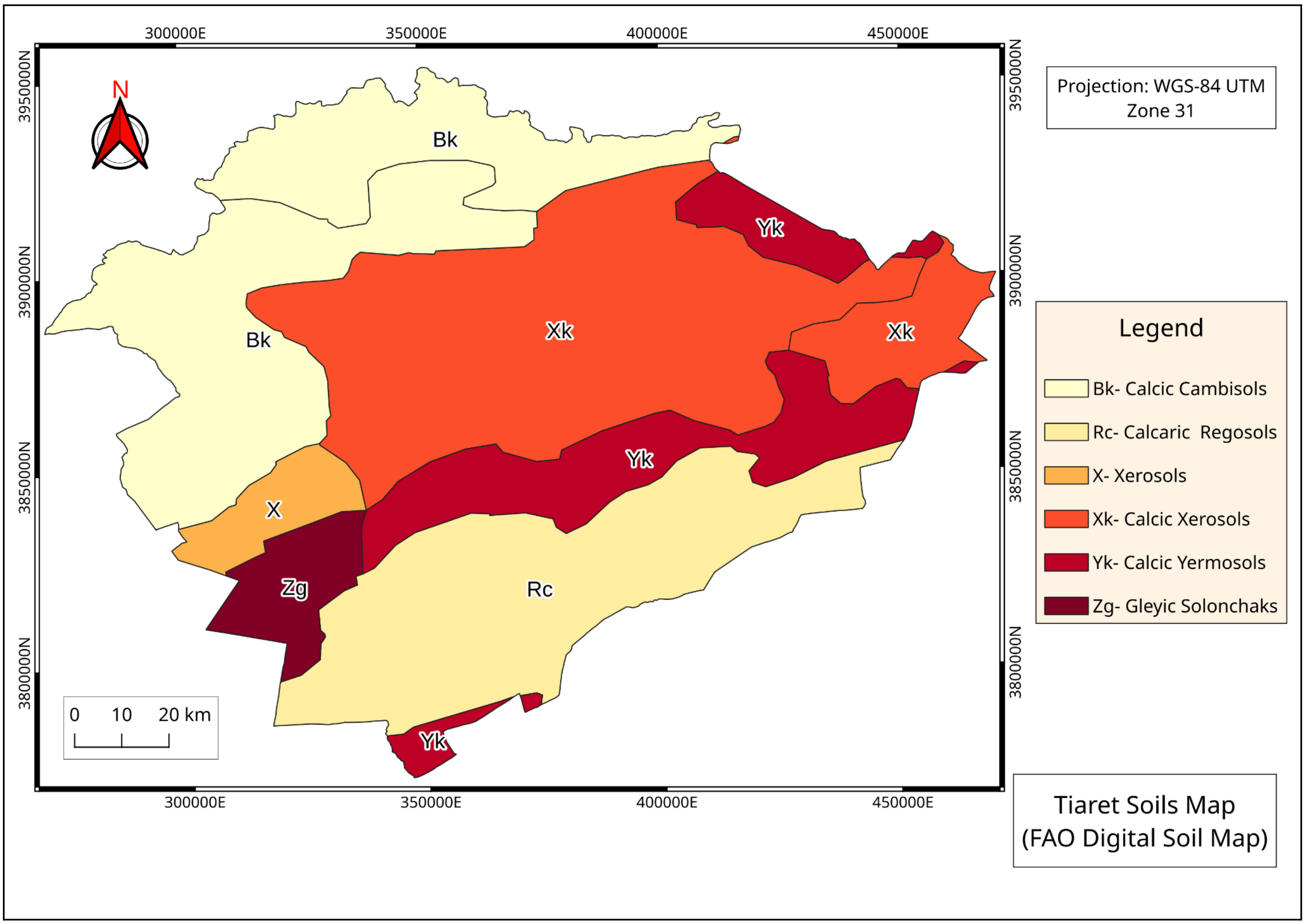

Figure 16: Tiaret Lithology map

IV.5 Climate

Tiaret climate is mostly a semi-arid climate, which is characterised by hot, dry summers and cool, relatively wet winters. The climate is influenced by the region's location in the interior of Algeria, away from the moderating effects of the Mediterranean Sea.

In general, the average annual temperature in Tiaret Province ranges from around 15 to 20°C . The warmest months are typically June through September, with average daily temperatures ranging from around 25 to 35°C . The coolest months are typically December through February, with average daily temperatures ranging from around 5 to 15°C .

The Province receives most of its precipitation during the winter months, typically from November through March. Average annual rainfall in the province ranges from around 300 to 500 mm , with the highest rainfall occurring in the mountains and the western part of the province. The summers in Tiaret are generally dry, with little to no rainfall.

Tiaret Province's climate is relatively harsh and dry, which can make water resources management a challenging task in the region. Figure (17) demonstrates the weather in Tiaret while figure (18) shows the climate classes.

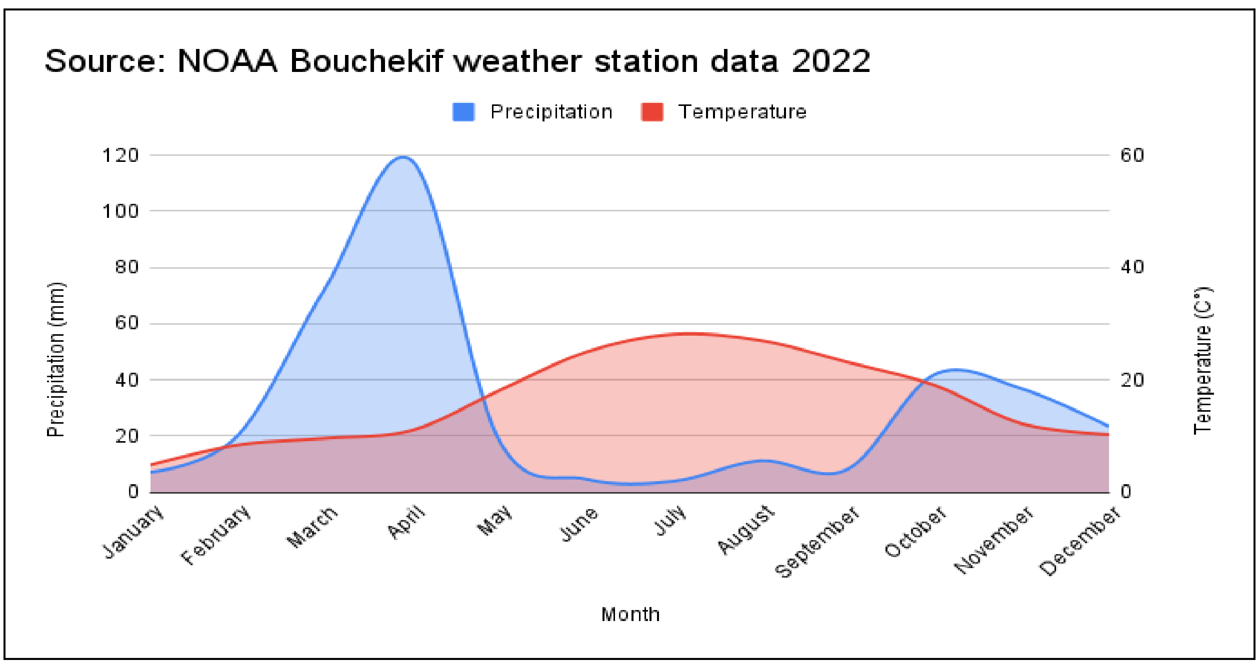

Figure 17: Ombrothermic Chart of Tiaret (2022)

