



**Spatiotemporal Dynamics of Drought and Desertification in Northern
Algeria: A Multi-Scale Analysis Using Remote Sensing and Ensemble
Machine Learning, From Regional Aridification to Local Land-Cover
Transformation in the Algerian Steppe.**

Thesis for the Degree of Doctor of Philosophy (PhD)

Ramzi Benhizia

Supervisor:

Dr. György Szabó

UNIVERSITY OF DEBRECEN

Doctoral Council for Natural Sciences and Engineering

Doctoral School of Earth Science

Debrecen, 2026

Hereby I declare that I prepared this thesis within the Doctoral Council for Natural Sciences, Doctoral School of Earth Sciences, University of Debrecen in order to obtain a PhD Degree in Natural Sciences at Debrecen University.

The results published in the thesis are not reported in any other PhD theses.

Debrecen, August 2026



Benhizia Ramzi

signature of the candidate

Hereby I confirm that Ramzi Benhizia candidate conducted his studies with my supervision within the Landscape Protection and Climate Doctoral Program of the Doctoral School of Earth Sciences between 2019 and 2026. The independent studies and research work of the candidate significantly contributed to the results published in the thesis.

I also declare that the results published in the thesis are not reported in any other theses.

I support the acceptance of the thesis.

Debrecen, August 2026

Dr. György Szabó

signature of the supervisor

**Spatiotemporal Dynamics of Drought and Desertification in Northern Algeria:
A Multi-Scale Analysis Using Remote Sensing and Ensemble Machine
Learning, From Regional Aridification to Local Land-Cover Transformation
in the Algerian Steppe.**

Dissertation submitted in partial fulfilment of the requirements for the doctoral
(PhD) degree in Earth Science

Written by Ramzi Benhizia certified MSc degree in Geography and urban planning

Prepared in the framework of the of Earth Sciences doctoral school of the
University of Debrecen

(Landscape Protection and Climate programme)

Dissertation supervisor: Prof. Dr. György Szabó

The official opponents of the dissertation:

Dr.

Dr.

The evaluation board:

chairperson: Dr.

members: Dr.

Dr.

Dr.

Dr.

The date and venue of the dissertation defence: ...20

Dedication:

This dissertation is dedicated to my **parents**, whose unwavering love, sacrifices, and lifelong support have been the foundation of every achievement I have reached. Their guidance, patience, and enduring belief in the value of education have shaped not only my academic journey but also my character. I remain deeply and sincerely grateful for everything they have done to help me reach this stage.

To my **wife**, whose patience, strength, and quiet sacrifices carried me through the most demanding moments of this journey. Her willingness to endure the long hours, the absences, and the weight of this undertaking alongside me was a form of support I could never have completed this work without. I am profoundly grateful for her understanding and for standing beside me, even when this path asked more of her than it should have.

To my **children (louiza & Mate)**, who are the light of my life and my deepest source of motivation. Your presence has given meaning to every challenge and strength in every difficult moment. This work is also yours, reflecting the perseverance, hope, and responsibility you inspire in me every day.

I also dedicate this work to my **brother** and **sister**, whose support and encouragement have been an important part of my journey, even when distance or circumstances made their presence indirect rather than constant.

Finally, I acknowledge the path that brought me here, from a childhood marked by very modest means, where even the simplest necessities for schooling were not always guaranteed, to the completion of a PhD. This journey has been defined not by what was lacking, but by resilience, determination, and the belief that education can transform even the most difficult beginnings into meaningful achievement.

Table of Contents

Title.....	I
1. Introduction:	1
1.1. Research Aim:.....	4
1.2. Specific Objectives:	4
1.3. Primary Research Question:	5
1.4. Sub-Questions:	5
1.5. Contribution and Broader Impact:	5
2. Literature Review:	5
3. Materials and methods:	24
3.1. Study area description:	25
3.2. Data:.....	31
3.3. Data Preprocessing:	34
3.4. Regional-Scale Analysis:	38
3.5. Sub-Regional Scale Analysis (Northwestern Algeria):	57
3.6. Local Scale analysis:	63
4. Results:	69
4.1. Drought Variability and Vegetation Response (2011–2022):	69
4.2. Multi-Index Drought Assessment in Northwestern Algeria (2003–2023):	76
4.4. Machine Learning-Based Desertification Assessment:	101
5. Discussion:.....	113
6. Summary:.....	129
References:	131

List of Abbreviations

AED:	Atmospheric Evaporative Demand
ANN:	Artificial Neural Network
ArcGIS:	Arc Geographic Information System
BSI:	Bare Soil Index
BFAST:	Breaks For Additive Season and Trend
CHIRPS:	Climate Hazards group Infrared Precipitation with Stations
CQI:	Climatic Quality Index
CNN:	Convolutional Neural Network
DEM:	Digital Elevation Model
DRI:	Desertification Risk Index
ECMWF:	European Centre for Medium-Range Weather Forecasts
ENVI:	Environment for Visualizing Images
EPM:	Erosion Potential Method
ERA5:	European Reanalysis 5th Generation
EVI:	Enhanced Vegetation Index
FLAASH:	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
FVC:	Fractional Vegetation Cover
GEE:	Google Earth Engine
IntErO:	Intensity of Erosion and Outflow
IoT:	Internet of Things
LCM:	Land Change Modeler
LDD:	Land Degradation and Desertification
LST:	Land Surface Temperature
LULC:	Land Use and Land Cover
MARD:	Ministry of Agriculture and Rural Development
MCDA:	Multi-Criteria Decision Analysis
MENA:	Middle East and North Africa
MK:	Mann-Kendall
MLC:	Maximum Likelihood Classifier

MLP: Multi-Layer Perceptron

MODIS: Moderate Resolution Imaging Spectroradiometer

MSAVI: Modified Soil-Adjusted Vegetation Index

NAO: North Atlantic Oscillation

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Index

OA: Overall Accuracy

OBIA: Object-Based Image Analysis

ONS: Office for National Statistics

PDSI: Palmer Drought Severity Index

PET: Potential Evapotranspiration

QA: Quality Assurance

RCP: Representative Concentration Pathway

RF: Random Forest

SAR: Synthetic Aperture Radar

SAVI: Soil-Adjusted Vegetation Index

SDGs: Sustainable Development Goals

SHAP: SHapley Additive exPlanations

SMAP: Soil Moisture Active Passive

SPI: Standardized Precipitation Index

SPEI: Standardized Precipitation Evapotranspiration Index

SRTM: Shuttle Radar Topography Mission

SSP: Shared Socioeconomic Pathway

SVM: Support Vector Machine

TCI: Temperature Condition Index

TGSI: Topsoil Grain Size Index

UNCCD: United Nations Convention to Combat Desertification

USGS: United States Geological Survey

VCI: Vegetation Condition Index

VHI: Vegetation Health Index

VQI: Vegetation Quality Index

WMO: World Meteorological Organization

XGBoost: Extreme Gradient Boosting

1. Introduction:

“The nation that destroys its soil destroys itself.”

This statement by Franklin D. Roosevelt in 1937 highlights the profound relationship between land resources and societal stability. Land degradation is a complex environmental process characterized by the decline in the quality, productivity, and ecological functioning of land resources, including soil, water, and biological components of terrestrial ecosystems (Katyal & Vlek, 2000; Safriel, 2007). The United Nations Convention to Combat - (UNCCD) defines land degradation as “the reduction or loss of biological or economic productivity in arid, semi-arid, and dry sub-humid areas. this includes rain-fed cropland, irrigated cropland, rangelands, pastures, forests, and woodlands resulting from land-use practices and processes driven by human activities and settlement patterns” (S. Feng et al., 2022). Global pressure on land resources has increased markedly over the last century. Four factors drive this: the spatial concentration and uneven distribution of rapid population growth, agricultural intensification, urban expansion, and unsustainable land management. (Milton et al., 1998; Olsson et al., 2022; Prabhakar, 2021).

Land degradation is currently one of the most significant environmental challenges globally, affecting approximately 40% of the Earth's land surface and generating economic losses estimated at US\$490 billion annually. Combined with desertification and drought, total annual losses may reach US\$878 billion (Nkonya et al., 2011; Pacheco et al., 2018). It directly affects the livelihoods and economic stability of nearly two billion people worldwide (IPBES, 2018), with more than 250 million individuals severely impacted in developing countries (Reynolds et al., 2007; Yirdaw et al., 2017). Beyond its socio-economic consequences, land degradation also threatens biodiversity, ecosystem services, and long-term environmental sustainability, with global economic losses estimated to exceed 10% of the world's annual gross domestic product (Pandit et al., 2020). Furthermore, approximately one billion people are at risk of poverty and food insecurity due to degraded land resources, a situation intensified by climate change, which increases the frequency and severity of droughts, floods, and temperature extremes, accelerating soil degradation and ecosystem instability (Emadodin et al., 2019).

Land degradation occurs in various forms all over the world, desertification represents a specific form of land degradation occurring primarily in dryland environments (Baartman et al., 2007). These regions are characterized by low and irregular rainfall, fragile ecosystems, and high vulnerability to environmental disturbances (Amiraslani & Caiserman, 2018; Ziadat et al., 2021). Since the late 1960s, the African drylands, particularly the Sahel region has experienced one of the most severe and prolonged droughts in recorded history (N. Zeng, 2003). In response to these crises, desertification was formally recognized as a global environmental issue during the United Nations Conference on Desertification (UNCOD) held in Nairobi in 1977 (UNEP, 1978). The UNCCD later defined desertification as “land degradation in arid, semi-arid, and dry sub-humid areas resulting from climatic variations and human activities” (Djeddaoui et al., 2017; Seely & Wöhl, 2004;

Sivakumar, 2007). In drylands, climatic variability interacts with anthropogenic pressures such as overgrazing, agricultural expansion, and unsustainable resource exploitation, creating a reinforcing feedback loop that accelerates soil degradation, vegetation loss, and ecosystem instability (Q. Feng et al., 2015; Sivakumar, 2007).

Land Use and Land Cover (LULC) change is a critical pathway for human-driven land degradation. Agricultural expansion, deforestation, overgrazing, and urbanisation alter vegetation structure, soil properties, hydrological cycles, and land–atmosphere interactions. These changes can either exacerbate or mitigate land degradation depending on land management practices and ecological conditions. Consequently, understanding the spatiotemporal dynamics of LULC is essential for identifying the anthropogenic drivers of desertification and assessing ecosystem resilience in vulnerable dryland regions.

Algeria, characterized by extensive arid and semi-arid landscapes, faces increasing pressure on its land resources from desertification and land degradation, particularly within the steppe region (Djeddaoui et al., 2017; Hirche et al., 2011; Wafa, 2019). The Algerian Steppe is a crucial ecological transition zone. It lies between the Mediterranean coastal region and the Sahara Desert. covering more than 20 million hectares, it's the largest rangeland system in North Africa (Ali, 2009; Oubadi et al., 2024; Salhi et al., 2022). nearly 44% of this steppe region is classified as highly to very highly susceptible to desertification (Djeddaoui et al., 2017). Four factors drive this: Rapid demographic growth, overgrazing, agricultural expansion, and changing land-use practices which put increasing pressure on these fragile ecosystems and accelerating vegetation degradation and soil erosion. In addition, desertification is progressively expanding northward. This threatens the ecological stability, agricultural productivity and socio-economic sustainability of the northern Algeria region.

Among the drivers of land degradation, drought stands out as one of the most widespread and economically damaging climate extremes. Approximately 70% of drylands worldwide experience recurrent droughts, particularly in semi-arid regions of Africa, Asia, and South America (Haile et al., 2020; Mathbout et al., 2021). According to the World Meteorological Organization (WMO), drought is a prolonged period of abnormally low precipitation, causing water shortages that negatively affect ecosystems, agriculture, water supply, and human livelihoods (Bazza et al., 2018; Wilhite & Glantz, 1985; WMO, 2006). Drought triggers and intensifies desertification processes, particularly in regions where climatic variability combined with unsustainable land management practices.

Northern Africa is considered one of the most climate-sensitive regions globally, evidence suggesting that climate change is intensifying drought frequency and severity (Derdous et al., 2021; Giorgi & Lionello, 2008). Algeria experiences strong climatic gradients. The humid Mediterranean north contrasts sharply with the hyper-arid Sahara desert. Annual precipitation reflects this range. It varies from less than 100 mm in the southern Sahara to 400–1000 mm along the northern coast. (Malika et al., 2018). The semi-arid steppe region lies between these two zones. It's particularly

vulnerable to drought-induced land degradation. (Elouissi et al., 2021). Algeria has experienced severe droughts historically. Notable periods include 1943–1948 and the 1980s–1990s. These significantly affected ecosystems, water resources, and agricultural systems (Fellag et al., 2021).

Early detection and monitoring of land degradation processes are essential for sustainable land management and environmental planning (Higginbottom & Symeonakis, 2014). Remote sensing technologies provide powerful tools for monitoring environmental change across large spatial and temporal scales. Satellite observations from sensors such as Landsat, MODIS, and Sentinel enable the assessment of vegetation dynamics, soil moisture conditions, surface temperature variations, and land-cover changes (Hermans & McLeman, 2021; Q. Liu et al., 2018; Rivera-Marin et al., 2022; X. Zhang et al., 2017).

Remote sensing and data-driven approaches now allow us to integrate multiple environmental indicators for assessing land degradation. Vegetation indices reveal vegetation health and productivity. Key examples include the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI) (Fadl et al., 2024; P. Hu et al., 2021; B. P. Kumar, Babu, Rajasekhar, et al., 2022; Lu et al., 2015). Climate-based drought indicators detect meteorological drought conditions. Key examples include the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) and Palmer Drought Severity Index (PDSI) (Keyantash, 2021; Kim et al., 2023; Q. Liu, Yang, et al., 2024). Additionally, composite indices such as the Vegetation Health Index (VHI), derived from the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI), allow the monitoring of vegetation stress during drought events (Bento et al., 2018, 2020; J. Zeng et al., 2023). Other indicators including the Normalized Difference Water Index (NDWI) and Land Surface Temperature (LST) further contribute to identifying moisture stress and thermal anomalies associated with land degradation (B. P. Kumar, Babu, Anusha, et al., 2022; Uyar, 2025; Zolfaghari et al., 2022).

More recently, remote sensing data has evolved rapidly using machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNNs) and Extreme Gradient Boosting (XGBoost). Unlike traditional statistical approaches, ML captures complex, non-linear relationships among environmental variables, integrates multi-source satellite indicators, and generates spatially explicit predictions of land degradation improving assessment accuracy and identifying key environmental drivers across diverse landscapes.

Remote sensing-based environmental monitoring has advanced significantly. However, comprehensive studies that includes land use and land cover change, drought dynamics, vegetation responses, and machine-learning-based desertification modeling remain limited in Northern Algeria, Understanding the interaction between Climate variability and human pressures is crucial in this region, where the fragile dryland ecosystems are highly vulnerable to land use transformation and increasing

drought frequency, this research investigates spatiotemporal land degradation dynamics integrating multiple analytical approaches, specifically, this dissertation analyses the long-term LULC changes in the Algerian steppe and Green Dam region. Drought dynamics using satellite-derived vegetation indicators like NDVI anomalies and vegetation stress by combining meteorological and remote sensing indices such as SPI and the Vegetation Health Index VHI, and developing a machine-learning framework for mapping and assessing desertification severity through a set of multi-indicator remote sensing data, By combining these complementary approaches, this study seeks to provide a comprehensive understanding of the processes driving land degradation in Northern Algeria and contributes to better monitoring strategies and sustainable land management in vulnerable dryland regions.

This dissertation adopts a multi-scale analytical framework including a regional scale (Northern Algeria), a sub-regional scale (Northwestern Algeria), and a local scale (the Green Dam region in southern steppe areas).

1.1. Research Aim:

The overall aim of this dissertation is to investigate the drivers, dynamics, and spatiotemporal patterns of land degradation in Northern Algeria. By integrating multiple analytical approaches including drought variability analysis, vegetation response assessment, LULC change detection, and machine-learning-based desertification modeling using multi-source remote sensing data. Specifically, this research seeks to understand how climate variability and human land-use changes interact and how they influence vegetation condition and desertification in Northern Algeria's dryland ecosystems?.

1.2. Specific Objectives:

- Assess long-term drought variability and vegetation responses across Northern Algeria (regional scale), utilizing satellite-derived indicators like NDVI anomalies.
- Analyze the relationship between meteorological drought and vegetation stress in Northwest Algeria (subregional scale), through combining meteorological indices SPI with remote sensing indicators VHI.
- investigate LULC dynamics and anthropogenic drivers of land degradation in the Green Dam region (local scale) through multi-temporal analysis of land-use transitions, population trends, and livestock expansion.
- develop a machine-learning framework to map and assess desertification severity in Northern Algeria using multi-indicator remote sensing data, and to identify the primary biophysical drivers of degradation patterns
- investigate land degradation across Northern Algeria by integrating climatic and biophysical indicators to identify spatial patterns and mechanisms of land

degradation, with anthropogenic drivers examined through complementary local-scale LULC analysis.

1.3. Primary Research Question:

How do drought dynamics, climate variability, and human land-use changes interact to shape the spatiotemporal patterns of land degradation and desertification patterns across the dryland ecosystems of Northern Algeria?

1.4. Sub-Questions:

- How has drought variability influenced regional vegetation dynamics across Northern Algeria using satellite-derived NDVI anomalies?
- How do meteorological drought conditions relate to vegetation stress in Northwest Algeria and can SPI and VHI actually capture these interactions well?
- To what extent have land-use and land-cover changes across the Green Dam region driven land degradation at the desert–steppe transition zone in Northern Algeria?
- What spatial patterns and severity levels of desertification can be identified across Northern Algeria through the application of machine-learning of multi-indicator remote sensing data?
- How do drought dynamics, climate drivers and human drivers interact to influence land degradation across Northern Algeria? What spatial patterns and mechanisms that comes out from this interaction?