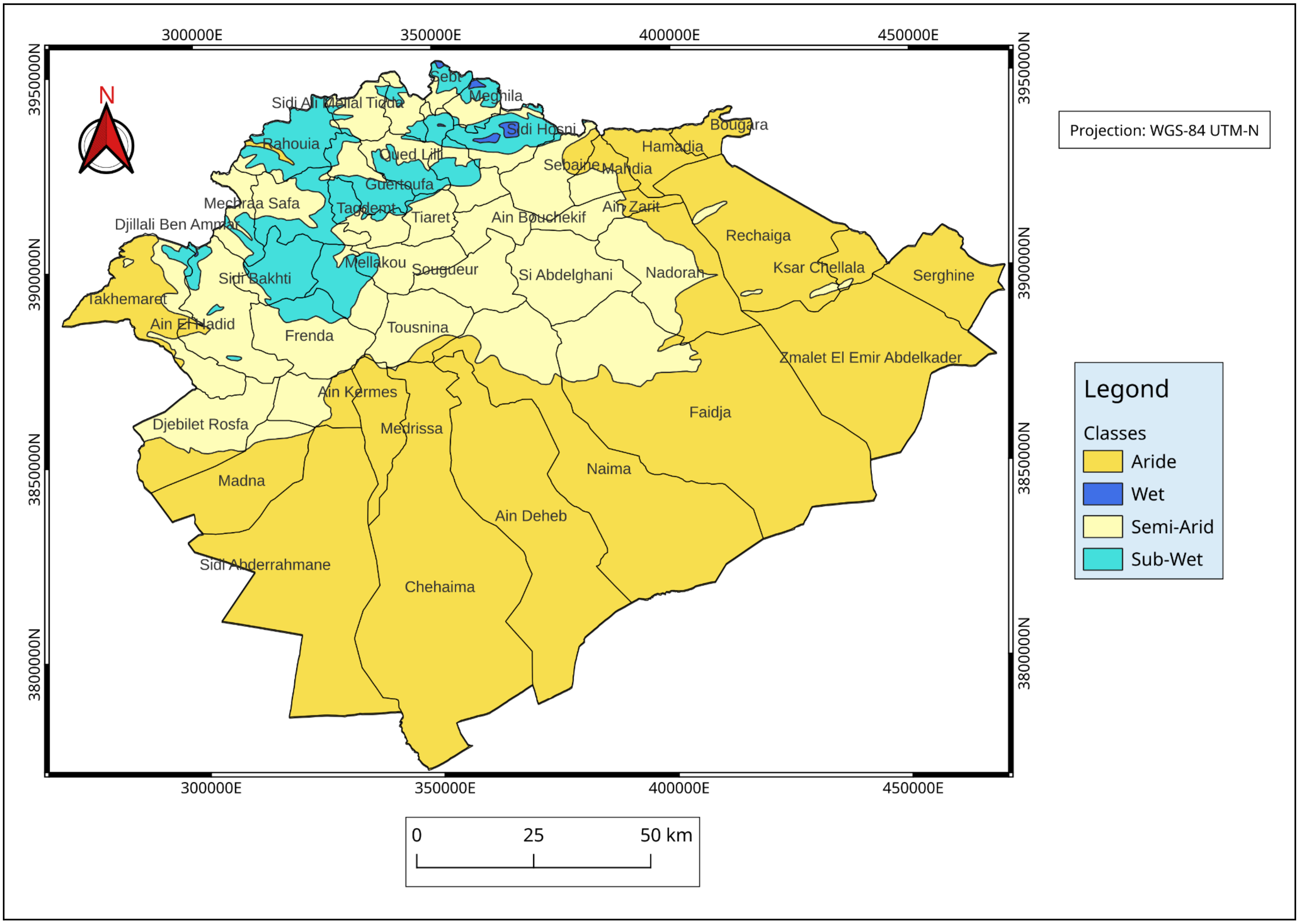

Figure 18: Climate chart of Tiaret

CHAPTER V

METHODOLOGY

Objective

The main objective of this study is to predict soil properties using machine learning and remote sensing data to generate a crop soil map.

V.1 Data collection

V.1.1 Sampling

This study is based on subjective soil sampling which involves a comprehensive approach that takes into account various factors such as soil colour, vegetation growth, slope, crop type, irrigation, and regional bioclimate. By considering these factors, a more holistic understanding of the soil composition and its potential characteristics can be gained. Soil colour can provide insights into the presence of certain minerals or organic matter, while vegetation growth patterns can indicate nutrient availability and soil fertility. Slope analysis helps determine the potential for erosion and water movement, influencing soil structure and drainage. Crop type and irrigation practices offer information on nutrient requirements and water availability. Lastly, regional climatic factors, including temperature and precipitation, impact soil formation processes and overall soil health. By incorporating these subjective observations, a more nuanced and site-specific assessment of soil conditions can be obtained, photos from the sampling sites are represented in figure (19).

We choose 5 communes to work in (Oued-lili, Rahouia, Rechaiga, Sidi-Abderrahmane, Sougueur) with total of 113 sample from 13 different fields, sample depth was at 30 cm with approximately 500g weight, figure 20 shows the samples location in the study area.

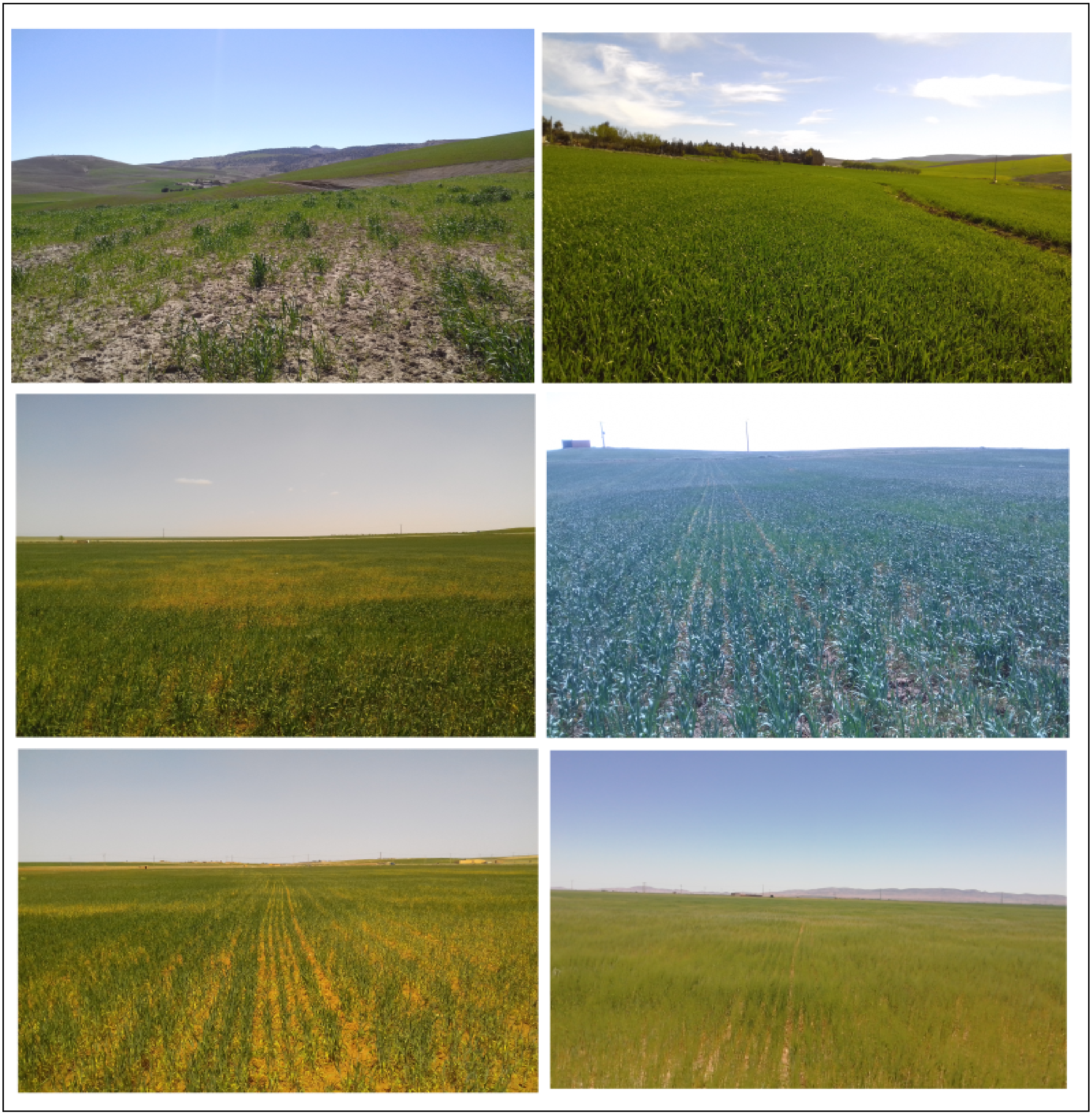

Figure 19: photos from the sampling sites (O.Bekouider)

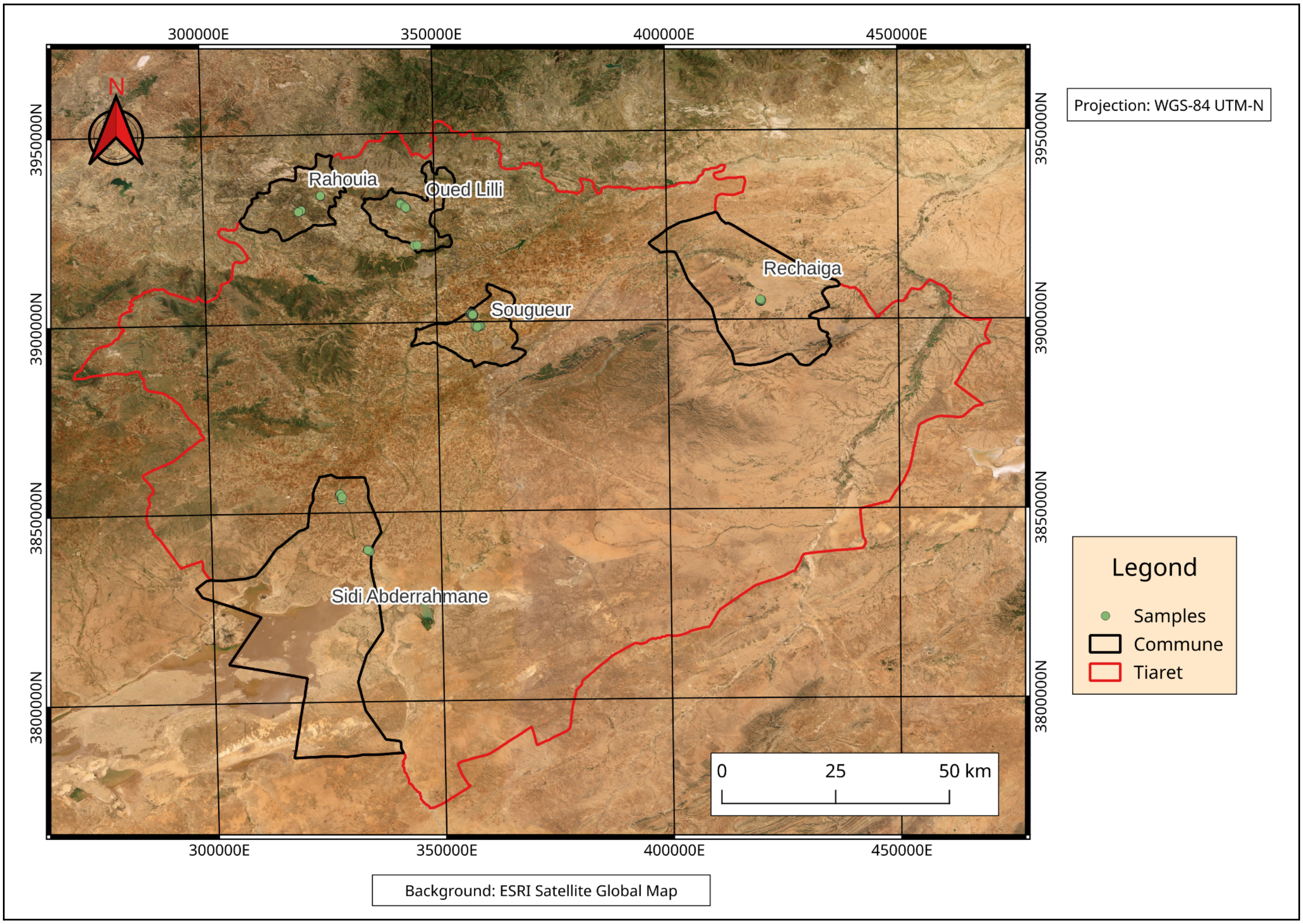

Figure 20: Samples Location in the study area

V.1.2 Soil Laboratory Analysis

V.1.2.1 Physico-Chemical Analysis

Moisture

Soil moisture affects soil structure and stability impacting the overall health and productivity of ecosystems (Wang & al. 2019), Insufficient moisture can lead to drought stress, stunted growth, and reduced crop yields. On the other hand, excessive soil moisture can result in waterlogging, hindering root development and causing oxygen deprivation in plants.