1.5. Contribution and Broader Impact:

this research takes a step toward a deeper, more grounded understanding of land degradation dynamics in Northern Algeria by combining remote sensing indicators, drought analysis, LULC change detection, and machine learning approaches within a single analytical framework, the findings offer critical insights for policymakers and land managers in three key areas: (1) combating desertification more effectively, (2) improving land management practices, and (3) enhancing ecosystem resilience in vulnerable drylands.

2. Literature Review:

2.1. Conceptual Foundations:

This chapter establishes the conceptual and methodological foundations for understanding environmental change in dryland ecosystems. Land degradation, desertification, drought, and land use/land cover (LULC) change are closely interconnected processes that collectively determine the ecological stability and resilience of arid and semi-arid environments. Drought acts as a primary climatic stressor, accelerating vegetation decline and soil degradation; in drylands, these impacts frequently culminate in desertification. At the same time, anthropogenic land use/land cover changes both intensify these natural vulnerabilities and provide measurable indicators of landscape transformation.

By synthesizing the theoretical foundations, evolving concepts, and remote sensing methodologies associated with these processes, this chapter provides the conceptual framework necessary for the integrated, multi-scale analytical approach adopted throughout this dissertation.

2.2. Land Degradation and Desertification: Concepts, Drivers, and Impacts

“Land degradation” represents a crucial environmental and socioeconomic challenge in arid and semi-arid regions worldwide (Huang et al., 2017; Lian et al., 2021; Stavi et al., 2022). This phenomenon is driven by the complex interplay of human pressure and the climate change (Burrell et al., 2020; Cosmas et al., 2025; Sivakumar, 2007), land degradation broadly refers to the decline in the productive capacity of land (S. Feng et al., 2024; Rastgoo & Hasanfard, 2022), encompassing various degradation forms including desertification and drought impacts (Vieira et al., 2023). Desertification specifically refers to land degradation in arid, semi-arid, and dry sub-humid areas caused by climatic variations and human activities (D’Odorico et al., 2013; Ravi et al., 2010). Drought, characterized by continuous precipitation insufficiency, accelerates land degradation by stressing vegetation and escalating soil erosion (Lian et al., 2021; Zhou et al., 2019). The interplay between desertification and drought creates a complex ecological cycle, where drought accelerates desertification, leading to additional land degradation and reduced resilience to future droughts (Ravi et al., 2010; Saco, 2018; Scholes, 2020).

This degradation is deeply rooted in human history, as natural resources are crucial for direct human wellbeing, providing a wide range of ecosystem services (AbdelRahman, 2023; Abdullahi et al., 2023; Pricope et al., 2023). Since the beginning of human existence on Earth, the consumption of natural resources has been a cornerstone of civilization's development. The construction of human societies is closely tied to the utilization of these resources, with the emergence of early civilizations since 5000 BC facilitated by the establishment of permanent settlements. Although the consequences of human exploration of natural resources have brought many benefits to the development of human life evolution, these practices have also disrupted the ecological balance and caused significant environmental damage (Azare et al., 2020; Prăvălie, 2021; Shao et al., 2024). In the modern era, the pressures exerted on land resources have intensified due to industrialization, population growth, and unsustainable agricultural practices (S. Feng et al., 2024; Prăvălie, 2021; Shao et al., 2024). Deforestation, overgrazing, and the expansion of agriculture continue to drive land degradation, exacerbated by the accelerating impacts of climate change (Moumane et al., 2026; Z. Xu et al., 2025), the urgent need for effective monitoring and management frameworks is underlined by the significant environmental and socioeconomic consequences of desertification, and drought in these fragile ecosystems. The need for proactive measures is vital to ensure sustainable development and environmental protection (Akbari et al., 2020; Akbari & Alizadeh Noughani, 2024).

To understand these modern pressures, it is essential to examine the specific physical mechanisms involved. The phenomenon of land degradation (LD) comprises various

processes that have a negative impact on the production capacity of land resources (AbdelRahman, 2023; Lal, 2015; Tarun & Rajeswari., 2025), It's defined as a the loss of land's productive capacity in terms of loss of soil fertility, soil biodiversity, and soil structure degradation (Rathi et al., 2024; Smith et al., 2024; Tarun & Rajeswari., 2025), this involves a variety of detrimental changes, such as reductions in soil fertility, the loss of organic matter content, and water-holding capacity (Ferreira et al., 2022; Liu et al., 2010). These changes can take on different forms, including soil erosion and compaction, to challenges like salinization and pollution (Chalise et al., 2019; Lal, 2015; Tsyganko et al., 2024), additionally, biological degradation which characterized by a loss of biodiversity in soil organisms and plays a significant role (Ferreira et al., 2022; Lal, 2015; Smith et al., 2024), the consequences of LD extend far beyond the direct impact ecological impact, significantly affecting the agricultural productivity, and threatening food security and critically influence human livelihoods, leading to poverty and social instability, the widespread nature of LD is alarming and posing a series issue with a large portion of the planet's cultivable land has already degraded (AbdelRahman, 2023; Smith et al., 2024).

Ultimately, the consequences of these physical and biological changes extend far beyond direct ecological impacts, significantly affecting agricultural productivity, threatening food security, and critically influencing human livelihoods, leading to poverty and social instabilit (AbdelRahman, 2023; Smith et al., 2024). The interconnection between processes have significant socioeconomic and environmental effects, environmentally, degradation causes biodiversity loss and disrupts ecosystem services (e.g., carbon sequestration, water regulation) (D'Odorico et al., 2013), and increases soil vulnerability to erosion, exacerbating risks of dust storms and habitat fragmentation (MEA et al., 2005; Sivakumar, 2007), the degradation and loss of the habitat contribute to biodiversity decline, resulting in the loss of the essential ecosystem services and intensify vulnerability to ecological disruptions and imbalances, moreover, water scarcity, which has often been aggravated by drought events escalating the tension and the competition for the resources leading to social conflicts, socioeconomically, decreasing agricultural productivity which effect food security and livelihoods, especially in rural regions, often leading to displacement and resource-based conflicts (Bazza et al., 2018; Jain et al., 2024; Zhou et al., 2019), the reduction of agricultural productivity and food security, which in turn effects people's livelihoods and may lead to displacement and migration (Burrell et al., 2020; Scholes, 2020). In arid and semi-arid regions like Northern Algeria, the consequences of these processes are particularly serious, given the existing resource limitations and the heightened vulnerability to environmental disturbances, for instance, the severity of recurring drought events, notably during the 2018-2021 period ($SPI < -2.0$) resulting in 30-40% decline in wheat yield, simultaneously, desertification processes has degraded 12% of agricultural lands since 1990 (Achour et al., 2020). These environmental challenges threatens agricultural sustainability for over 60% of the region's population dependent on agriculture.

2.3. Land Use Land Cover (LULC) Changes In Dryland Ecosystems And North Africa:

Land Use and Land Cover (LULC) change (LULCC) is widely regarded as a fundamental force shaping both the physical and human environment (Kilama Luwa et al., 2021), driving global concerns regarding climate change, food insecurity, soil degradation, and biodiversity loss (Appiagyei et al., 2023; Smail et al., 2024). These transitions pose substantial threats to natural resources at local, regional, and global scales (Martin & Watson, 2016; Watson et al., 2018), with profound implications for water balance, soil erosion, and biodiversity (Bajocco et al., 2012; Hoffmann & Beierkuhnlein, 2020; Mohammed et al., 2024). Understanding the impact of LULC on land degradation dynamics is therefore crucial for effective environmental management, particularly in Mediterranean and arid ecosystems. In this context, LULC analysis is critical for understanding environmental changes in dryland ecosystems. Remote sensing has proven highly effective in tracking desertification processes and drought conditions; since these two phenomena are fundamentally connected and both accelerate land degradation (Rivera-Marin et al., 2022). Specifically, remote sensing enables the monitoring and analysis of LULC changes, ranging from vegetation loss and soil erosion patterns to sand encroachment (Zolfaghari et al., 2022). Time-series analysis of LULC data (e.g., Landsat, MODIS, or Sentinel-2 imagery) reveals critical patterns, allowing researchers to identify degradation hotspots, trace anthropogenic pressures like deforestation and overgrazing, and evaluate the efficacy of ecological restoration efforts (Reis, 2008). By integrating spatial scales and combining multi-source data (optical, thermal, radar), remote sensing provides a reliable framework for understanding these closely related dynamics, which is a key step toward guiding sustainable land management in the world's arid regions.

Within these arid regions, LULC changes are mainly shaped by population growth, rapid industrialization, and rising living standards. However, decisions on land-use change made without considering sustainability often lead to direct adverse effects on land quality. While the nature and scale of LULC change vary considerably from one region to another, its consequences fall hardest on arid and semi-arid environments (Bernstein & IPCC, 2008). In these climatically vulnerable zones, rapid land-cover transformation compounds the pressures of climate change and resource overexploitation, intensifying land degradation, heightening the risk of drought and flooding, and steadily eroding local livelihoods (Bernstein & IPCC, 2008; El-Beltagy & Madkour, 2012). Globally, over the last 50 years, the world has lost 33% of its forest cover and 25% of its topsoil, underscoring the urgent need for sustainable land management practices (Jagdish & Vlek, 2000). As population and land use pressures grow in dryland environments, a key scientific contribution is to develop a predictive understanding of the interactions between drought and land use within systems that function in disequilibrium. Specifically, the overuse and mismanagement of soil and water resources (e.g., overexploitation without restorative management) drive land degradation in drylands, thereby contributing to desertification. To monitor these processes, remote sensing studies reveal contrasting trends across dryland regions: re-greening in some areas (e.g., parts of the Sahel) and localized browning due to

anthropogenic pressures. For instance, long-term research in the Sahel has documented substantial shifts in woody vegetation and land cover between 1967 and 2011, painting a picture of the complex interplay between climate variability and human activity. Building on earlier remote sensing work, (Eklundh & Olsson, 2003) traced shifts in vegetation indices across the African Sahel over the final two decades of the twentieth century (1982-1999), identifying a significant 'greening' trend largely driven by increased rainfall recovery. Similarly, (Herrmann & Hutchinson, 2005) examined recent trends in vegetation dynamics in the African Sahel and their relationship to climate, highlighting that while precipitation played a major role, localized human management practices and land-use changes also significantly influenced vegetation recovery patterns.

These complex dryland dynamics are highly evident in North Africa, which has experienced major LULC transformations with serious consequences for LDD. While some studies have pointed to a degree of stabilization in forest cover across the southern Mediterranean since the 1990s, particularly in Algeria, broader regional analyses highlight ongoing vulnerabilities. These dynamics appear in the broader West African context as well. For example, in a semi-arid area of approximately 2,500 km² surrounding Kano, Nigeria, the human-environment system underwent a fundamental transition between the 1960s and 1990s. This period combined climatic and demographic pressures: mean annual precipitation dropped by 25% and rural population density increased from 140 to >220 per km², reflecting the high sensitivity of sub-Saharan socio-ecological systems to desiccation and anthropogenic expansion. Similarly, the Sahel region provides critical insights into LULC dynamics relevant to North Africa. (Spiekermann et al., 2015) documented woody vegetation and land cover changes in the Sahel of Mali from 1967 to 2011, revealing complex patterns of change that cannot be characterized as uniform desertification. These changes tell a mixed story, greening in some areas and localized degradation in other areas, underscoring just how nuanced LULC transformations in the region can be.

Focusing specifically on Algeria, recent research on Djelfa City, described as the gateway to the Sahara and the capital of the steppes, offers a revealing case study of these LULC dynamics. Drawing on Landsat imagery processed by GEE and classified using Support Vector Machine (SVM) techniques, a recent study achieved a classification accuracy exceeding 90%, revealing a clear and consistent trend of decreasing forest cover accompanied by the expansion of urban and steppe areas between 1990 and 2020 (Bendechou et al., 2024). These changes reflect the broader ecological fragility of arid and semi-arid regions. Although bare land dominated the study area in 1990, the decades that followed brought sweeping change driven by overgrazing, soil degradation, and sustained pressure on rangelands, which gradually reshaped the landscape in ways that are difficult to undo. The Markov transition matrix confirms these visual observations, indicating agricultural land converting to steppe, bare land transforming into urban areas, and forest land declining as steppe expands. Furthermore, population dynamics have played a key role in driving these changes; during a single decade, Djelfa recorded a substantial population increase alongside a positive net migration balance (ONS, 2011). These broad demographic

shifts correlate directly with the rapid urban expansion patterns observed across the region (Bendechou et al., 2024).

Additional research in Algeria highlights a similar pattern of rapid urbanization at the expense of agricultural land. (Abdi Nidal & Allaoua Boulehouache, 2024) found that built-up areas in Constantine expanded significantly between 1984 and 2020, with construction activity responsible for converting vast areas of farmland during earlier periods. To anticipate such transformations, more sophisticated modeling approaches, notably Multi-Layer Perceptron algorithms embedded within Land Change Modeler frameworks, have made it possible to project future LULC scenarios by analyzing historical patterns and incorporating socioeconomic drivers (Bendechou et al., 2024). Such predictive capacity matters greatly in a country like Algeria, where understanding how future land cover changes will affect key hydrological processes including runoff, evapotranspiration, and groundwater recharge is essential for managing vulnerable dryland ecosystems (Abdelkebir et al., 2024).

2.4. Desertification.

2.4.1. Historical Origins, Evolution, and Conceptual Ambiguities.

The term of “*Desertification*” was initially used in the late 1940s to describe various environmental degradation occurring in tropical Africa (Glantz & Orlovsky, 1983; Helldén, 2003; Verstraete, 1986), since then, the word has evolved, acquiring multiple and wide range of meanings, many of which are inconsistent with each other, and do not provide a clear or consistent understanding (Sivakumar, 2007; Verstraete, 1986). Historically, the concept of desertification was formally introduced by Aubréville (1949) to describe the human-induced degradation of forest cover in tropical Africa. He emphasized that this process was driven by unsustainable local human practices rather than the natural expansion of the Sahara (Davis, 2004).

Despite early academic efforts to develop a clear definition of the term “desertification”, but the concept remained unclear. Dregne later defined desertification as “desertification is the impoverishment of terrestrial ecosystems under the impact of man. It is the process of deterioration in these ecosystems that can be measured by reduced productivity of desirable plants, undesirable alterations in the biomass and the diversity of the micro and macro fauna and flora, accelerated soil deterioration, and increased hazards for human occupancy.” However, even after the attention given to desertification in the international conferences, no global accepted definition has yet to be established (Kosaki & Gabriels, 2015). Dregne and other scholars underscored that the desertification should be framed as a continuous land degradation process, primarily resulting from human activities, instead of viewing it as a phenomenon that occurs just in specific regions (D’Odorico et al., 2019; Kar, 2018), this absence of widely recognized definition of desertification has led to ongoing academic controversy between the researchers, according to research by (Grove, 1977; Helldén, 1991), demonstrate that the topic of desertification remains an issue of debate not in the scientific research but also in political discussions and media narratives, Critical perspectives regularly blame the failures to combat “the desertification problem” resulting from limitations in research approaches and methodological frameworks (Briassoulis, 2019). Some believe scientific knowledge

is partially responsible for the discontinuing progress (Lewin et al., 2026; Reynolds, 2021).

2.4.2. Definitions and Conceptual Perspectives.

In this context, desertification, is more precisely defined by the UNCCD as land degradation in arid, semi-arid, and dry sub-humid areas resulting from various factors, including climatic variations and human activities (Ambalam, 2014), desertification is a particular kind of land degradation affecting drylands (arid, semi-arid, and dry sub-humid), the phenomenon characterized by the progressive decline of biological productivity and decrease in soil quality in the absence of proper actions (Katyal & Vlek, 2000; Sivakumar, 2007; Sterk & Stoorvogel, 2020), these degradation processes can lead to permanent ecological transformations and radically modify the ecosystem structure and function, the combination of these changes frequently surpass critical thresholds, making the natural recovery and the land restoration more challenging, without extensive remediation efforts (Berdugo et al., 2020; Y. Gao et al., 2011).

Over the years, various scholar and international institutions have provided complementary definitions that capture the complexity of the phenomenon (Sterk & Stoorvogel, 2020), for example, (Berdugo et al., 2020) which defines desertification as “the impoverishment of arid, semi-arid and some sub humid ecosystems by the impact of man’s activities.” And the United Nations (1978) described it as “the diminution or destruction of the biological potential of the land, which can ultimately lead to desert-like conditions.” Meanwhile, (LE HOUEROU et al., 1977) viewed it as “the extension of typical desert landscapes and landforms to areas where they did not occur previously.” Moreover, (Verstraete, 1986) defines desertification as the result of a progressive drying of the climate of Africa, a trend that began 5000 years ago, all of these perspectives highlight how human pressures and environmental stressors as the primary drivers of land degradation in drylands.

2.4.3. Causes and Consequences.

For over five decades, desertification has been a central concern on the agenda of African and global environmental issues, receiving extensive attention from media and policymakers. It is frequently framed as a primary driver of human insecurity across the continent, particularly in the Sahel region, where environmental fragility intersects with subsistence livelihoods (Azare et al., 2020; Lombe et al., 2024). Nations such as Niger, Chad, and Mali, exemplify regions where desertification has precipitated multifaceted socio-economic and environmental crises, including population displacement, food insecurity, and intercommunal resource conflicts.

Desertification comes from a variety of causes, encompassing both natural and anthropogenic factors, some of the natural drivers that accelerate land degradation (Dregne, 1986; El-Baz & Hassan, 1986), such as repeated drought events, precipitation decline, and soil erosion, however, the effects are exacerbated by human activities including, deforestation, overgrazing, over cultivation, unsustainable agricultural practices, industrialization and non-proper land management (AbdelRahman, 2023; Abdullahi et al., 2023), furthermore over-extraction of

groundwater, urban growth through fragile ecosystems, these process contribute even more which frequently leading to irreversible degradation (Právělie et al., 2021; Zhou et al., 2019), the global expansion of the drylands in regions such as southwest north America, north Africa and southern Australia, is a major concern under scenarios of elevated greenhouse gas emissions (Huang et al., 2016; Koppa et al., 2024). According to the MEA report, 10-20% of the world's drylands are already degraded, while the ongoing desertification poses a significant threat to the ecological systems worldwide (MEA et al., 2005). These processes result in increased water scarcity, reduced agricultural productivity, and heightened vulnerability to extreme climatic events (D'Odorico et al., 2013; Lian et al., 2021).

Desertification causes damage that goes beyond the environment and has profound socio-economic consequences, such as the rise of food insecurity and poverty as a results of the loss of arable land (Lombe et al., 2024; Vieira et al., 2023), environmental degradation accelerating the migration of people from rural to urban areas, putting additional pressures on urban centres (AbdelRahman, 2023; Abdullahi et al., 2023). Moreover, when land degrades, this creates regional instability through increased competition for diminishing natural resources (Jain et al., 2024), which in turn to social and political tensions. At the same time, these affected areas are also facing an increased frequency of wildfires due to increasing aridity (Lian et al., 2021). Consequently degrading soil quality and make restoration efforts even more difficult (D'Odorico et al., 2013; Lian et al., 2021).

2.5.4. Global responses, Institutional frameworks, and Mitigation Strategies.

The global spread of desertification is causing a major concern, with nearly 77% of the world's terrestrial areas have seen an increasing aridity (S. Feng et al., 2024), this shifts has far-reaching socio-economic impacts, for instance, Africa have lost roughly 12% of its GDP between 1990 and 2015 due to increasing aridity (Cowie et al., 2018), currently, drylands are home of more than 2.3 billion people worldwide, exceeding 30% of the world's population, which has already doubled since 1900 and is projected to increase to more than a double by 2100 under worst-case climate change scenarios (Ahmed et al., 2024; S. Feng et al., 2022).

The early major steps to officially recognize desertification as a pressing global environmental challenge came through international meetings like the United Nations Conference on Desertification held in Kenya in 1977, this conference led to the adoption of the Plan of Action to Combat Desertification, which became a cornerstone for later policy development subsequent global environmental interventions, during the Earth Summit, which held in Rio de Janeiro, Brazil, highlighted the importance of addressing environmental challenges and global environmental policies, as part of the Earth Summit, the (UNCCD) was introduced alongside with other two other important conventions, Since its establishment in 1994, the (UNCCD) serves as global key instrument, for fostering cooperation, developing policies, and mobilizing resources aiming to sustainable land management and the restoration of the areas affected by degradation (Akhtar-Schuster et al., 2017; Chasek et al., 2019). Furthermore, the conference of the parties

(COP) serves as primary decision making for the UNCCD, gathering periodically to assess developments and define strategic objectives. Notably. In December 2024, the sixteenth session (COP16) which took a place in Riyadh, Saudi Arabia, stood out as a crucial milestone, coinciding with the UNCCD's 30th anniversary, this session was the first COP to take a place in the Middle East and North Africa region and became the first major UN conference to take a place in Saudi Arabia.

The severity of this environmental crisis recognized globally and international efforts have been undertaken to develop strategies to combat desertification and to restore degraded lands, such as sustainable land management, afforestation, agroforestry, and policies aimed to reduce the impact of climate change have shown promising results (Islam et al., 2025; Schwilch et al., 2014; Stavi et al., 2024), megaprojects such as Africa's Great Green Wall and China's reforestation programs highlight significant actions undertaken to combat desertification and promote ecological restoration (Cai et al., 2020; Lei et al., 2025; C. Li et al., 2021; M. D. Turner et al., 2023), these efforts are aimed to reinforcing land resilience, improving soil moisture capacity, promote biodiversity, with the of reducing the consequences of desertification (Deng et al., 2024; H. Liu et al., 2022).

2.5. Drought:

2.5.1. Definitions and Conceptual Complexity.

“Drought” is a complex climatic phenomenon characterized by persistent water scarcity, with interconnected impacts on ecosystem, food security, socioeconomic stability, and human health and livelihoods, a drought event can be short, lasting for just a few months, or it can persist for multiple years, despite its variable temporal scale, the absence of a globally accepted definition of drought continues to present challenges for research and policy frameworks, primarily due to its geographically various indications and the disparate disciplinary perspective that have shaped its research, drought has been outlined by numerous scholars, including (Keyantash & Dracup, 2002; Mishra & Singh, 2010; Sheffield & Wood, 2012; Van Loon, 2015; Wilhite, 2000), generally, drought is defined by prolonged deficits in precipitation, soil moisture, and surface/groundwater availability over an extended period, leading to negative impacts on agricultural, ecological, and socio-economic systems (Mishra & Singh, 2010; Van Loon, 2015), major international organizations have developed definitions of drought throughout their operational protocols (Kchouk et al., 2022; Satoh et al., 2021), the UNCCD, for instance, describes drought as a persistent precipitation deficit within the natural climate cycle, that occurs in all regions of the planet, poses significant risks to environmental stability, social, and economic systems (Hermans & McLeman, 2021). Moreover, The World Meteorological Organization (WMO) defined drought as a prolonged dry period in the natural climate cycle that can occur anywhere in the world. It is typically a slow on-set phenomenon caused by a lack of rainfall (Vicente-Serrano et al., 2020), additionally, the National Drought Mitigation Centre (NDMC) at the University of Nebraska Lincoln describes drought as: “drought is a protracted period of deficient precipitation resulting in extensive damage to crops, resulting in loss of yield” (Lloyd-Hughes, 2014; Zargar et al., 2011). This agricultural perspective highlights the tangible socioeconomic

consequences of drought, particularly in regions where livelihoods depend heavily on rain-fed agricultural systems (Omar et al., 2022).

2.5.2. Causes and Types of Drought.

The phenomenon of drought is caused by combination of natural climatic fluctuations such as meteorological anomalies, and anthropogenic activities including groundwater extraction (AghaKouchak et al., 2021; He et al., 2025). Natural climatic variability comes from main sources external natural forces such as solar radiation changes and internal climate system process like the Pacific Decadal Oscillation and El Niño-Southern Oscillation (J. Jiang & Zhou, 2023; Y. Liu et al., 2023). Anthropogenic activities including water transfer projects and groundwater extraction can affect the local water balance resulting in to drought recurrence (Alonso Vicario et al., 2025; Wu et al., 2023). Global warming resulting from human activities significantly may significantly exacerbate drought events, increasing their duration and severity and shifting regimes toward temperature-dominated drought conditions (Vicente-Serrano et al., 2022; Zhuang et al., 2024).

Drought is a terrestrial system phenomena, resulting from multiple meteorological, hydrological, and biophysical processes with a high socio-economic impact (Mazen & Mohammed, 2023; X. Zhang et al., 2022), while droughts universally originate from precipitation deficits, their spatial and temporal complexity arises from dynamic interactions between temperatures fluctuation, pressure, atmospheric circulation patterns and the wide range of weather patterns, which presents challenges to identify regions with uniform drought development processes (Nandgude et al., 2023; Tanarhte et al., 2024), droughts are typically categorized into four distinct types: meteorological drought, hydrological drought, agricultural drought and socioeconomic drought; Meteorological drought occurs when there is persistent deficit of precipitation during a period of time, measured by consecutive days below statistically derived thresholds (e.g., long-term averages) (Cavus & Aksoy, 2020); Agricultural drought is caused by reduction of soil moisture within the root zone, which leads to limit water access for the roots zone and creates a stress on plant growth (J. Jiang & Zhou, 2023; Oukaddour et al., 2023), Hydrological drought is characterized by the depletion of the water availability in the surface and groundwater reserves, resulting in persistent water scarcity across the hydrological cycle (Alonso Vicario et al., 2025; Y. Liu et al., 2023), and Socio-economic drought described as a condition where water scarcity has direct impacts societal well-being and threatens key sectors such as energy production, urban service and agricultural irrigation, thus intensifying socio economic inequalities and increasing poverty (AghaKouchak et al., 2021; Q. Wang et al., 2025).

2.6. Global Trends and Impacts.

2.6.1. Patterns of Drought occurrence and severity over time.

Drought affects millions of people around the world, leading to significant economic costs, and far-reaching impacts on society and environment, according to the Intergovernmental Panel on Climate Change (IPCC) reports highlights a trend of increasing drought frequency and severity in many regions globally during the last

several decades (Cook et al., 2018; Spinoni et al., 2014). Furthermore, As reported in the IPCC's Sixth Assessment Report (AR6), states that anthropogenic climate change has exacerbated agricultural and ecological drought conditions, primarily due to elevated evapotranspiration resulting from increased land surface warming (Chiang et al., 2018; Gu et al., 2020), these findings from the WMO's State of the Global Climate report show that global temperatures have reached historic levels recorded between 2015 and 2022 which were the warmest in the recorded history, this global warming trend has significantly exacerbated drought severity across various regions (H. Liu et al., 2024; X. Yang et al., 2023). According to the report, nearly half of the global population, approximately 3.6 billion people are already affected by faces water scarcity for at least one month each year, and this number is expected to increase to more than 5 billion by 2050 (Sheffield & Wood, 2008; X. Yang et al., 2023), while the drought accounting for just 5% of all natural disasters , affect nearly 30% of the global population impacted by disasters (Spinoni et al., 2014). As reported by the International Disaster Database, drought's significant human impact is reflected in annual economic costs estimated at USD 6 to 8 billion (Fernández et al., 2023; Fleming-Muñoz et al., 2023). The National Center for Atmospheric Research (NCAR) revealed that the percentage of the global lands experiencing drought conditions expanded dramatically between 1970 and 2000, this expansion strongly associated with the anthropogenic global warming during that time (Chiang et al., 2018; Tang et al., 2025). Furthermore, The IPCC highlights that future climate scenarios predict an increased risk of drought with rising of global temperatures and the increasing occurrence of extreme weather events (Sheffield & Wood, 2008; Tripathy et al., 2023).

The Food and Agriculture Organization (FAO) also documents that drought exerts the most substantial impact on global agricultural production, contributing to approximately 80% of all economic damages and loss within the agricultural sector (Bogale & Erena, 2022; H. Liu et al., 2024), drought events caused approximately USD 29 billion in direct economic losses to the agricultural sector in developing countries, between 2005 and 2015 (Fernández et al., 2023; Fleming-Muñoz et al., 2023).

2.6.2. Socioeconomic and Environmental Impacts.

The socioeconomic consequences of drought are extensive and multifaceted, affecting various sectors across different dimensions, among the most severely affected sectors are agriculture and food security, however, the severity of drought impacts is often shaped and exacerbated human-driven factors including unsustainable land use practices, and deficiencies in policy frameworks. Furthermore, scholars have consistently shown that drought is not an anomalous or temporary climatic event in dryland regions, not a temporary deviation from climatic norms, however, the rising frequency, intensity, and spatial spread of drought events under climate change are increasingly intersecting with socioeconomic weaknesses.

The socioeconomic impacts of drought are both widespread and persistent, particularly in regions where local populations depend mainly on rain-fed agriculture and natural resources (Rastgoo & Hasanfard, 2022). Furthermore, the significance of

drought cannot be fully understood apart from its societal context, since its consequences persist well beyond the duration of the physical phenomenon itself (Jain et al., 2024). As a result, drought contributes to economic challenges and instability, including job losses, population displacement, and the deepening of systemic poverty (Scholes, 2020). Moreover, these interconnected effects create feedback loops that can perpetuate vulnerability, thereby making communities increasingly susceptible to future drought events (Ravi et al., 2010).

The agricultural sector is typically the first and most severely affected by drought, particularly in rain-fed systems, where crop and livestock production mainly dependent on seasonal precipitation (Rastgoo & Hasanfard, 2022), reduced soil moisture due to drought limits the water availability in the root zone, leading to plants stress, reduced biomass accumulation, and decline in crop productivity (Lian et al., 2021), these conditions also reduce pasture and forage production, exacerbating livestock stress, reducing growth rates, and raising mortality levels, agriculture in drylands is particularly vulnerable to rainfall variations, which lead to reduced crop yields and economic viability, in addition to the climate challenge, human factors including poor land management practices, in particular through overgrazing and inadequate irrigation, and ineffective land use has a negative impact on agricultural production. Collectively, these factors exacerbate soil deterioration, reduced productivity (AbdelRahman, 2023), and increased the exposure of rural populations to socioeconomic risks (Abdullahi et al., 2023).

The impacts of drought go beyond agricultural and food security, in fragile economies, drought often leads to unemployment, increase migration, and expand the social and economic inequalities (Jain et al., 2024), according to (Wilhite & Glantz, 1985) Human and social factors frequently exacerbate the impacts of drought, these include policy failures, institutional fragility, and poor early response mechanisms.

Water scarcity also contributes social instability, leading to conflicts that trigger mass migrations, often triggering long-term demographic changes (Scholes, 2020). According to the Internal Displacement Monitoring Centre (IDMC), natural disasters cause the displacement of approximately 21.5 million people globally in 2022. Furthermore, drought-induced displacement has increased significantly by 37% compared to the previous decade (IDMC, 2023) , these displacements leads to increased pressure natural resources availability and public services, (Le Houérou, 1996) states that the interaction between climatic stress and poor land management can trigger a 'catalytic spiral,' where land degradation and drought mutually reinforce one another; this results in the gradual degradation of the resilience of natural ecosystems and human livelihoods (Ravi et al., 2010).

Drought is a major challenge to terrestrial and aquatic ecosystems worldwide, this climatic phenomenon charactirized by persistent water scarcity, drought disrupts ecological functions and change the biodiversity patterns (Moss et al., 2024; Tariq et al., 2024), furthermore, it destabilizes the critical land-atmosphere interactions. This often leads to progressive environmental degradation such as desertification and soil erosion, notably, climate change driven by human activity excarebate the frequency

and severity of drought events (AbdelRahman, 2023; Moss et al., 2024; Zhou et al., 2019). This creates a feedback loop intensifies hydrometeorological stress on fragile ecosystems, this intensification raises serious concerns regarding the capacity of fragile ecosystems to remain resilient under increasingly prolonged and intense droughts (Knapp et al., 2024; Müller & Bahn, 2022), for instance, prolonged water scarcity has been demonstrated to degrade soil structure, reduces organic matter, and disrupt the hydrological processes, thereby intensify the dryland's, remote sensing studies reveal how temporary drought impacts can transition into long-term desertification, particularly where recovery is comprimized by overgrazing or farming practices that push the land beyond its natural limits (Hashemi et al., 2024; Rivera-Marin et al., 2022). As population growth and land use are intensifying in arid and semi-arid regions, the risk that human activity will interrupt post-drought recovery. This can trigger lasting environmental changes (AbdelRahman, 2023; Müller & Bahn, 2022).

2.7. Land Degradation and Drought Assessment:

2.7.1. Vegetation Indices: Selection and Calculation

Vegetation indices are essential tools for monitoring land degradation and drought in drylands, among them, the Normalized Difference Vegetation Index (NDVI) remains the most widely used, where negative trends serve as reliable markers of declining land productivity (J. Wang et al., 2023), vegetation and soil stability are closely linked, with healthy vegetation covering playing a key role in maintaining degraded landscapes by slowing down wind speeds and reducing erosion (H. Wang et al., 2023). Advanced vegetation indices, including the Enhanced Vegetation Index (EVI) and Soil-adjusted Vegetation Index (SAVI), have significantly improved the effectiveness of the monitoring (Alahacoon & Edirisinghe, 2022), Fractional Vegetation Cover (FVC) and Net Primary Productivity (NPP) have become crucial for wind erosion modeling frameworks with systematic negative correlations confirmed between FVC and soil erosion amounts (J. Wang et al., 2023), recent research has shown that when vegetation cover falls below 40 percent, soil erosion risk increases significantly, with erosion rates increasing exponentially when vegetation cover falls below this level (Jiao et al., 2021).

Vegetation indices combined with thermal infrared data enables the development of water stress indicators that provide early warning of drought conditions before visible vegetation decline occurs (Agarwal et al., 2025). Time-series analysis of vegetation indices reveals contrasting trends across drylands. Some areas show re-greening, like parts of the Sahel, most notably parts of the Sahel, set against localized browning driven by human pressures (H. Wang et al., 2023). The spatial distribution of vegetation cover has emerged as a key factor in shaping erosion patterns, with fragmented or patchy cover often offering far less protection against erosion than vegetation spread more evenly across the landscape (H. Wang et al., 2023).

2.7.2. Climatic and Drought Indices:

The climatic and drought indices provide a reliable way of quantifying drought severity and monitor the impact on land degradation. The Standardized Precipitation

Index (SPI) is typically computed across multiple timescales 3, 6, and 12 months, which allows researchers to trace connections between short-term vegetation responses and the long-term drought impacts that leave their mark on land cover (Haied et al., 2023). The Standardized Precipitation Evapotranspiration Index (SPEI), which combines for both precipitation and potential evapotranspiration, has gained considerable traction as a more comprehensive indicator of drought conditions, particularly in the context of a changing climate (Alahacoon & Edirisinghe, 2022). Comprehensive reviews of the literature have identified over 50 drought indices in use worldwide, although their effectiveness varies considerably depending on the region and the specific application (Alahacoon & Edirisinghe, 2022).

Recent satellite advancements have significantly improved soil moisture data availability for drought monitoring, in particular the Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS) missions (Kumar et al., 2024), combining multiple drought indices into a single composite indicator has emerged as a promising way to overcome the limitations of any one index, since no single index can fully capture all drought dimension (Kumar et al., 2024).