Moisture measurement is easy, soil has to be fresh from site or preserved in sealed bags for max 24 h, we can measure the soil moisture by the weight of sample before and after drying in the autoclave then use the following weight function:

H%= (((capsule + soil)- (capsule+soil after 24h))/ capsule)*100.

Figure 21: Soil moisture by drying technique (O.Bekouider)

Nutrient content (NPK)

Adequate nutrient levels in the soil are necessary to support healthy plant growth, optimal crop yields, and improved resistance to diseases and pests (Awad & al. 2022). Regular assessment and management of soil nutrient content through soil testing and appropriate fertilisation practices are essential for maintaining soil fertility, optimising nutrient availability, and ensuring sustainable agricultural practices.

To measure the NPK (nitrogen, Phosphorus, Potassium) we used a portable electric sensors which give values in mg/kg, the sensors require a wet soil in order to work correctly, we prepared a soil solution then we let it rest to precipitate the solid particles and separate the nutrients, after about 30 min we separated the resulted water in-top in a graduated test tube and took measurements, figure (22) shows the measurement methodology.

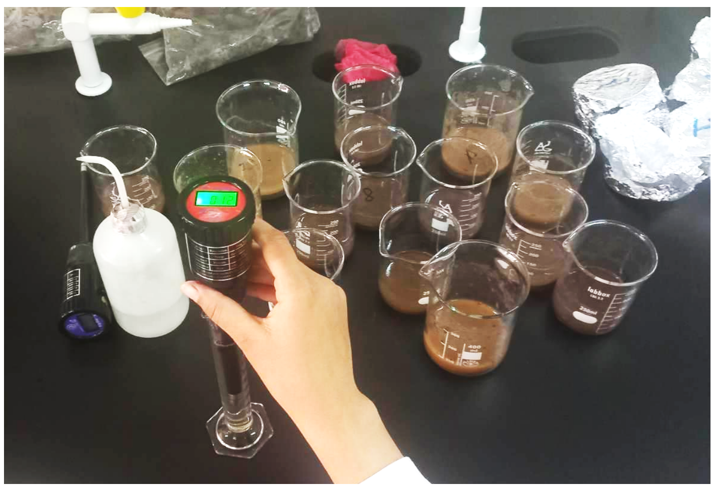

Figure 22: NPK Measurements (S.Saadna)

PH

PH influences nutrient availability and microbial activity in the soil. It affects the solubility and availability of essential nutrients for plant uptake, acidic soils tend to have higher levels of available iron, manganese, and aluminium, while alkaline soils may limit the availability of phosphorus, iron, and zinc (Neina D. 2019). Imbalanced pH levels can lead to nutrient deficiencies or toxicities, impacting plant growth and productivity.

We used a ph-metre in order to measure the soil ph, however we had to prepare a soil solution in a 10 ml beaker.

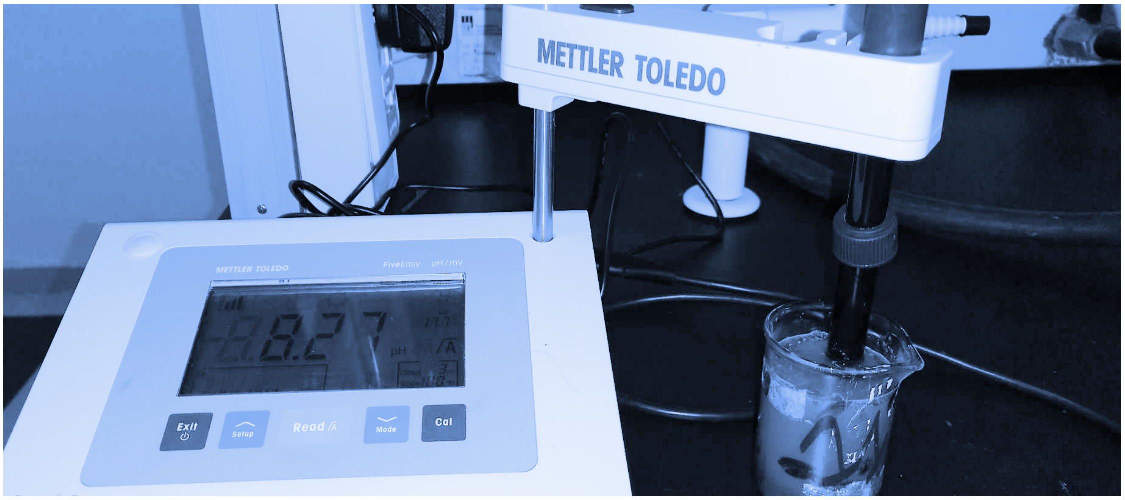

Figure 23: PH measurement (O.Bekouider)

Organic Carbon And Organic Matter

Soil organic matter and organic carbon are essential components of healthy soils with significant implications for soil fertility, structure, and nutrient cycling (Bhattacharyya & al. 2022).

We used the Walkley-Black method to estimate the organic carbon content using 1g of soil, 15 ml sulfuric acid, 10 ml potassium dichromate, and ferrous sulphate for titration, figure() shows the material used. The resulted volume measured after titration is then used for carbon content measurement as follows:

OC% = (17-(Titration volume)*0.3

The Organic matter is a derivative of organic carbon and can be calculated as follow:

OM% = OC%*1.72

Electric Conductivity (EC)

Soil electrical conductivity (EC) is a measure of the soil's ability to conduct an electrical current. It is an important parameter used to assess soil salinity and the availability of nutrients for plant growth (Corwin et al. 2020). Electrical conductivity is influenced by the concentration of dissolved salts in the soil solution. Salts, such as sodium, potassium, calcium, and magnesium, when dissolved in water, increase the soil's conductivity (Othaman et al.2020).

We used an electronic EC-meter to capture measurements at a temperature of 25 C° in µs/cm.

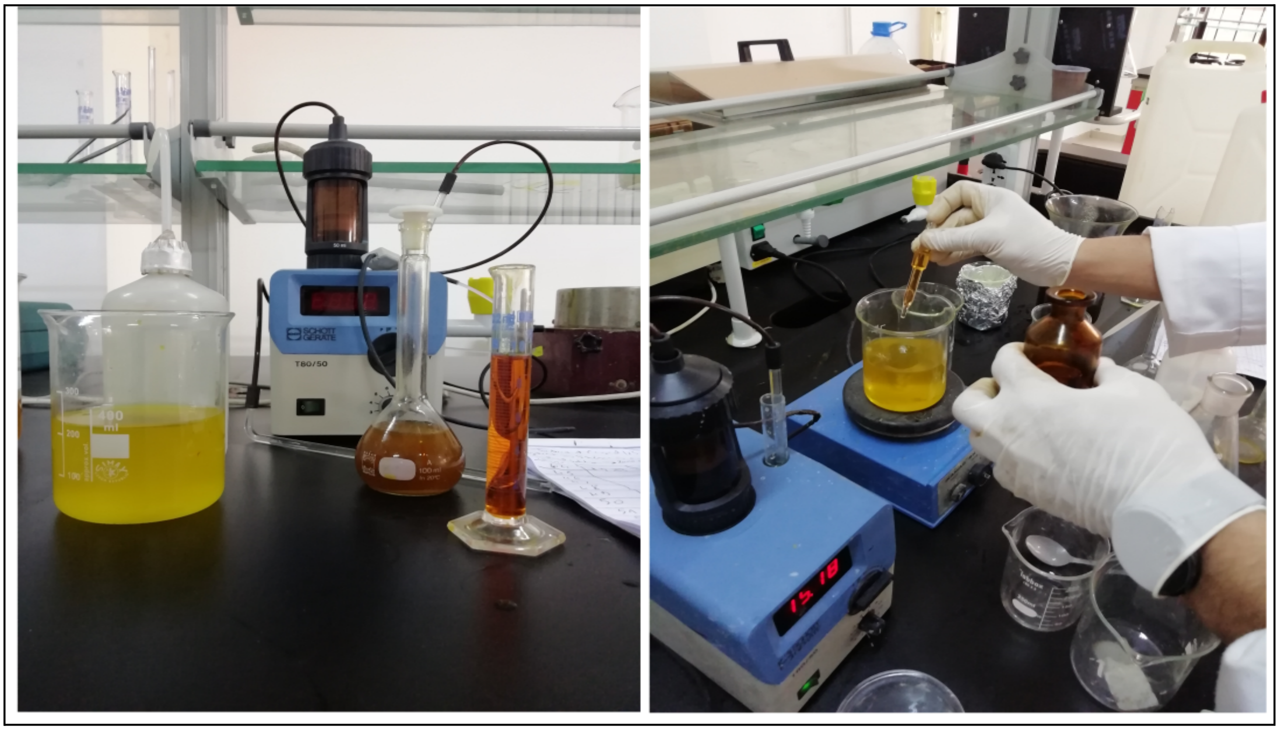

Figure 24: Organic carbon/matter analysis (S.Saadna)

Figure 25: EC measurement (O.Bekouider)

Limestone (CaCo3)

Limestone is a sedimentary rock primarily composed of calcium carbonate. Total limestone (TL) is the complete quantity or content of limestone present in a soil or sample, while active limestone (AL) refers to limestone that actively reacts with soil acidity, neutralising it and raising the soil pH. This reaction occurs due to the presence of calcium carbonate, which releases calcium ions (Ca^{2+}) and reacts with hydrogen ions (H^{+}) in the soil solution, reducing soil acidity. Active limestone is beneficial in acidic soils as it helps create a more favourable pH range for plant growth and improves nutrient availability (Yang et al. 2021) .

We measured the (TL) by volumetric calcimetry in which we measured the volume of evolved CO_2 gas resulting from the reaction of a known weight of sample with an excess of hydrochloric acid, the reaction is as follows:

$CaCO_3 + 2\ HCl \rightarrow CaCl_2 + H_2O + CO_2$.

Figure 26: TL measurement using the Bernard-calcimeter (O.Bekouider)

For active limestone measurement we used the titration method, after preparing soil solution with oxalate and agitating it we added sulphuric acid to the solution and used potassium-permanganate for titration.

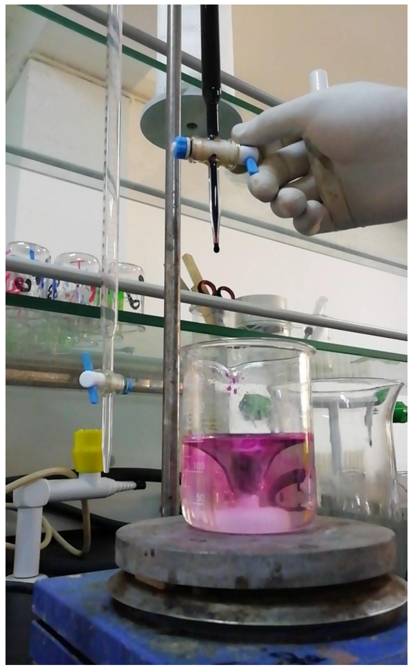

Figure 27: Active-limestone titration (O.Bekouider)

V.1.2.2 Laboratory Data Processing

After the laboratory tests we worked on the data including calculations, sorting and cleaning. The result is a table that contains training data for the DSM model.

V.1.3 Geoprocessing Tools and Data

V.1.3.1 Sentinel-2

Sentinel-2 imagery, provided by the European Space Agency (ESA), is a satellite-based Earth observation system that captures high-resolution optical images of the Earth's surface. It enables monitoring and analysis of land cover, vegetation, water quality, and other environmental parameters, supporting various applications in agriculture, forestry, and urban planning.

We used the sentinel-2 bands to calculate the next indices:

- NDVI : (Normalised Difference Vegetation Index) is a numerical indicator it's values range from-1 to 1 derived from satellite imagery that quantifies vegetation health and density by analysing the reflectance of near-infrared and red light, which is calculated from Sentinel-2 as follows:

  (RED+NIR) / (RED-NIR) => (B4+B8) / (B4-B8)
- NDMI: (Normalised Difference Moisture Index) is a remote sensing index that measures the moisture content of vegetation and soils using near-infrared and shortwave infrared bands, providing insights into drought and water stress conditions, which is calculated from Sentinel-2 as follows:

  (NIR- SWIR) / (NIR + SWIR) => (B08 - B11) / (B08 + B11)
- BI: (Brightness index) is sensitive to the brightness of soils. High soil brightness is linked with soil humidity and the presence of salts in the soil, it's calculated from sentinel-2 as follows:

  sqrt((Red^2 / Green^2) /2) => sqrt($(B4^{\wedge 2} / B3^{\wedge 2})$ /2)

V.1.3.2 Google Earth Engine (GEE)

GEE is a cloud based platform used to load and process geospatial data using the programming language javascript, it has a large amount of data collections ready to use from several satellite imagery providers and geospatial data sources.

We used GEE to load the following data collections:

- Sentinel-2 Level-1C from 2023-03-01 to 2023-04-30 by European Union/ESA/Copernicus
- Soil texture at 30cm By (Tomislav H. 2018)
- Slope by (Farr et al. 2007)

Then we used a shape file containing the points data and extracted the NDVI, NDMI, BI, Texture, Slope values for each point into a CSV (Comma Separated Values) file.

Figure (28) shows snippets from the GEE javascript code.

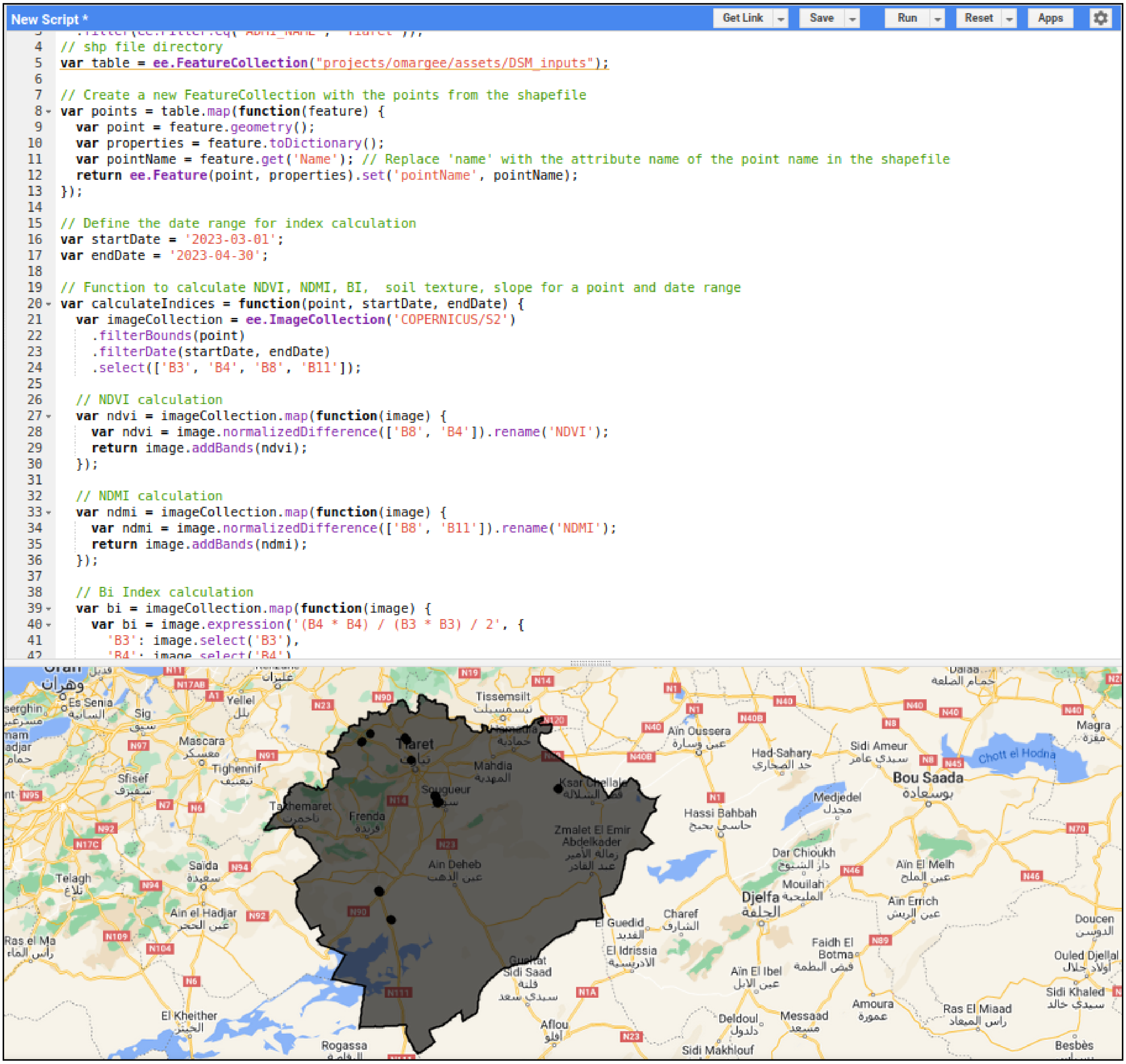

Figure 28: GEE code Snippets

V.1.3.3. Google Colaboratory

Colab basically is a cloud based python environment programming platform which can be used to create and manipulate notebooks (Webmaster 8), directed especially for data science and machine learning applications based on cloud processors.