2.7.3. LULC Change Analysis:

LULC change analysis serves as a fundamental approach for understanding land degradation dynamics in dryland ecosystems. Optical remote sensing has provided consistent data for over five decades, with Landsat series (since 1972), SPOT (since mid-1980s), MODIS (since 1999), and Sentinel-2 (since 2015) providing increasingly detailed spatial and temporal coverage (H. Wang et al., 2023).

Recent studies in Algeria's drylands have utilized increasingly sophisticated classification techniques. For instance, Support Vector Machine (SVM) algorithms implemented via Google Earth Engine (GEE) have achieved over 90% accuracy in mapping multi-decadal LULC changes (Bendechou et al., 2024). Markov transitional probability matrices effectively document specific transformation patterns within these regions, such as agricultural land degrading into steppe, bare land transforming into urban areas, and forest land declining as steppe expands (Bendechou et al., 2024). To predict future LULC changes, the CA–Markov hybrid model has emerged as a powerful tool, combining cellular automata for spatial modeling with Markov chains for transition probabilities (Selmy et al., 2023). Additionally, integrating object-based image analysis (OBIA) with pixel-based approaches improves classification accuracy, particularly in heterogeneous landscapes, although results remain dependent on data quality (Ontel et al., 2023). Finally, decomposing time-series LULC data allows researchers to isolate seasonal vegetation cycles from long-term degradation trends, thereby providing more accurate assessments of land degradation (Kumar et al., 2024).

2.7.4. Multi-Indicator Remote Sensing Approaches:

Land degradation does not follow simple patterns, which is why researchers rely on multi-indicator remote sensing approaches that draw on diverse data sources and analytical frameworks. For monitoring soil degradation in relation to the Sustainable Development Goals (SDGs), several factors must be tracked soil mineral

composition, organic matter, surface roughness, erosion, salinity, desertification, and pollution. However, managing this wide range of indicators is not always practical, particularly in data-scarce regions (J. Wang et al., 2023).

Researchers often use the Erosion Potential Method (EPM) alongside Intensity of Erosion and Outflow (IntErO) software to gauge soil erosion risk by combining multiple indicators. While these approaches have been validated across numerous watershed areas worldwide (Sabljic et al., 2024). Additionally, the application of multi-criteria decision analysis (MCDA) techniques to remote sensing data has enabled the creation of comprehensive land , land degradation indices that integrate biophysical, social, economic and climatic factors (Alahacoon & Edirisinghe, 2022).

The integration of remote sensing with Internet of Things (IoT) sensor networks has created new opportunities for real-time monitoring of land degradation processes with high spatial and temporal resolution (J. Wang et al., 2023). Integrated approaches that combine vegetation indices, drought, drought indices, land use change analysis and land area have proven particularly effective in monitoring drought , drought and land degradation dynamics (Agarwal et al., 2025). The development of open-access platforms integrating multiple remote sensing datasets and analysis tools , tools has improved the accessibility of multi-indicator approaches for land degradation assessment in data-poor regions (J. Wang et al., 2023).

2.8. Machine Learning and Advanced Modelling in Desertification Assessment:

2.8.1. Why machine learning matters:

The growing complexity of desertification processes, shaped by the dynamic interplay among climatic variability, soil degradation, vegetation decline, and anthropogenic pressures, has increasingly revealed the inherent limitations of conventional linear and index-based analytical approaches. Traditional statistical approaches, including regression-based analyses, often struggle to adequately represent the non-linear patterns and large-scale spatiotemporal variability that characterise dryland degradation environments, thereby limiting their ability to capture the inherently multidimensional dynamics of desertification (Chouikhi et al., 2025). Machine learning algorithms are rapidly recognized as Robust analytical tools for desertification assessment, due to their capability of capturing the complex interactions among environmental variables (K. Feng et al., 2022).

Most previous studies have predominantly relied on single-method approaches or individual remote sensing indices to monitor desertification, which has limited the development of efficient and high-precision monitoring frameworks (K. Feng et al., 2022). To address these limitations, integrated monitoring frameworks have been developed that incorporate combinations of multiple indicators alongside diverse machine learning techniques, including Classification and Regression Tree (CART), Random Forest (RF), and Convolutional Neural Networks (CNN), to analyse spatiotemporal patterns of desertification (K. Feng et al., 2022), these approaches have demonstrated markedly improved classification accuracy when compared with conventional methods (Berdyyev et al., 2024). The algorithm's capacity to effectively

capture complex, non-linear interactions among climatic, vegetation, soil, and anthropogenic factors renders it particularly well suited to the inherently multi-causal nature of desertification. XGBoost has consistently demonstrated superior predictive accuracy relative to other machine learning models across multiple study periods, as reflected in higher R^2 values and lower prediction errors, thereby confirming its robustness for environmental classification tasks (Abdullah & Mustafa, 2025).

Machine learning approaches address the limitations of traditional statistical methods by enabling the analysis of high-dimensional datasets, facilitating the identification of complex patterns, and enhancing predictive accuracy across heterogeneous landscapes (Jiao et al., 2021). In contrast to conventional univariate analyses, which typically isolate individual drivers and often overlook feedback mechanisms among factors, machine learning techniques can simultaneously process multiple variables, thereby revealing latent patterns and complex interactions (Von Schoenborn & Bick, 2023). This capability is particularly valuable, as the complexity of desertification processes, arising from interactions among multiple environmental and anthropogenic factors, necessitates advanced modelling approaches capable of capturing non-linear relationships and complex spatial patterns (Bashiri et al., 2025). Deep learning architectures, such as Convolutional Neural Networks (CNNs), may further enhance spatial precision by directly analysing raw satellite imagery rather than relying on preprocessed indices (Al-Tameemi et al., 2025). The XGBoost model, incorporating entropy-weighted indices, assigns greater importance to variables exhibiting higher variability. In this context, the Vegetation Quality Index (VQI) accounted for the largest contribution to the overall Desertification Risk Index (31.9%), followed by climatic stress (Climate Quality Index CQI: 24.9%) (Al-Tameemi et al., 2025). However, at the sub-index level, specific variables exert varying degrees of influence; for instance, within the VQI calculation specifically, soil protection plays a comparatively minor role (entropy weight = 0.083) compared to dominant drivers such as drought resistance (0.462) and vegetation cover (0.454). This hierarchical distribution underscores the dominant role of broad climatic and vegetative stress in shaping overall desertification risk, while highlighting the nuanced, localized contributions of soil factors.

These approaches effectively bridge technical rigour with applied relevance by identifying priority areas for intervention, particularly in zones where climatic aridity intersects with unsustainable land-use practices, thereby providing a robust evidence base to inform strategic action (Von Schoenborn & Bick, 2023). The integration of time-series satellite data with machine learning models has facilitated the detection of early warning signals of desertification, thereby enabling more proactive and timely land management interventions (H. Jiang et al., 2024).

2.8.2. Advantages over traditional statistical approaches:

The application of machine learning in desertification assessment offers clear advantages over conventional approaches. In contrast to the rule-based framework of the DRI, XGBoost is able to capture complex, non-linear interactions, thereby enabling a more refined spatial differentiation of desertification risk levels (Al-Tameemi et al., 2025). This enhanced capability translates into improved

performance metrics, as evidenced by studies reporting high model accuracy, with an overall accuracy of 94.46% and a kappa coefficient of 0.9261, indicating a strong level of predictive agreement (Al-Tameemi et al., 2025).

Machine learning models exhibit a heightened sensitivity to early-stage degradation processes that may not be adequately captured by traditional approaches. In this context, the XGBoost model classified 28.35% of the area as Extreme risk, with corresponding proportions of High (19.15%), Moderate (26.06%), and Low (26.43%) risk categories. These distributions reflect the model's ability to detect subtle degradation patterns, particularly within zones characterized by early-stage risk (Al-Tameemi et al., 2025). Validation studies further substantiate these advantages, indicating that the Hybrid model produced a clearer and more systematic decline in NDVI across risk levels, thereby supporting its capacity to effectively reflect vegetation stress. Statistical validation using the Kruskal–Wallis test also demonstrated that the Hybrid model yielded smoother transitions across risk categories and higher chi-square values for vegetation indices, suggesting a stronger differentiation of desertification levels (Al-Tameemi et al., 2025).

Furthermore, Random Forest algorithms have been widely and successfully applied to classify land degradation patterns in arid regions, consistently demonstrating superior performance relative to traditional classification methods (Huang et al., 2020). Machine learning models are well suited to capturing the non-linear relationships between environmental variables and desertification processes, relationships that traditional linear models often fail to represent with sufficient accuracy (Rampone & Valente, 2019). The application of ensemble learning methods has demonstrated substantial gains in accuracy relative to single-model approaches, with classification errors reduced by up to 20% in complex desertification assessment contexts (AlAmri et al., 2026).

The capacity of machine learning to manage high-dimensional data and extract meaningful patterns from complex environmental datasets represents a notable paradigm shift in desertification monitoring. These approaches extend beyond the constraints of traditional methods, which often rely on univariate analyses that isolate individual drivers and consequently overlook the feedback mechanisms operating among interacting factors (Von Schoenborn & Bick, 2023).

2.8.3. Current applications:

Machine learning techniques have been applied across a wide range of contexts in desertification assessment and monitoring. In particular, XGBoost has been employed to enhance the classification of desertification risk beyond the Hybrid Desertification Risk Index (DRI) model, which relies on entropy-weighted indices and assumes linear relationships among predictors (Al-Tameemi et al., 2025). This approach leverages the strengths of entropy-based weighting, whereby the Hybrid model assigns greater importance to variables exhibiting higher statistical variability. Within this framework, VQI accounted for the largest contribution (31.9), followed by climatic stress (CQI: 24.9), while soil protection exerted a comparatively minor influence (0.083) (Al-Tameemi et al., 2025).

Interpretability has become a critical component of these applications, with SHapley Additive exPlanations (SHAP)-based interpretation applied alongside XGBoost classification providing a transparent, data-driven foundation for the spatial prediction of desertification risk (Al-Tameemi et al., 2025). Researchers have successfully applied SHAP analysis in a post-classification framework to interpret the predictions of the XGBoost model, ranking features according to their influence on the predicted desertification risk classes and enabling comparison with the entropy-weighted index structure (Al-Tameemi et al., 2025). These methods employ XGBoost, a decision tree-based ensemble algorithm capable of capturing complex, non-linear relationships among environmental variables (Al-Tameemi et al., 2025).

The practical implementation of these approaches requires careful methodological consideration. In this context, a stratified random sampling strategy was employed to ensure adequate representation of all classes across the study area. To address class imbalance, oversampling techniques were applied to underrepresented categories, thereby reducing the likelihood of biased predictions (Al-Tameemi et al., 2025). The integration of multiple data sources has proven particularly effective, as the combination of multimodal remote sensing data with machine learning algorithms has been shown to significantly enhance the accuracy of desertification monitoring in complex landscapes (Jiao et al., 2021).

Recent advances have increasingly incorporated deep learning approaches, particularly Convolutional Neural Networks (CNNs), which have shown considerable potential for extracting complex spatial patterns from satellite imagery in the context of desertification monitoring (Rayne et al., 2023). By leveraging these tools, scholars are able to efficiently and accurately capture data on key environmental variables, including changes in land use, vegetation cover, and soil moisture, and subsequently utilise this information to inform the development of more effective strategies for mitigating and preventing desertification (Boali et al., 2024).

Crucially, stakeholder collaboration remains an essential component of these efforts. Translating risk maps into actionable strategies requires meaningful engagement with local communities to incorporate indigenous knowledge related to land resilience and historical degradation patterns. In parallel, the transparent communication of uncertainty metrics is necessary to ensure that policymakers clearly understand both the limitations and the confidence levels associated with model outputs (Al-Tameemi et al., 2025). The integration of time-series satellite data with machine learning models has enabled the identification of early warning signals of desertification, thereby facilitating more proactive and timely land management interventions (H. Jiang et al., 2024).

2.8.4. Limitations and challenges:

Despite the promising applications of machine learning in desertification assessment, several limitations and challenges persist. Monte Carlo simulations have revealed spatial variability in classification outcomes, indicating the need for additional field-based data prior to the implementation of mitigation measures, thereby reducing the

risk of resource misallocation (Al-Tameemi et al., 2025). This finding underscores the persistent challenges associated with data scarcity and quality, particularly in developing countries, which continue to constrain the effective implementation of machine learning approaches for desertification monitoring and assessment (Bashiri et al., 2025).

Model interpretability remains a persistent challenge in machine learning applications for desertification assessment, as complex models often function as ‘black boxes’, making it difficult to clearly understand the underlying mechanisms driving their predictions (Rampone & Valente, 2019). This challenge is further compounded by the fact that current machine learning applications in desertification assessment continue to face constraints related to data availability, limited model interpretability, and the need for robust field validation to ensure both accuracy and relevance to local environmental conditions (K. Feng et al., 2022).

Technical barriers also constrain widespread adoption, as the computational complexity associated with advanced machine learning models poses significant challenges in regions with limited technical infrastructure and expertise (P. Li et al., 2022). The prominence of human impact factors within the model highlights broader socio-ecological challenges, underscoring the urgency of land-use policy reforms, particularly the need to curb unsustainable agricultural practices and overgrazing in ecologically fragile regions (Al-Tameemi et al., 2025).

To address these limitations, several directions for future research have been proposed, with particular emphasis on three key priorities. First, expanding ground validation through field surveys in conjunction with time-series satellite data would help reduce uncertainty in desertification risk assessment (Al-Tameemi et al., 2025). More comprehensively, future research should integrate expanded field validation, enhanced temporal analysis, and adaptive uncertainty modelling approaches in order to further refine classification accuracy (Al-Tameemi et al., 2025).

Perhaps most importantly, the integration of machine learning with participatory approaches advances desertification assessment beyond static index-based frameworks, enabling more adaptive and context-specific land management in Iraq and comparable arid regions (Al-Tameemi et al., 2025). This integrated approach acknowledges that technological solutions must be coupled with appropriate social and institutional frameworks to effectively address the complex challenge of desertification. In this context, the study’s risk maps provide policymakers with practical tools to prioritise interventions in high-risk zones, such as implementing soil conservation measures in areas affected by severe erosion or improving water management in overexploited aquifers (Al-Tameemi et al., 2025).

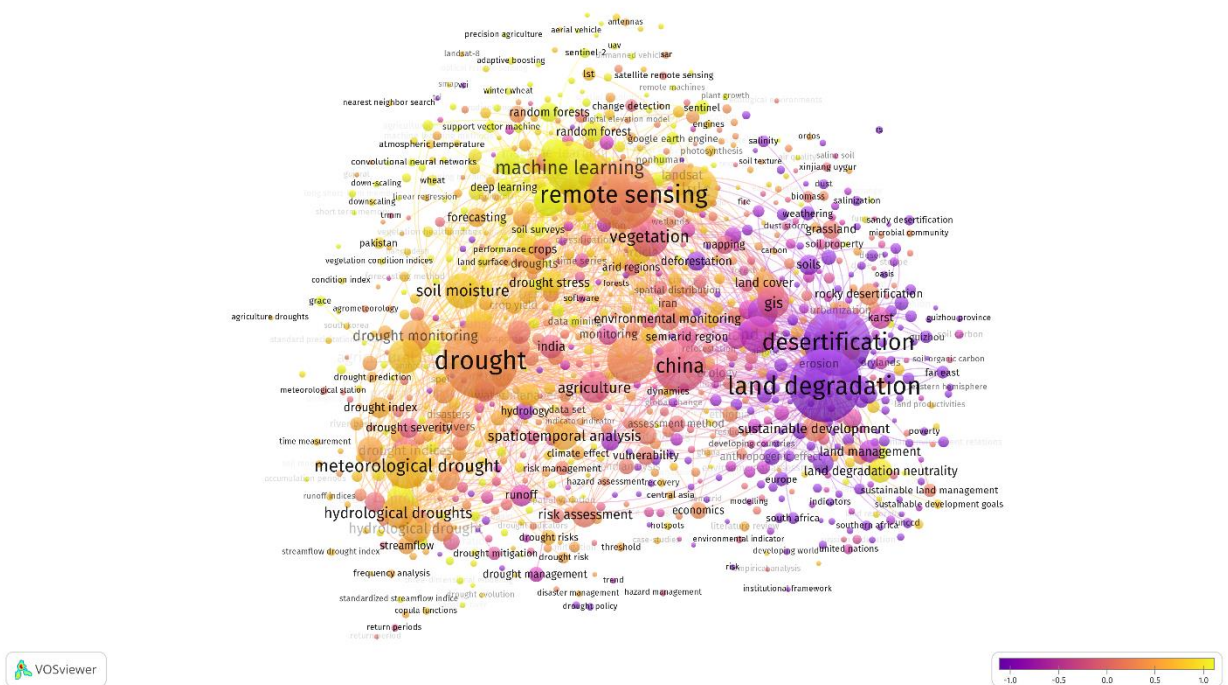


Figure 1. A literature-based visualization illustrating the network of keywords related to land degradation, drought, and desertification assessment approaches and indicators.

3. Materials and methods:

To provide a comprehensive overview of the research design, Figure 1a illustrates the integrated methodological framework adopted in this dissertation. It explicitly links the primary research objectives (O1–O5) and research questions (Q1–Q5) to the four interconnected analytical pathways across regional, sub-regional, and local scales. The framework encompasses multi-source data acquisition, preprocessing, and the cross-scale synthesis of climatic, vegetation, and anthropogenic drivers, culminating in an integrated interpretation of land degradation dynamics in Northern Algeria.