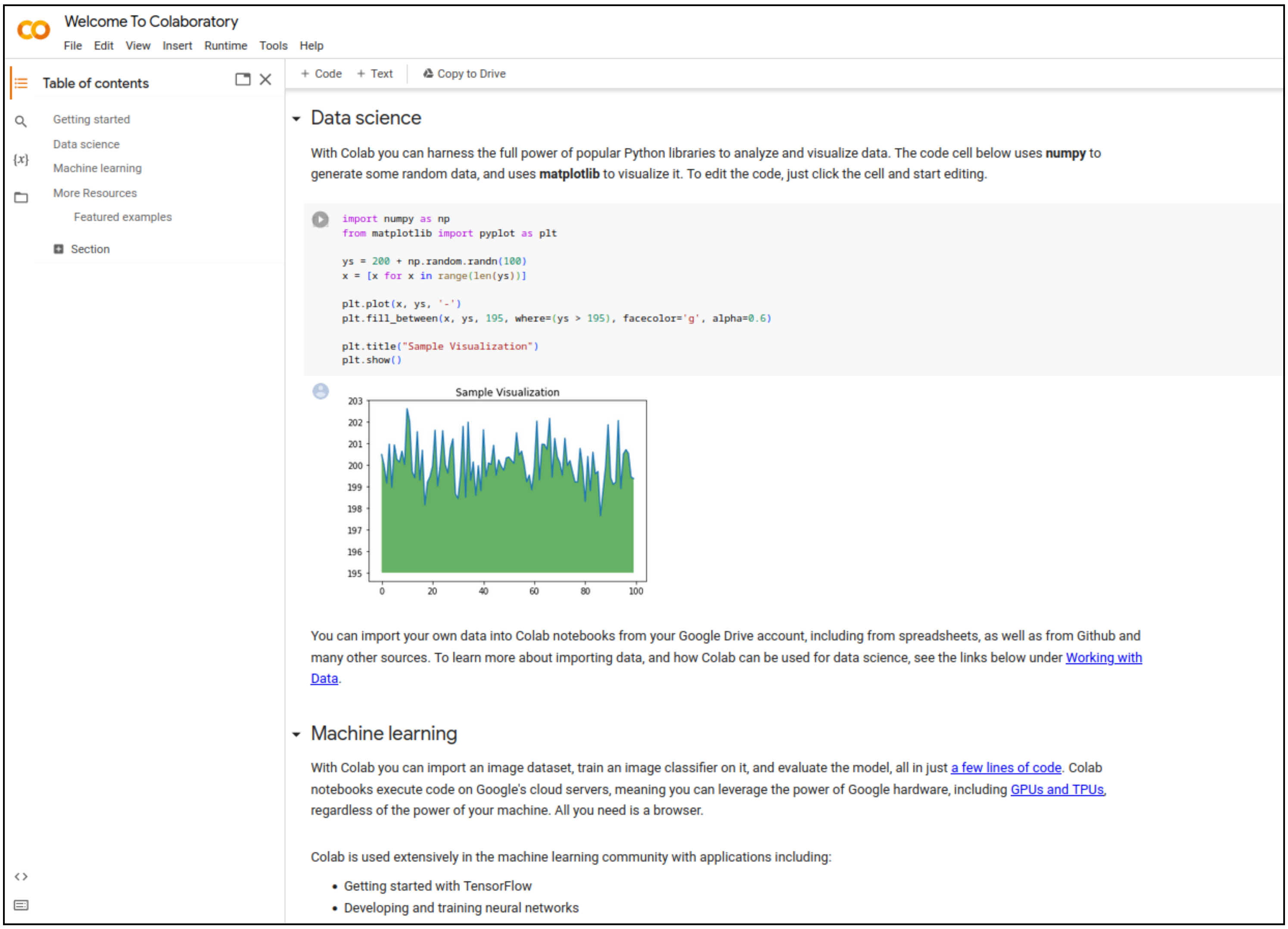

Figure 29: Google Colaboratory welcome page (Webmaster 8)

V.1.3.4 QGIS (Quantum Geographic Information System)

Qgis is an open source geospatial data processing software used to create, edit, visualise, analyse and publish geospatial information on different operating systems (Webmaster 9).

The shape file containing the points data was created by QGIS by creating a points grid vector file on the study area at 1 km scale.

QGIS is used in this study to generate maps from data and analyse geospatial information.

V.2 Model Building

We used google colaboratory environment to perform the algorithm, where we followed the next steps:

V2.1 Import Libraries

We imported the necessary python libraries to the code such as pandas, numpy, sklearn, scipy, statsmodels and matplotlib.

V.2.2 Data Upload And Identification

We uploaded a CSV1 file that contains the 113 sampling points full data of NPK and NDVI, NDMI, BI, Slope and Texture, then we identified the features as floats.

V2.3 Correlation matrix

A correlation matrix is a square matrix that displays the correlation coefficients between multiple variables. It provides a summary of the pairwise relationships among the variables, indicating the strength and direction of their linear associations. Correlation coefficients range from -1 to 1, with values close to -1 indicating a strong negative correlation, values close to 1 indicating a strong positive correlation, and values close to 0 indicating a weak or no correlation(Hair, J. F et al, 2019).

V.2.4 Multi linear regression (MLR)

Linear regression is a statistical modelling technique used to analyse the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the independent variables and the dependent variable, where the dependent variable can be predicted or explained by the independent variables (Kuhn M. & al. 2013). In a linear regression model, the relationship between the dependent variable (Y) and the independent variables (X) is represented by the equation:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn + \varepsilon$$

We used the linear_model.LinearRegression() function from scikit-learn (sklearn library) to fit a linear regression model to the data.

V.2.5 Intercept And Model Coefficient

In multiple linear regression, the intercept and coefficients are the parameters that define the relationship between the independent variables (predictors) and the dependent variable (target). Intercept indicates the starting point or the constant term of the linear relationship between the variables (Fox J. & al. 2019), the intercept (β_0) represents the predicted value of the dependent variable (Y) when all independent variables (X) are equal to zero. In our case, when all N, P or K values are zero.

The coefficients (β_1, β_2, β_3, β_4) indicate the change in the dependent variable (Y) for a one-unit change in the corresponding independent variable (X), assuming all other variables are held constant. Each coefficient represents the estimated effect of the corresponding independent variable on the dependent variable.

V.2.6 Model Training

For the training we performed a multi-linear regression algorithm where we selected NDVI, NDMI, BI, Slope and texture from the CSV1 as the independent variables Y and the N, P or K as the dependent variable X .

V.2.7 Prediction

After finishing the model, we uploaded a CSV2 file that contains the dependent variables NDVI, NDMI, BI, Texture and Slope with empty values of NPK, then we used the trained model to predict the NPK values and exported the data. Figure (30) a caption of the model code from the colab.

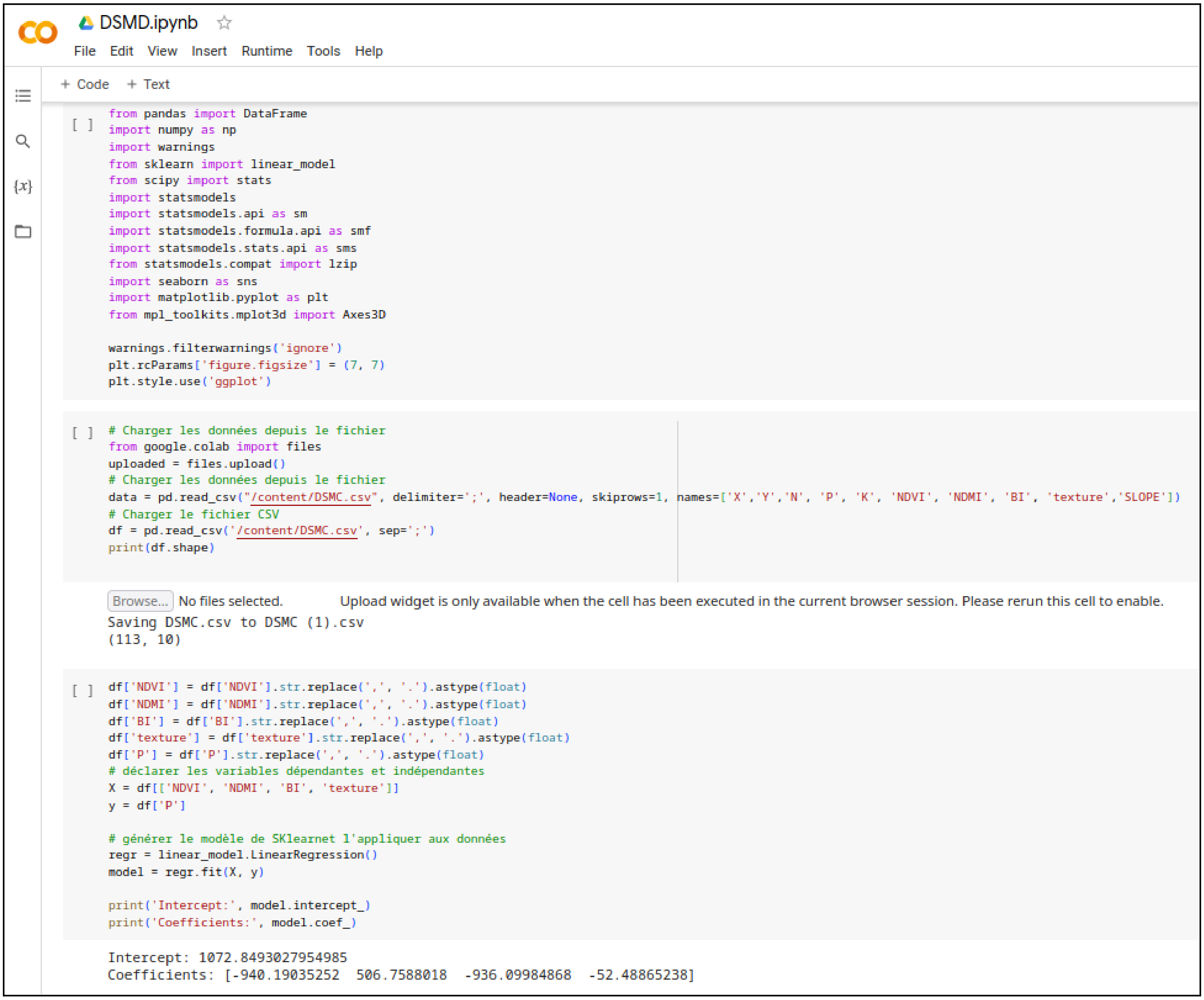

Figure 30: model initiative code

V.2.8 Model evaluation

After the model prediction we evaluated its performance using the olsmod from statsmodels library to get the appropriate evaluation metrics in order to assess the model's accuracy and robustness, we used two methods:

Linear Assumption

The linearity assumption in multiple linear regression refers to the assumption that the relationship between the independent variables (Y) and the dependent variable (X) is linear. It assumes that the effect of each independent variable on the dependent variable is constant and additive (Schmidt et al. 2018).