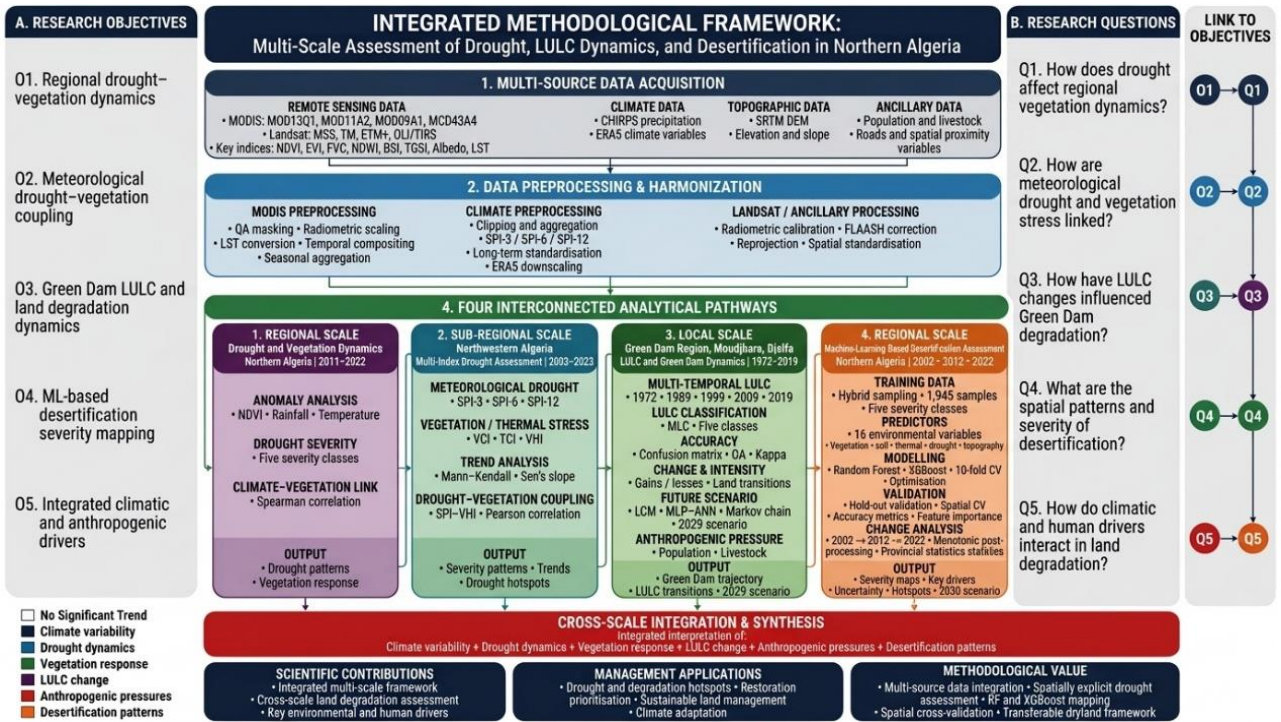


Figure 1a. Integrated methodological framework illustrating the multi-scale assessment of drought, LULC dynamics, and desertification in Northern Algeria.

3.1. Study area description:

This dissertation adopts a multi-scale analytical framework encompassing three levels: a regional scale (Northern Algeria), a sub-regional scale (Northwestern Algeria), and a local scale (the Green Dam region within the southern steppe areas), as outlined in the Introduction. This hierarchical structure directly responds to a key research gap identified in the literature, namely the absence of integrated multi-scale analytical frameworks for Northern Algeria (Alliouche & Kouba, 2023; Bouzekri et al., 2023). At the regional scale, Northern Algeria provides the broad climatic context necessary for understanding large-scale patterns of land degradation. At the sub-regional scale, Northwestern Algeria captures the critical transition between Mediterranean and arid zones (Achite et al., 2025), where desertification processes tend to be particularly dynamic. At the local scale, the Green Dam region enables a more focused examination of desert–steppe transition dynamics, especially in areas where ecological restoration initiatives have been implemented (Ilhame et al., 2025; Mohamed et al., 2025).

By explicitly linking processes across these scales, the dissertation enables an examination of how regional climatic patterns are expressed within sub-regional hydrological systems and, in turn, influence local land degradation dynamics at the critical desert–steppe interface. This multi-scale perspective is essential for the

development of effective monitoring and management strategies that operate across the full continuum of desertification processes in Northern Algeria.

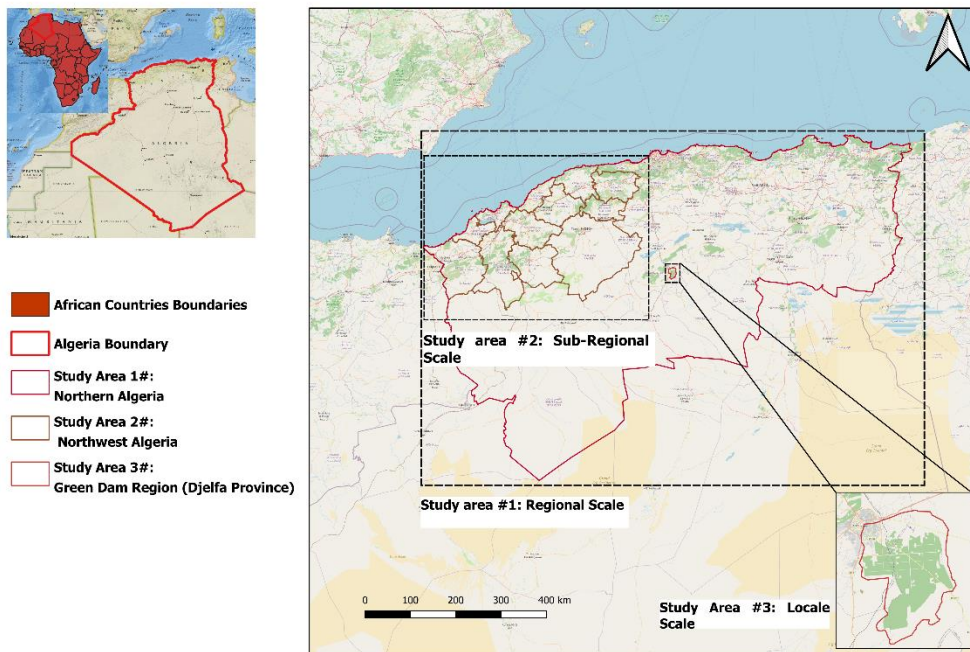


Figure 2. Location of four study areas in the Northern Algeria.

3.1.1. Study Area #1 Regional Scale; Northern Algeria:

Algeria, the largest country in Africa, covers an area of approximately 2,381,741 km². Geographically, the country is broadly divided into northern and southern zones. The southern part is predominantly desert, while the northern region situated between the Mediterranean Sea and the Sahara features a diverse landscape of mountains (the Tell and Saharan Atlas), valleys, and the High Plateaus. This study focuses exclusively on Northern Algeria, which encompasses 40 provinces and covers 375,815 km² (15.77% of the nation's total area), with elevations ranging from 36 m to 2,301 m.

Northern Algeria exhibits a pronounced north–south climatic gradient that renders it highly vulnerable to desertification (Azzouzi et al., 2017; Bensaïd, 2006; Halima, 2003; Hirche et al., 2011; Zerouali, 2021). This gradient comprises three distinct zones (Boudiaf et al., 2021; Jean-Pierre et al., 2010; Mellak & Souag-Gamane, 2020): (i) a coastal Mediterranean zone with annual precipitation of 400–800 mm; (ii) a sub-humid zone with relatively cool winters and occasional frost events; and (iii) the northern Algerian steppes, a semi-arid to arid ecosystem along the southern Saharan boundary characterized by notably warm summers (averaging 27 °C in July) and limited annual precipitation (typically 100–250 mm). In these steppe regions, precipitation is highly irregular and concentrated mainly in the winter season, while prolonged summer dry periods result in frequent drought conditions (Belala et al.,

2018). Furthermore, interannual rainfall variability is characterized by alternating drought and wet cycles, with a marked general declining trend observed over recent decades, particularly in the northwestern region (Meddi & Toumi, 2013; Merniz et al., 2019). The combination of this pronounced climatic aridity and anthropogenic pressures such as intensive agriculture, overgrazing, and urban expansion drives severe land degradation. Consequently, desertification in the region manifests as soil degradation, declining vegetation cover, and biodiversity loss (Lydia, 2023).

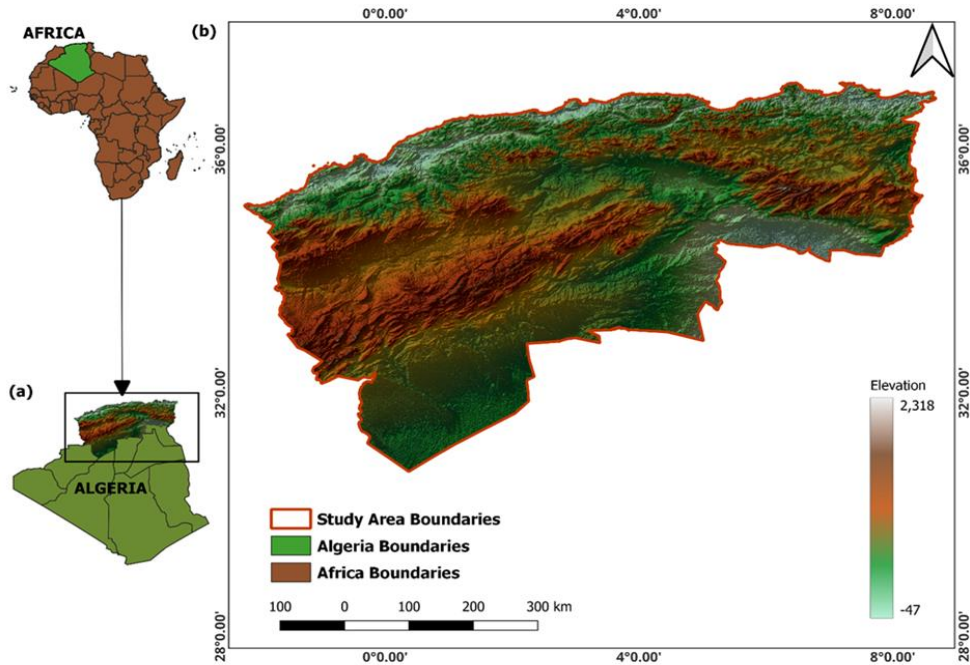


Figure 3. Location of the study area 1# in Northern Algeria.

Data source: Shuttle Radar Topography Mission (SRTM) 30m DEM. Note: Minor negative elevation values near coastal areas are known interpolation artifacts of the SRTM dataset and do not represent true topographic depressions.

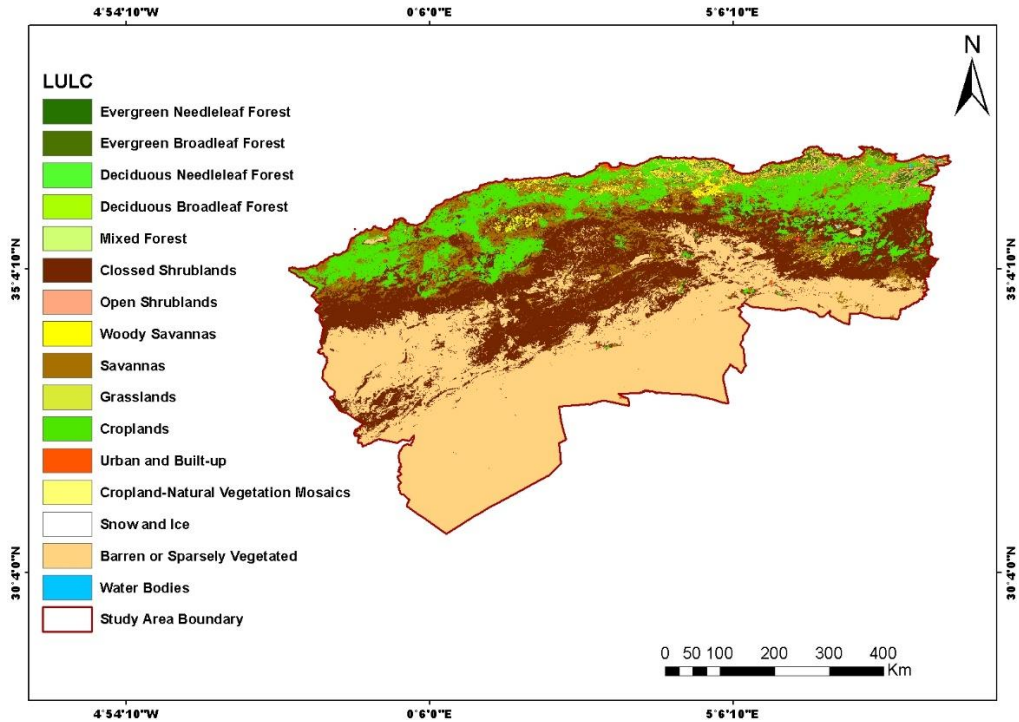


Figure 4. land use land cover of the study area 1# in Northern Algeria.

3.1.2. Study Area #2 Sub-regional Scale: Northwestern Algeria:

The second study area encompasses the northwestern region of Algeria, extending approximately 500 km from west to east between longitudes 2°10'10" W and 3°10'11" E, and latitudes 34°18'54" and 36°48'12" N. The region exhibits a semi-arid to Mediterranean climate with pronounced spatial and temporal precipitation variability that strongly influences hydrological processes and land degradation patterns (Hamitouche et al., 2024; Mahcer et al., 2024). Mean annual precipitation varies considerably across the region, ranging from approximately 240 mm yr⁻¹ in interior basins such as the Tafna to over 700 mm yr⁻¹ in coastal and mountainous areas, particularly in the northern Chelif basin (Achite et al., 2021).

Northwest Algeria exhibits a pronounced vegetation gradient that closely reflects its precipitation regime, transitioning from Mediterranean forest ecosystems along the northern coastal fringe to more open steppe vegetation across the interior basins (Djeddaoui et al., 2017). In the northern coastal and mountainous regions, Mediterranean forest communities constitute the dominant land cover, with species such as *Pinus halepensis*, *Quercus* spp, *Tetraclinis articulata*, and *Juniperus oxycedrus* forming the primary woody vegetation (Kiouss et al., 2024). Progressing southward into the interior basins, the landscape transitions into open steppe plains underlain by predominantly calcareous soils (El Zerey et al., 2017). These steppe areas support a heterogeneous mosaic of shrublands and grasslands, with characteristic species including *Macrochloa tenacissima*, *Lygeum spartum*, *Artemisia herba-alba*, and *Stipa*

parviflora (Macheroum et al., 2021). The Algerian steppes in this region are characterised by soils typically composed of a single, relatively shallow horizon, varying in limestone content and containing an appreciable proportion of organic matter, generally ranging between 5 and 8% (Tayeb & Kheloufi, 2019). Agricultural land constitutes a substantial proportion of the region's overall land cover (Mahcer et al., 2024). Forest cover has declined since the 1980s, primarily as a result of wildfires and agricultural expansion, while scrubland reconstitution has been observed following fire events (Appiagyei et al., 2023). This vegetation heterogeneity provides an essential context for interpreting vegetation-based indices, as different land cover types may respond to hydrological variability in markedly distinct ways (Belabbes & Si Tayeb, 2025).

The region encompasses several major basins and wadis that play a dominant role in shaping regional hydrology and land degradation processes. The Chelif basin ($\approx 44,694 \text{ km}^2$) represents Algeria's largest watershed, originating in the Tell Atlas and draining into the Mediterranean Sea. Its extensive catchment area makes it a critical region for understanding sediment transport, water resource management, and desertification dynamics across northwestern Algeria (Achite et al., 2021). The Tafna basin represents a key transboundary catchment along the Algeria–Morocco frontier, supporting both regional agricultural activities and biodiversity (Bougara et al., 2021; Fettam et al., 2025). The Macta basin receives inflows from the Habra and Sig rivers and ultimately drains into the Gulf of Arzew in the Mediterranean Sea. It also encompasses ecologically significant wetlands, including Lac El Macta, which are designated under the Ramsar Convention, thereby underscoring the basin's ecological importance (Elouissi et al., 2021; Ismail et al., 2022).

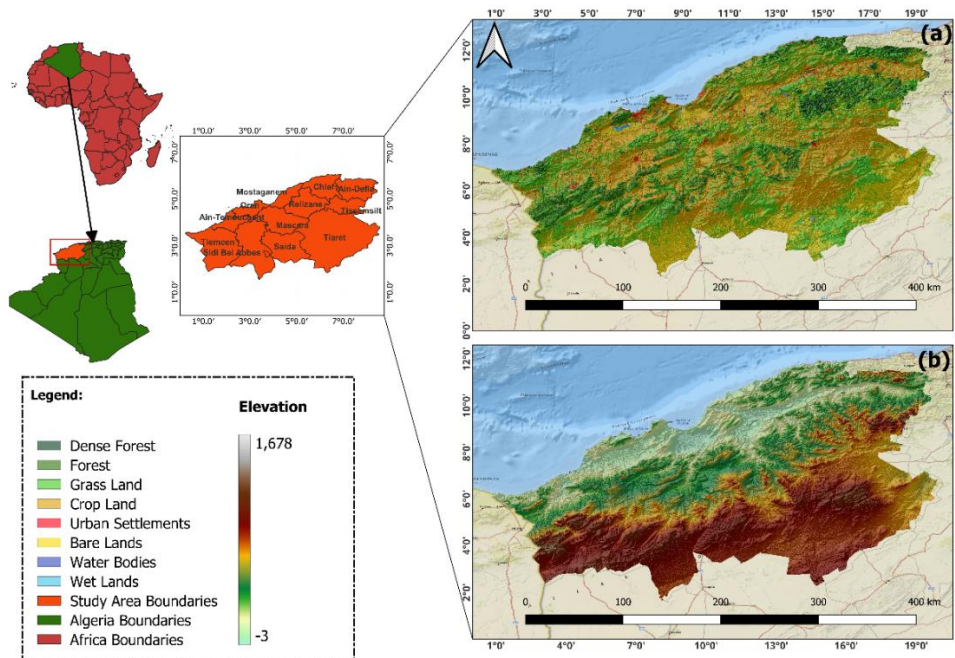


Figure 5. Location of the study area 2# in Northwestern Algeria.

3.1.3. Study Area #3 Local Scale: Green Dam Region (Djelfa Province):

The third study area is the Moudjbara perimeter, located in the southeastern part of Djelfa Province within the Saharan Atlas, approximately 300 km south of Algiers. The study area extends between 34°31'3.19"–34°41'33.23" N and 3°19'36.64"–3°23'0.26" E, covering approximately 10,000 ha. Elevation ranges from 1,200 to 1,400 m above sea level, with gently undulating terrain typical of the desert–steppe transition zone. The climate is semi-arid, characterised by cold winters (mean minimum temperature of 0.1 °C) and hot, dry summers (mean maximum temperature of 33.8 °C), with an average annual precipitation of approximately 300 mm (Bourbouze, 2006). A long-term drying trend has been documented in the region since 1972 (Adair, 1983). Geographically, the study area occupies a strategic desert–steppe transition zone between the more humid northern regions and the arid Sahara. Often referred to as the "gateway to the Great Sahara," it functions as a natural buffer against desert expansion and is therefore particularly vulnerable to land degradation, wind erosion, and climatic variability (Lydia, 2023).

The soils of the Moudjbara region are typical of the Algerian steppe and consist predominantly of shallow, poorly developed rendzina and calcareous soils. They are generally characterized by a single shallow horizon with variable limestone content and an organic matter content ranging from 5 to 8% (Tayeb & Kheloufi, 2019). Owing to their limited depth and weak profile development, these soils are highly susceptible to erosion and land degradation (Bouzekri et al., 2023; Hammouda et al., 2019).

The Moudjbara perimeter was the first area to be afforested with Aleppo pine (*Pinus halepensis*) under Algeria's Green Dam programme in 1972, with plantations established adjacent to existing natural stands. The present landscape consists of a heterogeneous mosaic of natural and planted Aleppo pine forests, urban areas (including Djelfa city and its surrounding settlements), cereal croplands, and degraded steppe rangelands. The steppe vegetation is dominated by *Macrochloa tenacissima* (*Stipa tenacissima*), *Artemisia herba-alba*, and *Lygeum spartum*, which support extensive livestock grazing and are characteristic of the region's semi-arid steppe ecosystem (Zerouali et al., 2021).

Over recent decades, the Moudjbara region has experienced substantial vegetation changes driven by the combined effects of climatic variability and anthropogenic pressures. Previous studies have reported a decline in the Normalized Difference Vegetation Index (NDVI), indicating deteriorating vegetation conditions associated with increasing temperatures and changing seasonal patterns (Mahcer et al., 2024). These pressures have altered vegetation distribution and structure, resulting in pronounced degradation and increased susceptibility to desertification (Hammouda et al., 2019; Ilhame et al., 2025; Mohamed, 2025). Owing to its location at the desert–steppe transition zone and its history as one of the earliest Green Dam afforestation sites, the Moudjbara perimeter provides an ideal case study for evaluating long-term ecological restoration efforts and investigating LDD dynamics. The spatial location

and geographical extent of the Green Dam study area in Djelfa Province are illustrated in Figure 6.

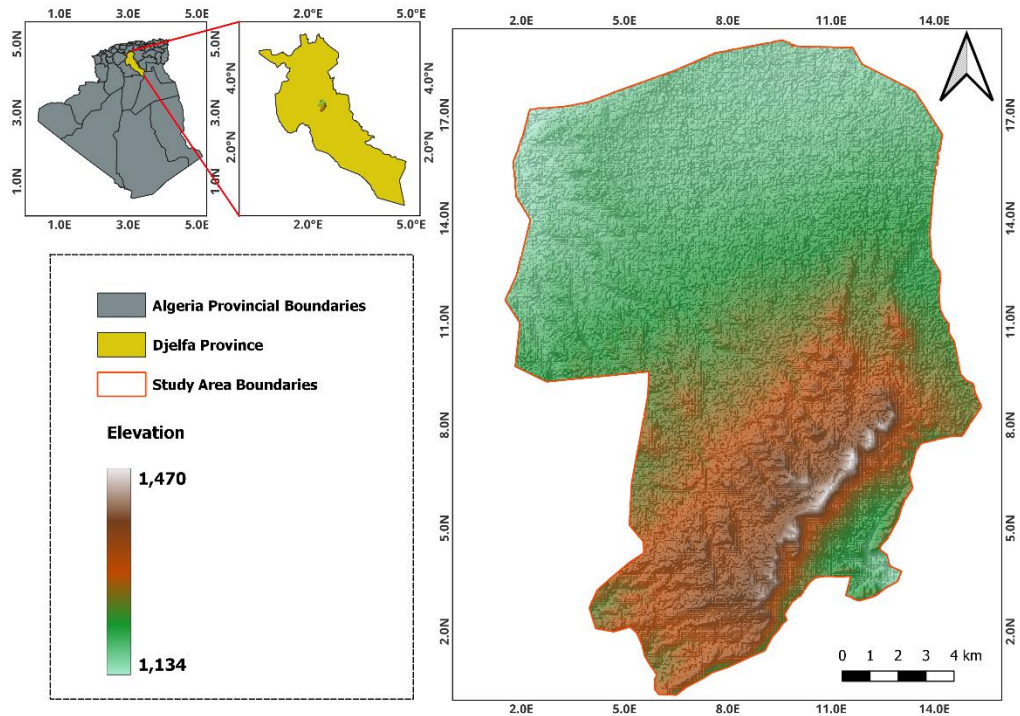


Figure 6. Location of the study area 3# in Green Dam Region (Djelfa Province).

3.2. Data:

This study integrates multi-source geospatial datasets to provide a comprehensive representation of the climatic, biophysical, and surface processes governing drought dynamics, land use/land cover (LULC) change, and desertification across Northern Algeria. The selected datasets include satellite-derived vegetation indices, surface reflectance products, land surface temperature, precipitation data, climate reanalysis variables, and topographic information.

The integration of these datasets ensures a complementary representation of environmental processes across multiple spatial and temporal scales. In particular, high-temporal-resolution MODIS products enable continuous environmental monitoring, Landsat imagery supports long-term LULC change detection, while Climate Hazards group Infrared Precipitation with Stations (CHIRPS) and European Reanalysis 5th Generation (ERA5) datasets provide a robust characterisation of climatic variability, especially in data-scarce regions. The characteristics, spatial resolution, temporal resolution, and analytical purpose of all datasets utilized in this dissertation are summarized in Table 1.

Table 1. Summary of all the datasets used in the dissertation.

Data Type	Product	Source	Spatial Resolution	Temporal Resolution	Time Range	Variables / Indices	Purpose
Precipitation	CHIRPS	CHG / USGS	0.05° (~5.3 km)	Daily	1990–2022	Precipitation	Meteorological drought analysis
Climate reanalysis	ERA5	ECMWF	~0.25° (~31 km)	Hourly / Monthly	2003–2023	Temperature, precipitation, climate variables	Climatic variability & drought analysis
Vegetation indices	MOD13Q1 V6.1	MODIS	250 m	16-day	2002–2022	NDVI, EVI, MSAVI	Vegetation dynamics
Vegetation (derived)	MOD13Q1 (NDVI-based)	MODIS	250 m	16-day	2002–2022	FVC	Vegetation cover / desertification
Land surface temperature	MOD11A2 V6.1	MODIS	1 km	8-day	2002–2022	LST	Thermal conditions / drought
Surface reflectance	MOD09A1	MODIS	500 m	8-day	2002–2022	NDWI, BSI, Blue, Red, NIR, MIR bands	Soil moisture & exposure
BRDF-corrected reflectance	MCD43A4	MODIS	500 m	Daily	2002–2022	Albedo, TGSi	Surface and soil characterization
Topography	SRTM DEM	USGS	~30 m	Static	2000 (Static)	Elevation, Slope, Aspect	Terrain analysis
LULC	Landsat MSS	USGS	~60 m	Multi-date	1972	Spectral bands	Long-term LULC change
	Landsat TM		~30 m		1989, 1999		
	Landsat ETM+		~30 m		2009		
	LandsatOLI-TIRS				2019		
							Recent LULC dynamics

3.2.1. Satellite Data Sources:

Satellite remote sensing data constitute the primary source of spatially explicit environmental information in this study. In particular, MODIS products, provided by NASA, were extensively utilised owing to their high temporal resolution and strong suitability for monitoring environmental dynamics across large spatial extents (Dhillon et al., 2023).

Vegetation dynamics were characterised using the MOD13Q1 V6.1 product, from which several vegetation indices were derived, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Modified Soil-Adjusted Vegetation Index (MSAVI) (Dhillon et al., 2023). These indices provide complementary insights into vegetation structure, with EVI offering improved sensitivity in densely vegetated areas and MSAVI effectively reducing soil background effects, a feature particularly relevant in semi-arid environments (Xiong et al., 2023). In addition, Fractional Vegetation Cover (FVC) was derived using NDVI-based methods to quantify vegetation density, which represents a key indicator in desertification assessment (D’Acunto et al., 2024).

Thermal conditions were assessed using MOD11A2 V6.1 Land Surface Temperature (LST) data, enabling detailed analysis of surface energy balance and heat stress (Dhillon et al., 2023). In parallel, surface reflectance datasets, including MOD09A1 and MCD43A4, provided multi-spectral information used to derive key environmental indicators such as the Normalized Difference Water Index (NDWI), Bare Soil Index (BSI), Topsoil Grain Size Index (TGSi), and surface albedo (Dhillon

et al., 2023). Collectively, these variables are essential for characterising soil exposure, moisture conditions, and surface properties associated with land degradation processes (Xiong et al., 2023).

To investigate long-term land use and land cover changes, Landsat imagery from multiple sensor generations (MSS, TM, ETM+, and Landsat 8 OLI-TIRS) was utilised. These datasets provide a unique historical archive spanning nearly five decades (1972–2019), thereby enabling consistent and systematic monitoring of landscape transformations (D’Acunto et al., 2024). Detailed characteristics of the Landsat imagery employed in this study, including sensor specifications, spectral bands, and acquisition dates, are presented in Table 2.

Table 2. Characteristics of Landsat imagery used for LULC analysis.

Satellite	Sensor	Resolution	Path/Row	Spectral bands	Wavelength (nm)	Acquisition date
Landsat	MSS	60 m	195/36	Green Red Infrared 1	500-600 600-700 700-800	13 th September 1972
Landsat	TM	30m	195/36	Infrared 2 Blue Green Red Near-Infrared 1 Near-infrared 2 Midinfrared	800-1100 450-520 520-600 630-690 760-900 1550-1750 2080-2350	5 th July 1989
Landsat	ETM+	30m	195/36	Blue Green Red Near infrared 1 Near infrared 2 Midinfrared	450-520 520-600 630-690 760-900 1550-1750 2080-2350	9 th July 1999
Landsat	TM	30m	195/36	Blue Green Red Near infrared 1 Nearinfrared2 Midinfrared	450-520 520-600 630-690 760-900 1550-1750 2080-2350	28 th July 2009
Landsat	OLI-TIRS	30m	195/36	Coastal aerosol Blue Green Red Near-infrared Short wave infrared 1 Short wave infrared 2 Cirrus	430-450 450-510 530-590 640-670 850-880 1570-1650 2210-2290 1360-1380	24 th July 2019

3.2.2. Meteorological Data:

Meteorological data were incorporated to characterise climatic variability and drought conditions through the use of complementary datasets.

Precipitation data were derived from the CHIRPS dataset, which integrates satellite observations with ground-based measurements to generate spatially continuous rainfall estimates at a resolution of approximately 0.05° (~5.3 km) with a daily temporal frequency (Funk et al., 2015). This dataset is particularly well suited for

drought analysis in regions where meteorological station coverage is limited (Funk et al., 2015; Mianabadi et al., 2022).

In addition, atmospheric variables were derived from the ERA5 (European Reanalysis 5th Generation) dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020). ERA5 provides globally consistent climate reanalysis data at a spatial resolution of approximately 0.25° (~31 km), coupled with high temporal resolution (Hersbach et al., 2020). This dataset was utilised to incorporate temperature and other key climatic variables, thereby enabling a more comprehensive and integrated characterisation of drought conditions (AghaKouchak et al., 2015; Wardlow et al., 2012).

The combined use of CHIRPS and ERA5 datasets provides both high spatial resolution in precipitation data and physically consistent atmospheric information, thereby enhancing the overall robustness of the climatic analysis (Vicente-Serrano et al., 2010).

3.2.3. Ancillary Datasets:

To account for terrain influences on environmental processes, topographic variables were derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model, obtained from the United States Geological Survey (USGS) Earth Explorer platform at a spatial resolution of approximately 30 m. The extracted variables include elevation, slope, and aspect, which are critical for understanding spatial variability in hydrological processes, vegetation distribution, and land degradation dynamics (AlAmri et al., 2026).

In addition, soil-related indicators derived from remote sensing data, such as BSI and TGSI, were employed as proxies for soil conditions, thereby complementing the topographic variables in the assessment of desertification processes (W. Yin et al., 2024). The TGSI has been identified as “the most appropriate index for evaluating soil surface texture,” with evidence indicating that “an increase in soil surface grain size constitutes a clear indicator of land degradation.” (W. Yin et al., 2024), when surface soil particles become coarser, this transformation is regarded as “a warning sign of the onset or progression of destructive processes such as erosion and desertification” (Guo et al., 2020). Similarly, the BSI provides valuable insights into soil exposure and degradation status, with evidence indicating that “different levels of desertification result in distinct topsoil textures, with more advanced stages of desertification associated with increasingly coarse soil particle composition” (Guo et al., 2020), these soil indicators, when integrated with topographic variables, provide a comprehensive basis for characterising the biophysical dynamics that influence vegetation health and land degradation across arid and semi-arid environments (AlAmri et al., 2026).

3.3. Data Preprocessing:

To ensure consistency, reliability, and comparability across the diverse datasets utilised in this study, a comprehensive preprocessing workflow was implemented. Given the integration of multi-source satellite imagery, climatic data, and topographic

information, preprocessing procedures were tailored to the specific characteristics of each dataset while maintaining a coherent and unified analytical framework (D’Acunto et al., 2024; Khan & Gilani, 2023).

3.3.1. MODIS Data Preprocessing:

MODIS datasets were primarily preprocessed within (GEE) environment, which enabled the efficient handling of large-scale time-series data while ensuring reproducibility across analyses.

Quality control represented a fundamental component of the preprocessing workflow. The MODIS Quality Assurance (QA) bands were systematically utilised to identify and mask pixels affected by clouds, cloud shadows, and other atmospheric disturbances. Binary logic operations were applied to QA flags to exclude low-quality observations, thereby ensuring the integrity and consistency of all derived products (Ackerman et al., 1998; Lyapustin et al., 2018).

Following quality filtering, radiometric scaling was applied to convert digital numbers into physically meaningful values using the official scale factors recommended by NASA. This step was essential to ensure the comparability of spectral indices and reflectance-based variables across time (Markham & Helder, 2012; Roy et al., 2016).

Thermal data from the MOD11A2 product were further processed by converting land surface temperature values from Kelvin to degrees Celsius, thereby improving interpretability within the context of environmental analysis.

To reduce short-term variability and atmospheric noise, temporal compositing strategies were applied in accordance with the specific objectives of the study. For desertification analysis, annual median composites were generated for selected reference years (2002 and 2022), thereby minimising the influence of outliers and seasonal fluctuations (K. Feng et al., 2022; Hashemi et al., 2024). While annual median compositing effectively captures broad, long-term changes in land degradation, it does not resolve seasonal phenological variability or short-term degradation events. Higher temporal-resolution analyses, using seasonal or monthly composites, could provide additional information on vegetation phenology and rapid degradation processes; however, these analyses were beyond the scope of this study, which focused primarily on multi-decadal spatial patterns and trends. Future research could incorporate time-series change-detection approaches, such as Breaks For Additive Season and Trend (BFAST) or LandTrendr, to capture both long-term trends and more rapid temporal changes in vegetation and land-surface conditions. In drought-related analyses, MODIS datasets (NDVI and LST) were aggregated into monthly composites, ensuring temporal consistency and alignment between vegetation and thermal variables (Mehmoud et al., 2024; Roustae et al., 2020).

For vegetation anomaly analysis, MODIS NDVI data were further processed to derive seasonal averages over the growing period (November–June), thereby enabling a more representative and temporally integrated assessment of vegetation dynamics (Lamchin et al., 2017).

3.3.2. Climate Data Preprocessing:

Climate datasets, including CHIRPS precipitation and ERA5 reanalysis variables, were processed to ensure both temporal and spatial consistency with satellite-derived observations.

CHIRPS daily precipitation data were first clipped to the study area and subsequently aggregated into cumulative values over 3-, 6-, and 12-month periods, corresponding to SPI timescales. To ensure data reliability, only time intervals with continuous and complete records were retained. The precipitation data were then standardised on a per-pixel basis using long-term statistical parameters, thereby enabling consistent and spatially explicit drought characterisation (Funk et al., 2015; McKee et al., 1993).

ERA5 climate data, including rainfall and temperature, were acquired at a spatial resolution of 0.25°. To ensure compatibility with MODIS-derived variables, these data were spatially downscaled to a resolution of 250 m using kriging interpolation techniques implemented through the KrigR package. This procedure ensured spatial coherence and alignment between climatic and vegetation datasets (Erdogan, 2009; Hersbach et al., 2020).

In addition, climate variables were temporally aggregated to correspond with the growing season (November–June) used in the vegetation analysis. Long-term baseline conditions were then computed using a 30-year reference period (1990–2020), in accordance with World Meteorological Organization (WMO) recommendations for defining climatological normals. While this fixed baseline provides a stable reference frame for measuring interannual variability, it is important to note that sustained positive temperature anomalies in the latter part of the study period inherently reflect the region's underlying warming trajectory. This compounding effect of rising temperatures on atmospheric evaporative demand and vegetation stress is further explored in the results and discussion sections. (Arguez & Vose, 2011).