R Squared (R2)

The R-squared (R^2) statistic, also referred to as the coefficient of determination, quantifies the extent to which the independent variables (Y) in a regression model explain the variation in the dependent variable (X). It indicates the proportion of the total variability in X that can be attributed to the independent variables. An R^2 of 0 implies that the independent variables do not account for any variance in the dependent variable. Conversely, an R^2 of 1 signifies that the independent variables perfectly explain all the variability in the dependent variable.

CHAPTER VI

Results and Discussion

VI.1 Laboratory Tests Results

We sorted the laboratory tests results using descriptive statistics for more understanding of the data in table (2).

Table 2 : Laboratory tests descriptive statistics

	H%	PH	N (kg/ha)	P (kg/ha)	K (kg/ha)	TL	AL	OC%	OM%	EC (µs/cm)
Min	1.44	7.12	18	14.4	50.4	0.39	0	0.033	0.05676	32.8
1st Qu	3.019	7.82	32.4	32.4	86.4	8.57	12.6	0.5437	1.1481	125.9
Median	4.027	8.08	44.4	44.4	119.9	18.31	14.5	1.0845	2.2494	148.5
Mean	13.842	8.055	62.73	62.99	162.2	38.24	13.87	1.0888	2.26254	180.7
3rd Qu	25.652	8.35	66.6	66.6	177.6	32.62	16.1	1.5893	2.85348	191.8
Max	110.221	8.73	590.52	603.84	1420.8	361.88	30.5	2.76	7.81	1183

VI.2 Data Collection Maps

We exported the resulting layers from GEE and used QGIS to create a map from each layer, the maps created from qgis are in figure (31). We can see that the layer data are similar in the geolocation distribution especially NDMI, NDVI and IB.

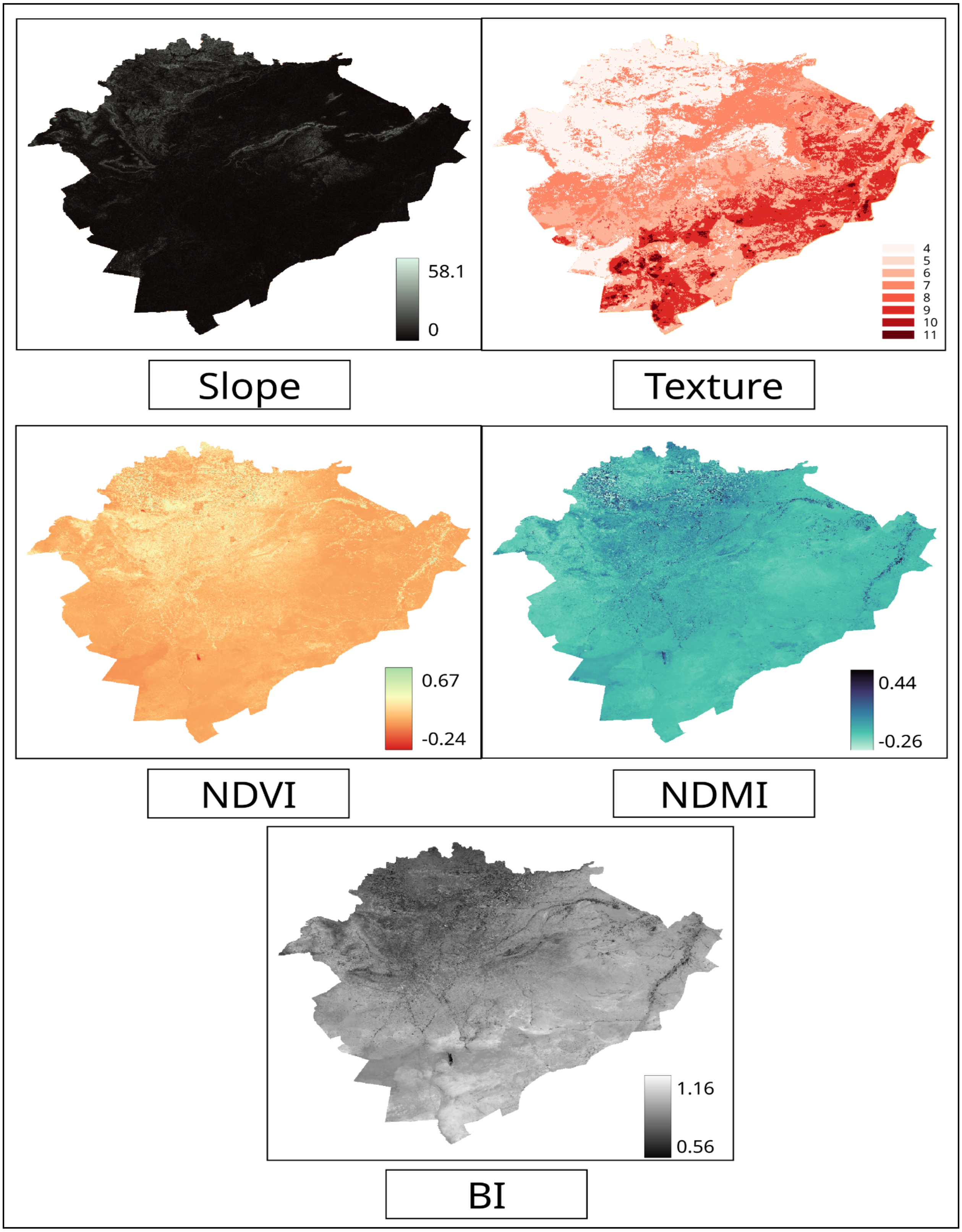

Figure 31: GEE data collections calculated maps for Tiaret

VI.3 Correlation

In the correlation between (N, P, K) values and (NDMI, NDVI, BI, Slope, Texture), we can refer to the correlation coefficients in the correlation matrix represented in figure (32) below.

Correlation between (N, P, K) and NDMI

The correlation coefficient between (N, P, K) and NDMI is 0.008517. This indicates a weak positive correlation between the nutrient levels (N, P, K) and the normalised difference moisture index (NDMI).

Correlation between (N, P, K) and NDVI

The correlation coefficient between (N, P, K) and NDVI is -0.054368. This indicates a weak negative correlation between the nutrient levels (N, P, K) and the normalised difference vegetation index (NDVI).

Correlation between (N, P, K) and BI

The correlation coefficient between (N, P, K) and BI is -0.136057. This indicates a weak negative correlation between the nutrient levels (N, P, K) and the brightness index (BI).

Correlation between (N, P, K) and Slope

The correlation coefficient between (N, P, K) and Slope is -0.083759. This indicates a weak negative correlation between the nutrient levels (N, P, K) and the slope.

Correlation between (N, P, K) and Texture

The correlation coefficient between (N, P, K) and Texture is -0.076342. This indicates a weak negative correlation between the nutrient levels (N, P, K) and the soil texture.

The crop development in this season has been negatively impacted by the absence of precipitation. As a result, we were unable to establish a strong and significant correlation between N P K values and NDVI. Precipitation plays a crucial role in influencing soil moisture, and its absence has also hindered the correlation with NDMI .

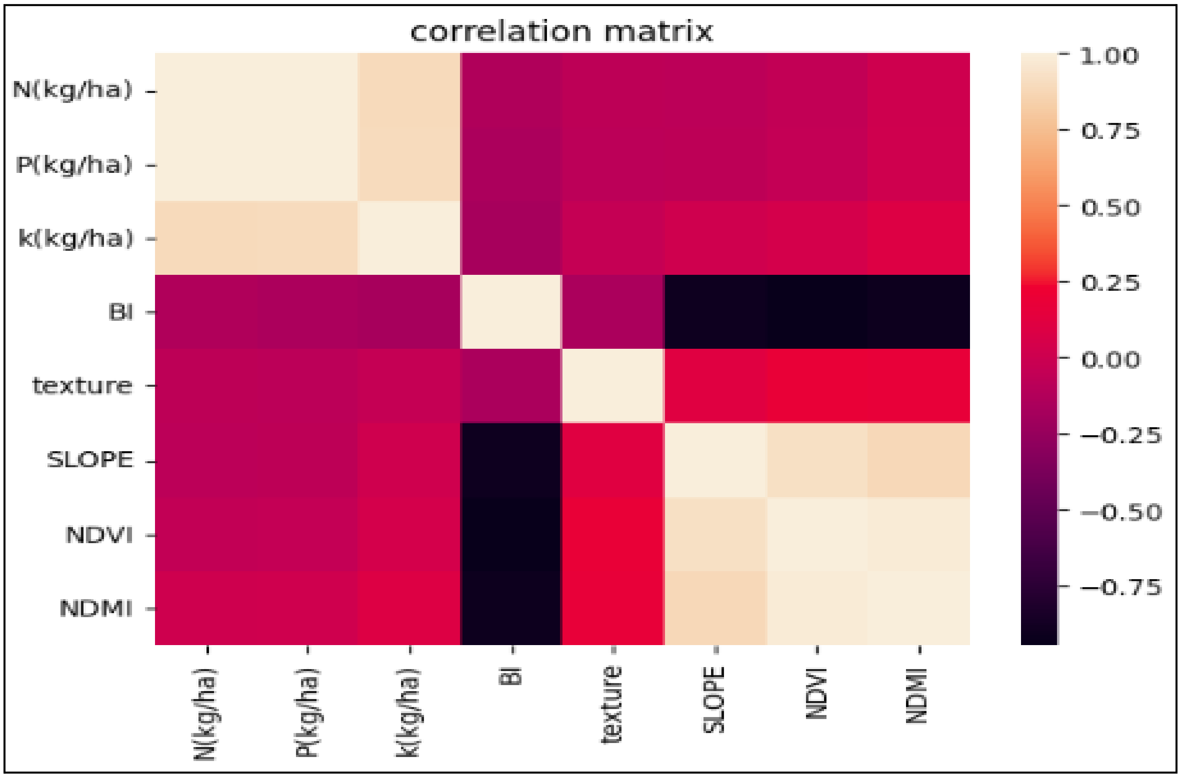

Figure 32: Correlation matrix of the variables.

VI.4 Model Evaluation

VI.4.1 Intercept and coefficients

The model interception and coefficients can also be used for model evaluation rather than estimation, from table (3) below we can say that the interception of the NPK values is high and unreasonable because when we look at the laboratory tests we can see that they have the same min range as it is for max.

Table 3 : NPK model interception and coefficients

	N	P	K
Intercept	1015.44	1073.18	1801.77
NDVI coefficient	-903.27	-944	-1686.94
NDMI coefficient	488.95	507.59	1045.91

BI coefficient	-879.35	936.59	-1517.56
Texture coefficient	-45.72	-52.52	-63.90
Slope coefficient	5.57	12.56	385.53

VI.4.2 Linear Assumption

According to the linear assumption graphs between the actual NPK and the predicted NPK from figure (31), the predicted values are near and in range of the actual variables.

The fact that the predicted values are near and in range of the dependent variables suggests that the model is able to make accurate predictions.

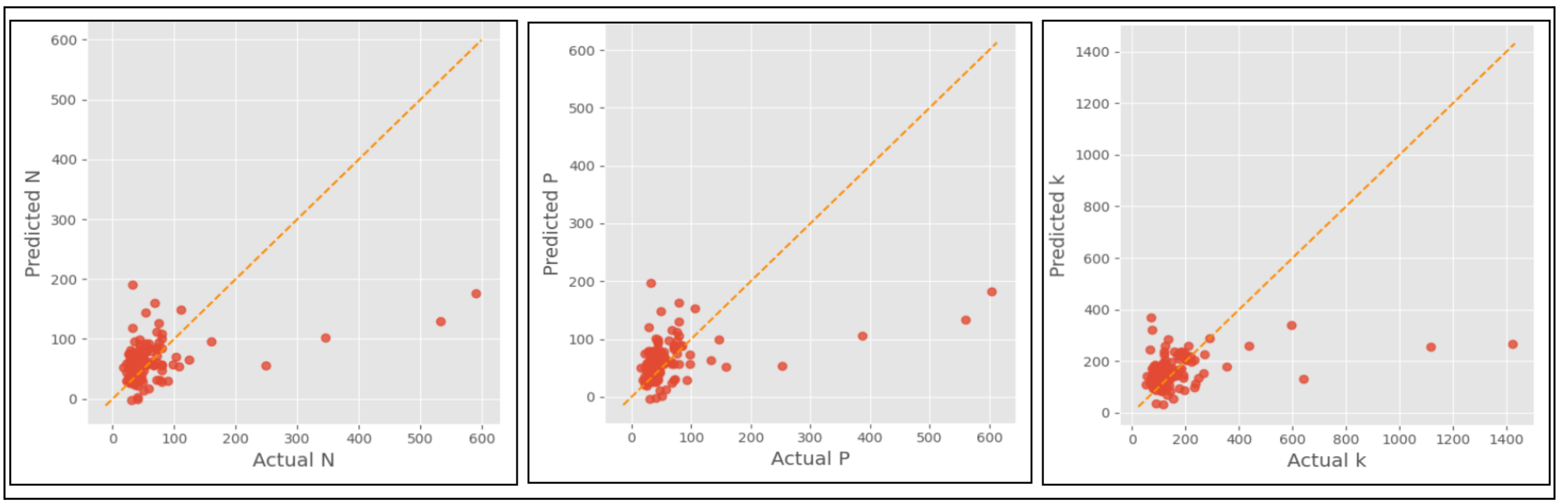

Figure 33: Linear assumption of the model.

VI.4.3 R Squared (R^2)

The $\mathbf{R^2}$ of the model for the NPK (table 4) shows weak values which means that the independent variables have a little influence on the dependent variables.

The low R^2 value could be due to a number of factors, including:

- The fact that NPK levels are influenced by a variety of factors, not just the factors that are included in the model, including the drought in this season.
- The fact that the data set was not large enough and well spatially distributed to accurately estimate the relationships between NPK levels and the other factors.

Table 4: R^2 of the model

	N	P	K
R^2	0.1853	0.1872	0.12

VI.5 NPK maps

After the prediction we used QGIS to generate maps from the resulting values of prediction using interpolation techniques such as Inverse distance weighted (IDW) interpolation, the 1 km scale NPK maps are in figures (34) (35) (36).

From the first Observation of the NPK values we can see that they have a similar spatial distribution which can be explained by the positive correlation in the laboratory tests, also with the used independent variables in prediction especially NDVI and NDMI.

The values range is influenced by the water surface reflection in the NDVI, NDMI and IB which results in low values.

In a geo-description of the NPK values in Tiaret we can say that they are descending in a graduation from the East-North to the West-South, that can be related to the fertility of the agriculture soils in the region alongside with the soil type and bioclimate.