3.3.3. Topographic Data Processing:

Topographic variables were derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM), originally available at a spatial resolution of approximately 30 m (Farr et al., 2007). The SRTM DEM was selected for this study due to its global coverage, open accessibility, and established utility in regional-scale environmental modelling applications (Rodríguez et al., 2006; Sampson et al., 2016).

Although the SRTM DEM is subject to known vertical uncertainties, with the USGS reporting a vertical accuracy of ± 16 m at the 90% confidence level, regional validation studies suggest that its performance may be considerably better under certain conditions. For example, in the Tebessa Basin of north-eastern Algeria, the SRTM DEM achieved a vertical accuracy of 8.3 m RMSE (Athmania & Achour, 2014). In addition, resampling the SRTM DEM to coarser spatial resolutions, ranging from 150 to 500 m, has been reported to improve its accuracy, with an R^2 value of 0.93, by reducing the influence of localized errors and high-frequency noise. These findings support the suitability of the SRTM DEM for regional-scale environmental

analyses, particularly where the influence of fine-scale elevation errors is reduced through spatial aggregation.

Elevation data were used to derive secondary terrain attributes, including slope and aspect, within the GEE environment. To ensure compatibility with MODIS-based variables, all topographic layers were resampled to a spatial resolution of 500 m using nearest-neighbour interpolation. This preprocessing step served two main purposes. First, it facilitated the integration of terrain-related variables into the broader environmental analysis framework (Khan & Gilani, 2023; Su & Guo, 2014). Second, resampling to a common spatial resolution helped reduce pixel-level noise and interpolation artefacts associated with the original 30 m data, thereby improving the consistency and reliability of the topographic inputs.

It should also be noted that elevation, slope, and aspect were treated as secondary modulating variables within the machine-learning framework rather than as the primary determinants of desertification severity. As shown by the feature-importance analysis in Section 4.4.5, these topographic variables consistently contributed less to the models than vegetation, moisture, and thermal indicators. This pattern suggests that residual vertical uncertainties in the SRTM DEM were unlikely to have had a substantial influence on the final classification results.

3.3.4. Landsat Data Preprocessing for LULC Analysis:

Landsat imagery from multiple sensor generations (MSS, TM, ETM+, and OLI-TIRS) was preprocessed to enable consistent multi-temporal land use/land cover (LULC) analysis.

To minimise atmospheric and sensor-related distortions, all images underwent radiometric calibration, whereby digital numbers were converted into top-of-atmosphere radiance and reflectance. Subsequently, atmospheric correction was applied using the Fast Line-of-sight Atmospheric Analysis of Spectral Hyp (FLAASH) algorithm in ENVI 5.3 to derive surface reflectance and to effectively remove atmospheric effects (Anderson et al., 2002; Prieto-Amparan et al., 2018), generating the Level-2 data locally via FLAASH, rather than using pre-packaged USGS Level-2 products, allowed for a uniform radiative transfer correction across all sensor generations (MSS, TM, ETM+, and OLI-TIRS), ensuring high consistency throughout the multi-decadal time series.

All images were selected under cloud-free conditions and, where possible, from similar seasonal acquisition periods to ensure comparability. The datasets were subsequently clipped to the study area boundary and reprojected into a common coordinate system using ArcGIS 10.8.1 (Roy et al., 2016).

3.3.5. Spatial Harmonization and Dataset Integration:

Given the integration of datasets with varying spatial and temporal resolutions, a harmonisation process was implemented to ensure consistency and compatibility across all variables. This process included the clipping of all datasets to the study area extent, the conversion of variables into consistent physical units, temporal

aggregation to monthly, seasonal, or annual scales depending on the analytical requirements, and the spatial resampling of auxiliary datasets to align with MODIS resolution where necessary.

Through these steps, a unified and standardised database was established, providing a robust foundation for the derivation of geo-environmental variables and subsequent modelling analyses.

3.4. Regional-Scale Analysis:

Given the multi-scale structure of this dissertation, Table 3.1 is included to help the reader navigate the overall methodological framework. The table explicitly links each methodological approach presented in Chapter 3 to the corresponding results in Chapter 4 and to the specific research objective it addresses. This cross-referencing structure makes it easier to trace each analytical result back to its methodological basis and to understand how the individual analyses contribute to the broader objectives of the dissertation.

Table 3.1. Methodology–Results Mapping for the Multi-Scale Analytical Framework.

Spatial Scale	Methodology Section (Chapter 3)	Key Methods	Corresponding Results (Chapter 4)	Research Objective
Regional (Northern Algeria)	3.4.1 Regional-Scale Drought Assessment	NDVI anomaly analysis; rainfall and temperature anomalies; drought severity classification; Spearman correlation	4.1 Drought Variability and Vegetation Response (2011–2022)	Objective 1
Regional (Northern Algeria)	3.4.2 Regional-Scale Desertification Assessment	Geo-environmental indicators (NDVI, NDWI, BSI, TGSi, LST, Albedo, etc.); Random Forest and XGBoost classifiers; spatial cross-validation; feature importance; provincial zonal statistics; future projection (2030)	4.4 Machine Learning-Based Desertification Assessment	Objective 4
Sub-Regional (Northwestern Algeria)	3.5.1 Meteorological Drought Indicator	Standardized Precipitation Index (SPI-3, SPI-6, SPI-12)	4.2.1 SPI-Derived Meteorological Drought Patterns	Objective 2
Sub-Regional (Northwestern Algeria)	3.5.2 Vegetation-Based Drought Indicators	Vegetation Condition Index (VCI); Temperature Condition Index (TCI); Vegetation Health Index (VHI)	4.2.2 Vegetation and Thermal Stress Dynamics	Objective 2
Sub-Regional (Northwestern Algeria)	3.5.3 Trend Analysis	Mann–Kendall test; Sen's slope estimator	4.2.3 Spatiotemporal Trends in Drought Indices; Tables 7 & 8	Objective 2
Sub-Regional (Northwestern Algeria)	3.5.4 Correlation Analysis	Pearson correlation (SPI–VHI)	4.2.4 Multi-Timescale Coupling Between SPI and VHI	Objective 2

Local (Green Dam Region, Djelfa)	3.6.1 LULC Classification and Accuracy Assessment	Maximum Likelihood Classifier (MLC); confusion matrix; Overall Accuracy and Kappa	4.3.1 Classification Accuracy Assessment	Objective 3
Local (Green Dam Region, Djelfa)	3.6.2 LULC Change Analysis	Land Change Modeler (LCM); intensity analysis; multi-temporal transitions	4.3.2 Spatiotemporal Dynamics of LULC (1972–2019); 4.3.3 Intensity and Rate of Change	Objective 3
Local (Green Dam Region, Djelfa)	3.6.3 Future Scenario Modelling	Markov chain; 2029 projection	4.3.4 Green Dam Trajectory and Future Dynamics	Objective 3
Local (Green Dam Region, Djelfa)	3.6.4 Anthropogenic Pressure Indicators	Population trends (ONS); livestock trends; exponential and power function projections	4.3.5 Anthropogenic Pressure: Population and Livestock Growth	Objective 3

3.4.1. Regional-Scale Drought Assessment:

3.4.1.1. Anomaly-Based Environmental Indicators:

Drought is a complex phenomenon that encompasses both meteorological deficits and ecological responses. To adequately capture this complexity, a combination of standardized indices and anomaly-based indicators was employed in this study (Alahacoon & Edirisinghe, 2022; Jalayer et al., 2023).

Anomaly-based indicators were employed to quantify deviations of vegetation and climatic variables from their long-term average conditions, thereby enabling the detection of abnormal environmental states associated with drought. In contrast to absolute indices, anomaly-based approaches provide a relative assessment of change, making them particularly well suited for identifying interannual variability and extreme events (AghaKouchak et al., 2015; Vicente-Serrano et al., 2010).

In this dissertation, anomalies were computed for vegetation (NDVI), precipitation, and temperature using a consistent methodological framework based on long-term reference conditions, as described below in this sub-chapter.

NDVI Anomaly:

The NDVI anomaly provides a dynamic measure of vegetation response to climatic variability by quantifying deviations from long-term mean conditions (Mehmoud et al., 2024; Rousta et al., 2020), to accurately assess vegetation response to climatic variability, the NDVI anomaly was computed using a multi-step approach based on growing season averages (Lamchin et al., 2017; Zhu et al., 2021).

First, the mean NDVI for each growing season (November to June) was calculated as follows:

$$NDVI_{mean_i} = \frac{(NDVI_1 + NDVI_2 + NDVI_n)}{n} \quad (1)$$

where:

- $(NDVI_{mean_i})$ represents the mean NDVI of the growing season for year (i);
- $(NDVI_1 \dots NDVI_n)$ correspond to the monthly NDVI values from November to June;
- (n) denotes the number of months within the growing season.

This step ensures that vegetation conditions are represented across the entire growing season rather than at a single time point (Khan & Gilani, 2023; Zhu et al., 2021).

Second, the long-term mean NDVI was calculated as follows:

$$\overline{NDVI} = \sum_{i=1}^n \frac{NDVI_{mean_i}}{n} \quad (2)$$

where:

- $(\overline{NDVI})$ denotes the long-term average NDVI;
- $(NDVI_{mean_i})$ represents the seasonal NDVI for each year;
- (n) corresponds to the number of years used for the baseline calculation (2000–2010).

This baseline provides a reference representing typical vegetation conditions, against which anomalies can be evaluated (Bichi et al., 2024; Eskandari Dameneh et al., 2021).

Finally, the NDVI anomaly was calculated using the following equation:

$$NDVI_{anomaly_i} = \frac{NDVI_{mean_i} - \overline{NDVI}}{\overline{NDVI}} \times 100 \quad (3)$$

where:

- $(NDVI_{anomaly_i})$ represents the anomaly for year (i);
- $(NDVI_{mean_i})$ denotes the seasonal NDVI for that year;
- $(\overline{NDVI})$ corresponds to the long-term mean NDVI.

This formulation expresses deviations as a percentage, thereby enabling consistent comparison across years.

Negative NDVI anomaly values indicate below-average vegetation conditions, typically associated with drought stress or land degradation, whereas positive values reflect above-normal vegetation growth.

3.4.1.2. Climatic Anomaly Calculation:

To ensure consistency with the vegetation-based analysis, rainfall and temperature anomalies were computed using a structured multi-step approach based on growing season averages (De Boeck & Verbeeck, 2011; Mehmoud et al., 2024).

Rainfall Anomaly:

First, the mean rainfall during the growing season (November to June) for each year was calculated using the following equation:

$$Rf_{mean i} = \frac{(Rf_1 + Rf_2 + Rf_n)}{n} \quad (4)$$

where:

- $(Rf_{mean i})$ represents the mean rainfall of the growing season for year i ;
- $(Rf_1 \dots Rf_n)$ correspond to the monthly rainfall values from November to June;
- (n) denotes the number of months within the growing season.

Second, the long-term mean rainfall was calculated using the following equation:

$$\overline{Rf} = \sum_{i=1}^n \frac{Rf_{mean i}}{n} \quad (5)$$

Where:

- $\overline{Rf}$ denotes the long-term mean rainfall;
- $Rf_{mean i}$ represents the seasonal rainfall values for each year;
- (n) corresponds to the number of years used for the baseline period (30 years: 1990–2020).

Finally, the rainfall anomaly was calculated using the following equation:

$$Rf_{anomaly i} = Rf_{mean i} - \overline{Rf} \quad (6)$$

Where:

- $Rf_{anomaly i}$ represents the rainfall anomaly for year i .

Negative values indicate below-normal rainfall conditions, typically associated with dry periods, whereas positive values correspond to wetter-than-normal conditions (Bichi et al., 2024; Roustia et al., 2020).

Temperature Anomaly:

Similarly, the mean temperature during the growing season was calculated as follows:

$$Tem_{mean i} = \frac{(Tem_1 + Tem_2 + Tem_n)}{n} \quad (7)$$

Where:

- $Tem_{mean i}$ represents the mean temperature of the growing season for year i ;
- $(Tem_1 \dots Tem_n)$ correspond to the monthly temperature values.

The long-term mean temperature was subsequently calculated as follows:

$$\overline{Tem} = \sum_{i=1}^n \frac{Tem_{mean_i}}{n} \quad (8)$$

Where:

- $\overline{Tem}$ denotes the long-term mean temperature;
- (n) represents the number of years considered in the baseline period (1990–2020).

Finally, the temperature anomaly was calculated using the following equation:

$$Tem_{anomaly_i} = Tem_{mean_i} - \overline{Tem} \quad (9)$$

Where:

$Tem_{anomaly_i}$ is the temperature anomaly for year i .

Positive values indicate warmer-than-normal conditions, while negative values indicate cooler conditions (De Boeck & Verbeeck, 2011; Eskandari Dameneh et al., 2021). In contrast to NDVI anomalies, which are expressed as relative percentage changes, rainfall and temperature anomalies are represented as absolute deviations from long-term means in order to preserve their physical interpretation and magnitude (Bichi et al., 2024; J. Wang et al., 2023).

These anomaly-based indicators complement the previously presented drought indices by explicitly capturing deviations from long-term environmental conditions, thereby enhancing the overall robustness of the drought assessment framework.

3.4.1.3. Drought Severity Classification:

Drought severity levels were determined by reclassifying NDVI anomaly values into discrete categories representing different degrees of drought intensity. This classification facilitates a more interpretable assessment of spatial and temporal drought patterns.

Following established approaches in remote sensing-based drought analysis, NDVI anomaly values were classified into five categories: non-drought, slight drought, moderate drought, severe drought, and very severe drought. This classification scheme has been widely applied in drought monitoring studies and provides a standardised framework for interpreting vegetation stress conditions (Gizachew & Suryabagavan, 2014; Moussa Kourouma et al., 2021; Nanzad et al., 2019; Vaani & Porchelvan, 2017).

To analyse the spatiotemporal dynamics of drought, the proportion of the study area corresponding to each drought class was calculated for each year. These proportions were subsequently visualised using the ggplot2 package in R, enabling a clear and effective representation of interannual drought variability.

Table 5. Drought classification based on NDVI anomaly values.

Drought Class	Non-Drought	Slight Drought	Moderate Drought	Severe Drought	Very Severe Drought
NDVI anomaly (%)	Above 0	0 to -10	-10 to -25	-25 to -50	Below -50

3.4.1.4. Relationship between NDVI and Climate Anomalies:

Statistical analyses were undertaken to quantify the relationships linking regional vegetation dynamics and climatic variability across Northern Algeria. Rather than serving only a descriptive role, this analysis helps reveal how meteorological conditions translate into measurable vegetation responses, offering a more grounded basis for interpreting drought processes across the regional study area. To address this, the first analytical strategy examines correlations between NDVI anomalies and key climatic variables, capturing how vegetation responds to climatic fluctuations.

To examine how vegetation dynamics respond to climatic variability, a correlation analysis was carried out linking NDVI anomalies with both rainfall and temperature anomalies. This approach makes it possible to directly trace how fluctuations in precipitation and thermal conditions are reflected in vegetation behaviour across the regional study area.

A total of 988 random sample points were distributed across the regional study area using ArcMap. At each location, annual values of NDVI anomaly, rainfall anomaly, and temperature anomaly were extracted at the pixel level. The full dataset exceeds 6.9 million pixels, so this sampling design was introduced to keep the analysis computationally tractable while still preserving statistical representativeness. While a larger sample size could further refine spatial resolution, 988 points were determined to be statistically sufficient to capture the regional heterogeneity while maintaining computational tractability for extracting multi-year time series from a dataset exceeding 6.9 million pixels, a methodology validated in our associated peer-reviewed research.

The Spearman rank correlation coefficient (ρ) was employed to assess the relationships between NDVI and climatic variables (Gizachew & Suryabhagavan, 2014; Moussa Kourouma et al., 2021; Nanzad et al., 2019). Unlike the Pearson correlation, this approach does not rely on assumptions of linearity or normal data distribution (Janse et al., 2021; C. Xiao et al., 2016), which makes it better suited to environmental datasets where responses are often irregular and non-linear. This consideration is particularly important in semi-arid environments, where vegetation responses to climatic forcing tend to be complex and not strictly linear.

Correlation coefficients were computed in R (Schober et al., 2018), while Microsoft Excel was used to visualise trends in NDVI and climate anomalies. For the NDVI–climate anomaly plots, annual mean anomaly values were derived by averaging across the 988 sampled pixels, providing a consistent basis for interannual comparison.

The strength of these relationships was interpreted using established correlation thresholds, as outlined in Table 6.

Table 6. Correlation coefficient values and their associated interpretations (Schober et al., 2018).

Correlation Coefficient (+/-)	Interpretation
0.00–0.10	Negligible correlation
0.10–0.39	Weak correlation
0.40–0.69	Moderate correlation
0.70–0.89	Strong correlation
0.90–1.00	Very strong correlation

3.4.2. Regional-Scale Desertification Assessment

3.4.2.1. Geo-environmental Variables and Desertification

Indicators:

This study employs a suite of geo-environmental variables derived from multi-source datasets to characterise vegetation dynamics, climatic variability, soil conditions, and topographic influences associated with drought and desertification processes (D’Acunto et al., 2024; J. Wang et al., 2023). These variables were selected to capture the complex interactions between climatic drivers and land-surface responses across multiple spatial and temporal scales.

The variables are organised into five principal categories: (i) vegetation and biophysical indices, (ii) soil, surface, and moisture indicators, (iii) thermal and climate-related variables, (iv) drought and anomaly-based indicators, and (v) topographic variables.