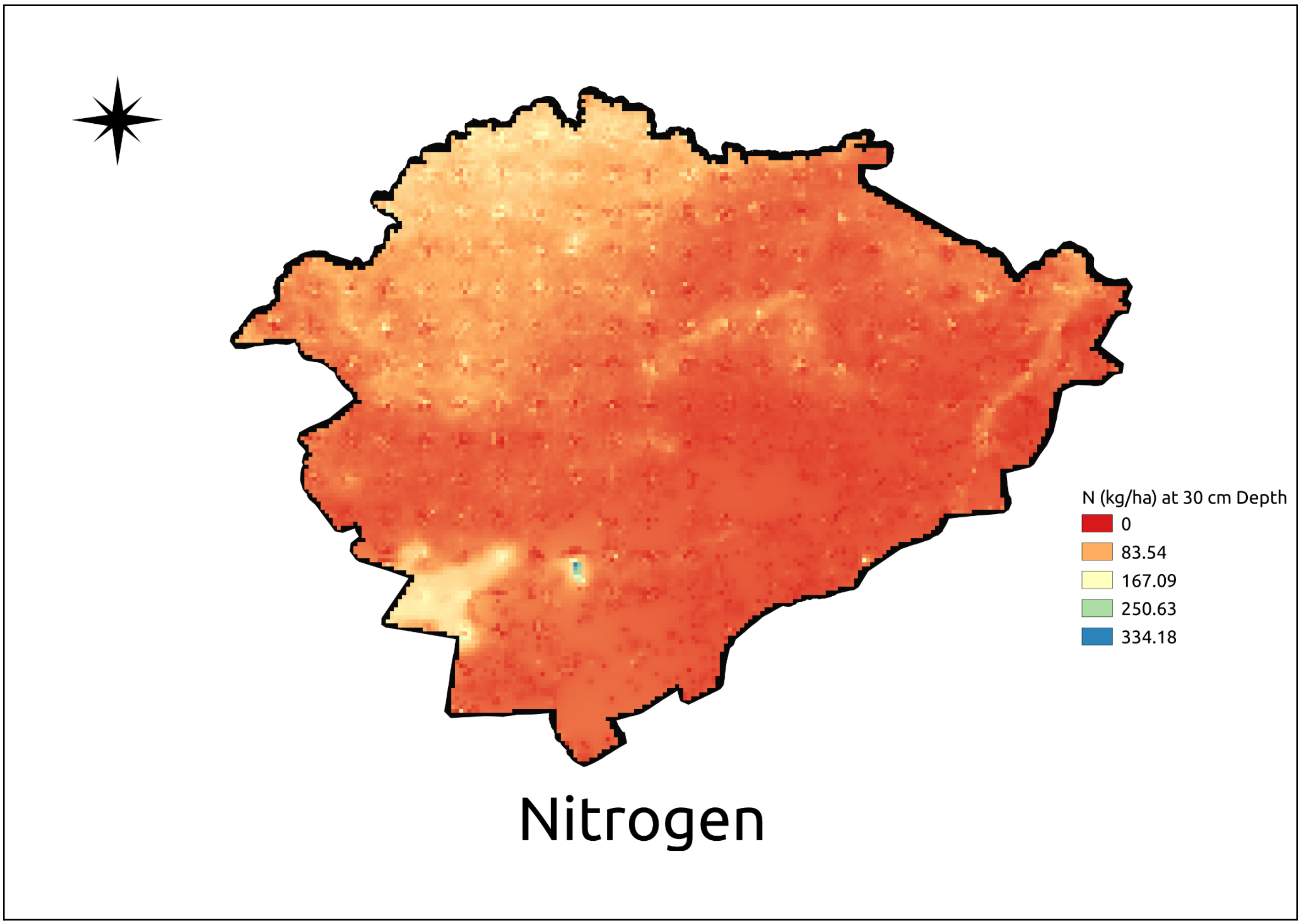

Figure 34: Nitrogen (N) IDW interpolated map

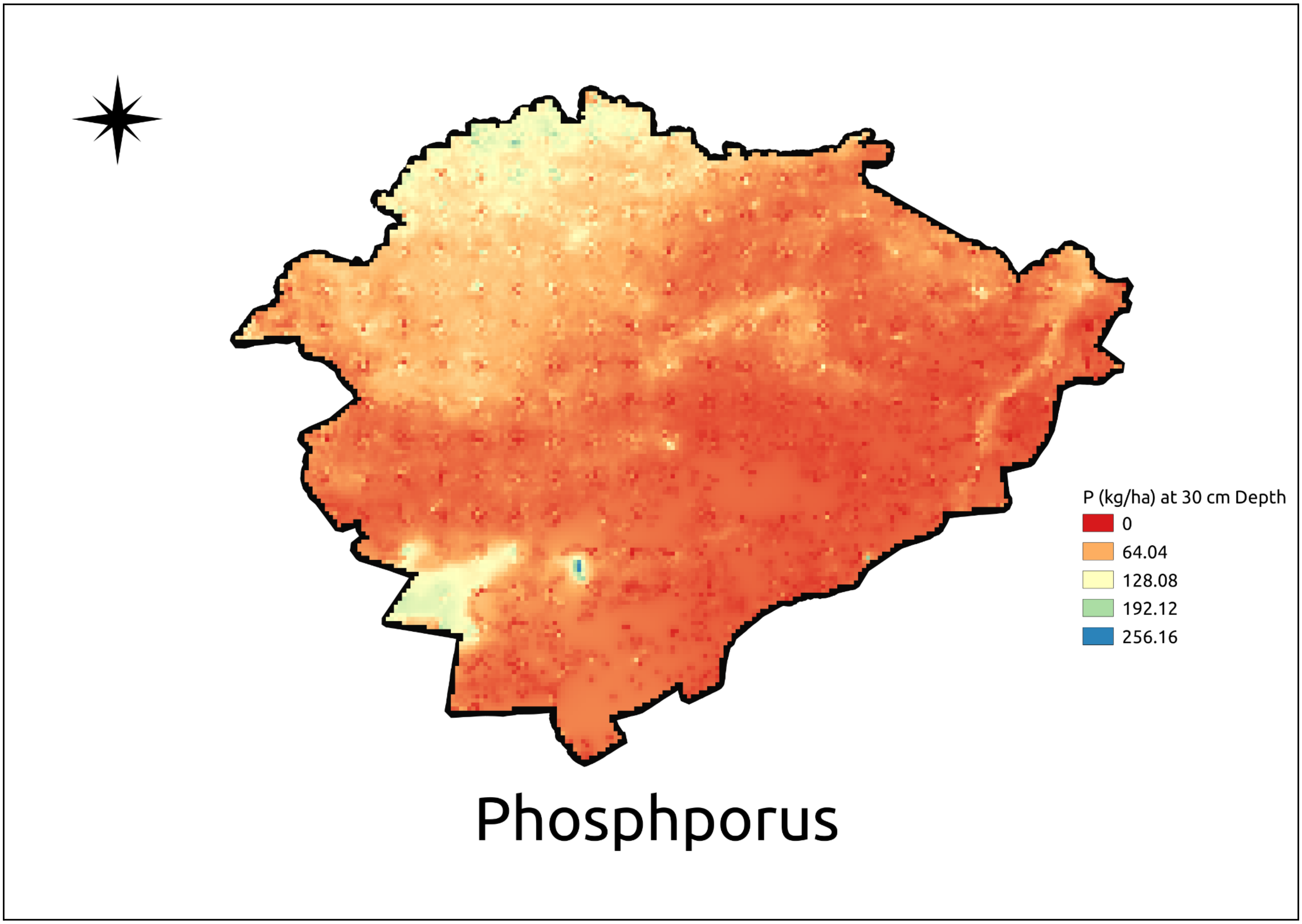

Figure 35: Phosphorus (P) IDW interpolated map

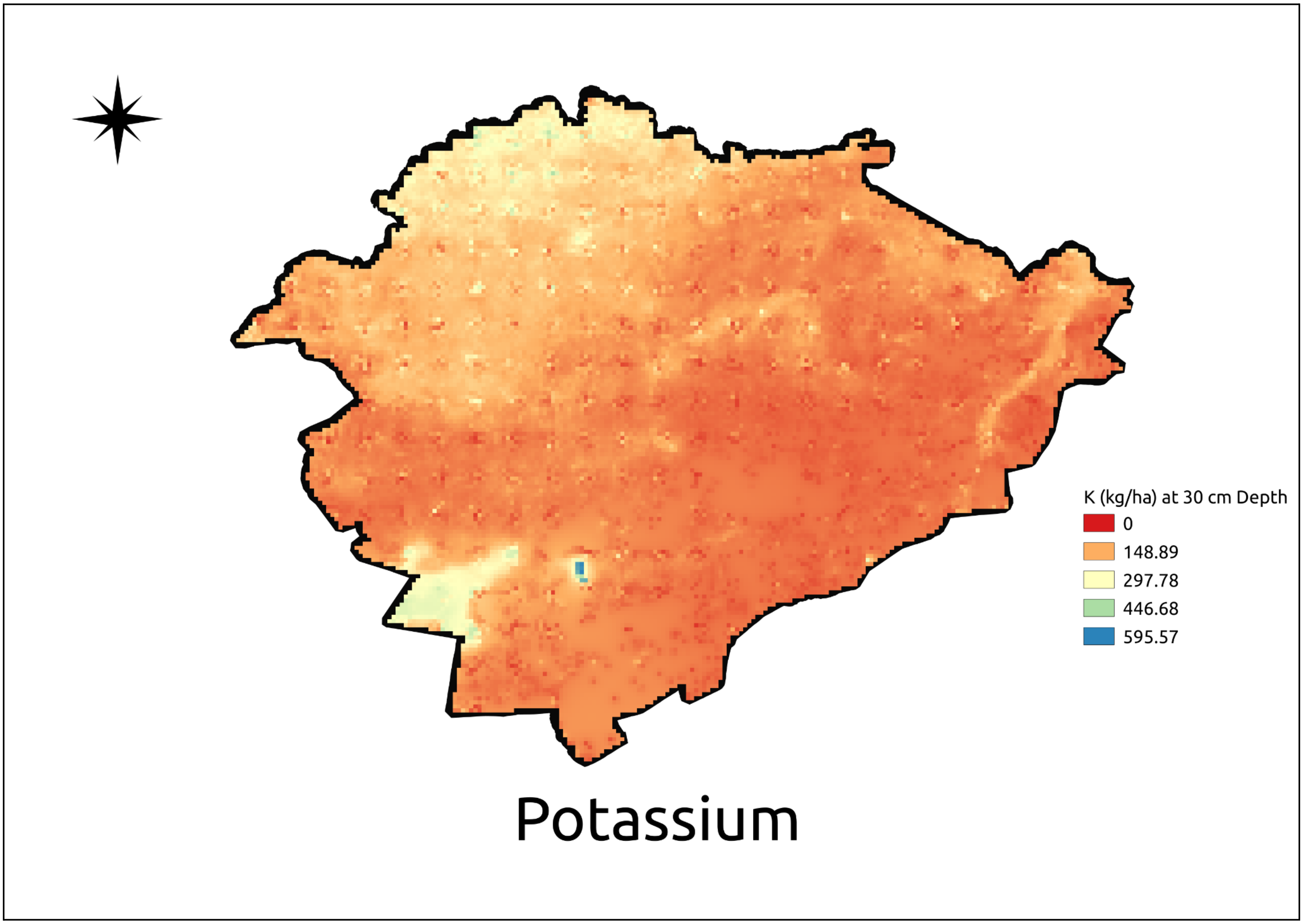

Figure 36: Potassium (K) IDW interpolated map

CHAPTER VII

Conclusion

Conclusion

The objective of this study was to create NPK charts by predicting the values using MLR as a machine learning algorithm in the Tiaret region. We used the laboratory tests data of 113 sampling points for training as dependent variables and the NDVI, NDMI, BI, Slope and texture as independent variables.

The trained model used for NPK values prediction which was then used in generating the NPK charts at 1 km scale, to test the model performance we applied linearity assumption and r-squared statistic.

After analysing this study results we can say the next:

In soil properties prediction using machine learning it is important to take in consideration the independent variables selection as well as for the algorithm used to generate the model.

Multi linear regression algorithm is a good choice for the soil properties prediction, however the independent variables in use have a great influence on the predicted data variability.

When predicting NPK of the crop soils, The NDVI, NDMI, BI, slope and soil texture can give approximate values but other factors such as bioclimate should not be neglected.

The predicted charts in this study are more suitable for crop cultivation areas which give significant values according to the region characteristics.

Tiaret region has a good NPK distribution due to its concentration in the north of the region where there is a more suitable characteristic for cereals agriculture and its decreased values in the south where there is an arid climate.

Crop soil mapping is efficient and essential to get insights on the cultivated area soil properties where the vegetation and soil are in an exchanged relation that one explains the other.

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- Webmaster 2 (https://apps.sentinel-hub.com/eo-browser/)
- Webmaster 3 (https://igcp638.univ-rennes1.fr/index.php/meeting/field-trips)
- Webmaster 4 (https://www.nrcs.usda.gov/resources/data-and-reports/digital-soil-mapping-dsm)
- Webmaster 5 (https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm)
- Webmaster 6 (https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soil/gis-and-digital-mapping-for-soil-survey)
- Webmaster 7 (https://www.nrcs.usda.gov/sites/default/files/2022-12/00-Digital-soil-mapping-job-aides-composite.pdf)
- Webmaster 8 (https://colab.research.google.com/)
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