All predictor layers were harmonised to a common spatial resolution of 500 m to ensure consistency across the multi-band raster stack used for model training and prediction. This resolution was selected as a practical balance between preserving landscape heterogeneity (given the 250 m MODIS NDVI input) and maintaining computational feasibility for regional-scale analysis. The 500 m resolution is also compatible with the coarser inputs (e.g., MODIS LST at 1 km, CHIRPS precipitation at ~5.3 km) after resampling.

A total of 16 environmental predictors were integrated into the modelling framework. It is important to note that socio-economic variables (e.g., population density, livestock numbers, land-use intensity) were not included in the regional machine learning model due to the lack of spatially explicit data at the required resolution (500 m). However, anthropogenic drivers are explicitly addressed through the local-scale LULC analysis (Section 3.6), which directly quantifies population trends, livestock expansion, and land-use conflicts (Section 3.6.4). This multi-scale design ensures that the research objective concerning anthropogenic factors is comprehensively addressed. While some degree of correlation among these variables is expected due to their shared biophysical basis (e.g., NDVI and FVC; NDWI and soil moisture), the ensemble tree-based algorithms employed in this study Random Forest and XGBoost are inherently robust to multicollinearity (Breiman, 2001; Chen & Guestrin, 2016). Unlike linear regression models, these algorithms are not sensitive to correlations among predictors, as they rely on recursive partitioning and regularization, which reduce the influence of redundant variables (James et al., 2013). The feature importance analysis presented in Section 4.4.5 empirically identifies the most influential predictors, providing insight into variable relevance despite the high dimensionality of the dataset.

3.4.2.1.1. Vegetation Indices: Spatial Distribution and Trends

Vegetation indices were employed to quantify vegetation condition, density, and responses to environmental stress. Derived primarily from MODIS data, these indices provide complementary information on vegetation structure and productivity (K. Feng et al., 2022).

Normalized Difference Vegetation Index (NDVI):

NDVI is widely used as an indicator of vegetation greenness and photosynthetic activity (Rouse et al., 1973) and is calculated using the following equation:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (10)$$

Where:

- (NIR) represents the reflectance in the near-infrared band, which is strongly reflected by healthy vegetation;
- (RED) denotes the reflectance in the red band, which is largely absorbed by chlorophyll.

Enhanced vegetation index (EVI):

To address the limitations of NDVI under conditions of dense vegetation and atmospheric interference (Huete et al., 2002) EVI was computed using the following equation:

$$EVI = \frac{2.5 \times (NIR - RED)}{(NIR + 6 \times RED - 7.5 \times BLUE + 1)} \quad (11)$$

Where:

- (NIR) denotes near-infrared reflectance;
- (Red) represents reflectance in the red band;
- (Blue) corresponds to reflectance in the blue band, utilised for atmospheric correction;
- 2.5 is a gain factor;
- 6 and 7.5 are coefficients applied to correct for canopy background and aerosol influences;
- 1 is a canopy background adjustment constant.

Modified Soil-Adjusted Vegetation Index (MSAVI):

To minimise soil background influence, which is particularly relevant in semi-arid environments (Qi et al., 1994), MSAVI was calculated using the following equation:

$$MSAVI = \frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)}}{2} \quad (12)$$

Where:

- (NIR) denotes near-infrared reflectance;
- (RED) represents reflectance in the red band;
- The square root term serves to minimise the influence of soil background effects.

Fractional Vegetation Cover (FVC):

FVC is used to estimate the proportion of vegetation cover using the following equation (Gutman & Ignatov, 1998):

$$FVC = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \quad (13)$$

Where:

- (NDVI) denotes the observed NDVI value;
- (NDVI_{min}) represents conditions corresponding to bare soil;
- (NDVI_{max}) corresponds to conditions of full vegetation cover.

3.4.2.1.2. Soil, Surface and Surface Indicators:

Soil and surface indicators play a crucial role in assessing land degradation, soil exposure, and moisture conditions (Ebrahimi et al., 2024; J. Wang et al., 2023).

Normalized Difference Water Index (NDWI):

NDWI is employed to assess surface and vegetation moisture (B. Gao, 1996) and is calculated using the following equation:

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \quad (14)$$

Where:

- (NIR) denotes near-infrared reflectance;
- (SWIR) represents shortwave infrared reflectance, which is sensitive to variations in water content.

Bare Soil Index (BSI):

BSI is used to quantify soil exposure (Rikimaru et al., 2002) and is calculated using the following equation:

$$BSI = \frac{(SWIR + RED) - (NIR + BLUE)}{(SWIR + RED) + (NIR + BLUE)} \quad (15)$$

Where:

- (SWIR) denotes shortwave infrared reflectance;
- (RED) represents reflectance in the red band;
- (NIR) corresponds to near-infrared reflectance;
- (BLUE) indicates reflectance in the blue band.

Topsoil Grain Size Index (TGSI):

TGSI is employed as a proxy for soil texture and surface condition (Lamchin et al., 2017; jun Xiao et al., 2007) and is calculated using the following equation:

$$TGSI = \frac{(RED - BLUE)}{(RED + BLUE + GREEN)} \quad (16)$$

Where:

- RED denotes reflectance in the red band;
- BLUE represents reflectance in the blue band;
- GREEN corresponds to reflectance in the green band.

Surface Albedo:

Surface reflectivity was quantified using albedo, which was calculated using the following equation (Liang, 2001):

$$Albedo = 0.356 \times BLUE + 0.130 \times RED + 0.373 \times NIR + 0.085 \times SWIR^1 + 0.072 \times SWIR^2 - 0.0018 \quad (17)$$

Where:

- Blue, Red, and NIR denote reflectance values in their respective spectral bands;
- SWIR 1 and SWIR 2 correspond to the shortwave infrared bands;

- the coefficients represent the relative contribution of each band to broadband surface reflectance.

Albedo represents the fraction of incoming solar radiation that is reflected by the surface. Higher albedo values are typically associated with bare soil or degraded land surfaces, whereas lower values generally indicate denser vegetation cover and higher moisture content (D'Acunto et al., 2024; Zongfan et al., 2022).

3.4.2.1.3. Thermal Variables:

Thermal conditions play a fundamental role in regulating land–atmosphere interactions, influencing processes such as evapotranspiration, soil moisture dynamics, and vegetation stress (Bichi et al., 2024; Rousta et al., 2020).

Land Surface Temperature (LST):

LST which reflects the radiative temperature of the Earth's surface (Wan, 2013), was calculated using the following equation:

$$LST = \frac{(LST_{day} + LST_{night})}{2} \quad (18)$$

Where:

- (LST_{day}) represents daytime land surface temperature;
- (LST_{night}) denotes nighttime land surface temperature.

3.4.2.2. Role of Geo-environmental Variables in the Study:

The selected geo-environmental variables collectively represent the key components of the land surface system, encompassing vegetation dynamics, soil conditions, moisture availability, thermal stress, and topographic controls. Their integration provides a comprehensive representation of environmental processes and constitutes the foundation for the derivation of drought indicators and the application of machine learning models in desertification assessment.

3.4.2.3. Machine Learning Modelling Framework:

3.4.2.3.1. Model Selection and Conceptual Framework:

Accurately mapping desertification in heterogeneous dryland environments demands modelling approaches that can resolve complex, non-linear interactions among vegetation, soil, moisture, and thermal variables. Conventional parametric techniques tend to struggle in this context, particularly in semi-arid landscapes where spatial variability is high and spectral responses are often mixed and difficult to separate.

To overcome these limitations, this study adopted two ensemble machine learning algorithms: RF and XGBoost. These models were chosen for their strong predictive capability, resilience to multicollinearity, and effectiveness in handling high-dimensional environmental datasets.

RF operates as a bagging-based ensemble method, where multiple decision trees are built from bootstrap samples of the training data and their outputs are aggregated to improve generalization, the final prediction is obtained through a majority voting mechanism:

$$\hat{y} = \text{mode}\{h_b(x)\}_{b=1}^B \quad (19)$$

Where ($\hat{y}$) denotes the predicted class, $h_b(x)$ represents the prediction from the b - the decision tree, and B is the total number of trees in the ensemble. Each tree is constructed through recursive partitioning, guided by the Gini impurity criterion, which iteratively selects splits that maximise class homogeneity within the resulting nodes.

$$G(t) = 1 - \sum_{k=1}^K p_k^2(t) \quad (20)$$

Where $p_k(t)$ denotes the proportion of samples belonging to class k at node t , and K represents the total number of classes.

XGBoost follows a different logic: it incrementally builds an ensemble of trees, each one correcting the errors of the previous iteration, while a regularization term constrains model complexity. This optimisation is expressed through the minimisation of a regularised objective function, which balances model fit against complexity to prevent overfitting.

$$L(\emptyset) = \sum_{i=1}^n l(\hat{y}_i, y_i) + \sum_{t=1}^T \Omega(f_t) \quad (21)$$

Where l denotes the loss function, and $\Omega(f_t)$ represents the regularisation term that constrains model complexity. Predictions are then refined iteratively, with each new tree adjusting the model based on the residual errors from the previous iteration.

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \quad (22)$$

Where η denotes the learning rate and f_t represents the decision tree introduced at iteration t . By progressively updating predictions while constraining model complexity, this mechanism maintains a balance between learning and regularisation, allowing XGBoost to improve predictive accuracy without drifting into overfitting.

Both algorithms are well suited to desertification studies, largely because their ensemble structures make them more tolerant of noisy predictors, correlated spectral indices, and the abrupt spatial variability that characterises dryland ecosystems. In practice, this means they remain stable even when the input data are imperfect or highly heterogeneous, a common situation in semi-arid environments.

3.4.2.3.2. *Training Data and Feature Preparation:*

A representative training dataset was constructed using a hybrid sampling strategy that combined outputs from unsupervised classification with expert-driven visual interpretation. This approach does more than balance methods. it anchors the dataset in both statistical representativeness and thematic reliability.

A total of 1,945 samples were collected and assigned to five desertification severity classes, each representing a different level of land degradation. The predictor set was intentionally comprehensive, drawing on all previously derived geo-environmental and drought indicators such as NDVI, EVI, MSAVI, FVC, BSI, TGSI, Albedo, LST, SPI, and VHI, so that the models could fully exploit the multi-source nature of the dataset rather than rely on a limited subset of variables.

Before model training, all predictor variables were standardised through a scaling procedure to bring them onto comparable value ranges. This step prevents variables with larger numerical scales from dominating the learning process and ensures consistent behaviour across the different models. Standardisation was carried out using Z-score normalisation, which rescales each variable based on its deviation from the mean relative to the standard deviation.

$$z_j = \frac{x_j - \mu_j}{\sigma_j} \quad (23)$$

Where x_j denotes the original value of feature j , and μ_j and σ_j correspond to its mean and standard deviation, estimated from the training dataset. Expressing each variable relative to its own distribution keeps numerical scales consistent, which in turn stabilises the optimisation process and supports more reliable model convergence.

3.4.2.3.3. *Model Calibration and Hyperparameter Optimization:*

Model calibration relied on stratified 10-fold cross-validation, so each fold retained the class proportions observed in the full dataset. This keeps evaluation stable across all desertification categories. Hyperparameters were then tuned via a grid search coupled with cross-validation, allowing the models to be refined iteratively while keeping overfitting under control.

For XGBoost, three key parameters were tuned: the learning rate (η), the maximum tree depth, and the number of boosting iterations. Each of these directly influences how the model learns η controls the pace of convergence, tree depth governs model complexity, and the number of estimators shapes the balance between bias and variance.

$$\hat{y}_i^{(t)} = y_i^{(t-1)} + \eta f_t(x_i) \quad (24)$$

Where $\hat{y}_i^{(t)}$ denotes the prediction for sample i at iteration t , η is the learning rate, and $f_t(x_i)$ represents the tree introduced at that iteration. Each update incrementally adjusts the prediction based on the residual error from the previous step. The learning

rate was tested across a range of values (0.01 to 0.3), tree depths were varied from 3 to 12, and the number of estimators was evaluated between 50 and 500. The parameter combination that yielded the highest mean cross-validation accuracy was selected for final model deployment.

For the Random Forest model, three parameters were systematically tuned: the number of trees, the maximum tree depth, and the number of variables considered at each split. The number of trees was tested across a range from 50 to 500, tree depth was allowed to vary from unrestricted to a maximum of 20, and the feature selection strategy was evaluated using both the square-root ($\sqrt{p}$) and logarithmic ($\log_2 p$) approaches. The optimal configuration was determined based on the highest mean cross-validation accuracy, ensuring that the model balanced predictive performance with computational efficiency and generalization capacity. The final optimized hyperparameters for both models are presented in the Results chapter (Section 4.4.2).

3.4.2.3.4. *Model Evaluation:*

Model performance was first examined through stratified cross-validation, then tested against an independent validation dataset to obtain a less biased estimate of predictive capability. This two-step evaluation makes it possible to assess both how consistently the model behaves during training and how well it generalises to unseen data, in addition, classification outcomes were examined through confusion matrices, from which a set of complementary performance metrics was derived, including overall accuracy, precision, recall, and the F1-score. Considered together, these measures move beyond a single summary value: they capture both the overall classification performance and how reliably each class is identified.

Particular attention was directed to class-level performance, since desertification mapping involves multiple severity classes that are rarely equally represented. Precision indicates how reliable the class assignments are, whereas recall reflects how effectively the model captures all instances of a given class. The F1-score brings these two perspectives together, offering a balanced measure that remains informative even when class imbalance influences the results. Relying on this combination of metrics prevents the evaluation from being reduced to overall accuracy alone, which can be misleading in multi-class environmental analyses. Instead, it allows performance to be examined in more detail, revealing where the model performs well and where limitations emerge across different desertification severity levels.

3.4.2.3.5. *Spatial Cross-Validation:*

In addition to conventional random cross-validation, a spatial cross-validation (SCV) scheme was implemented to obtain a more realistic estimate of model generalisation under spatial dependence. Rather than sampling points independently, the study area was divided into spatially contiguous blocks, and all samples within each block were assigned entirely to either the training or validation set in a given fold. This design limits spatial leakage and mitigates the bias introduced by spatial autocorrelation, leading to a more reliable assessment of model performance.

By explicitly incorporating the spatial structure of the data, SCV offers a more realistic test of model performance under spatial extrapolation. Rather than assuming independence between samples, it evaluates how well the model holds when applied to unseen areas. The variation in classification accuracy across spatial folds was therefore examined to assess both the stability of the models and their capacity to transfer across heterogeneous eco-climatic conditions. This spatial partitioning can be formally expressed as a constraint whereby samples belonging to the same spatial block are never simultaneously allocated to both the training and validation subsets within a given fold.

3.4.2.3.6. Accuracy Assessment Metrics:

Classification performance was evaluated using a set of metrics derived from the confusion matrix. Overall Accuracy (OA) captures the proportion of correctly classified samples across the dataset.

OA was computed as:

$$OA = \frac{\sum_{K=1}^K TP_K}{N} \quad (25)$$

Where TP_K denotes the number of correctly classified samples for class k , and N represents the total number of samples.

Precision reflects how often predictions within a given class are actually correct, while recall indicates how effectively the model retrieves all true instances of that class.

Precision and recall are defined as:

$$P_K = \frac{TP_K}{TP_K + FP_K}, \quad R_K = \frac{TP_K}{TP_K + FN_K} \quad (26), (27)$$

The F1-score combines these two perspectives, providing a balanced measure through the harmonic mean of precision and recall.

To ensure a balanced evaluation across all classes, both macro-averaged and weighted-averaged metrics were computed. These metrics are especially important when class distributions are uneven, as they reduce the bias toward dominant classes and provide a more representative assessment of overall model performance.

F1-score is expressed as:

$$F1_k = \frac{2P_K R_K}{P_K + R_K} \quad (28)$$

3.4.2.3.7. Feature Importance Analysis:

To make the models easier to interpret and to pinpoint the main drivers of desertification, feature importance was analysed using methods specific to each algorithm.

For the Random Forest model, feature importance was examined using two complementary approaches: the mean decrease in Gini impurity and permutation-based importance. The first reflects how much each predictor contributes to improving class separation during tree construction, while the second tests how sensitive model performance is to random perturbations of individual variables. Considering both perspectives together makes it possible to identify variables that are not only structurally influential within the model but also critical for maintaining predictive performance.

For the XGBoost model, feature importance was derived from gain-based metrics, which track how much each predictor contributes to reducing the loss function across the ensemble of trees. In practice, this reflects not only how often a variable is used, but also how effectively it improves the model at each split during the boosting process.

To allow a direct comparison between models, all importance scores were normalised and then ranked. This step makes it easier to isolate the variables that consistently exert the strongest influence, offering a clearer view of the key drivers shaping desertification patterns across the study area.

Beyond simply ranking variables, this analysis helps bridge the gap between data-driven outputs and the environmental processes they represent. By showing the relative influence of vegetation indices, soil properties, climatic variables, and topographic factors, it becomes possible to interpret the model in terms of the mechanisms driving land degradation rather than treating it as a black box. This added interpretability strengthens the scientific credibility of the framework, ensuring that strong predictive performance is grounded in ecologically meaningful relationships.

3.4.2.3.8. Model Agreement and Uncertainty Assessment:

To reinforce model validation and better gauge the robustness of the classification outputs, an agreement and uncertainty analysis was carried out through a systematic comparison of predictions produced by the Random Forest and XGBoost models.

Spatial agreement between the two models was assessed through a pixel-wise comparison of their classification outputs across the study area. Pixels where both models assigned the same class label were interpreted as high-confidence zones, indicating stable and reliable predictions. Conversely, areas of disagreement were treated as zones of higher classification uncertainty, likely reflecting complex environmental conditions, mixed spectral responses, or transitional stages of land degradation.

To further quantify predictive uncertainty, the standard deviation of class probabilities was derived from the Random Forest model. For each pixel, the Random Forest classifier generates a probability for each of the five desertification severity classes. The standard deviation (σ) of these class probabilities was calculated as:

$$\sigma = \sqrt{(1/K) \sum (P_K - P)^2} \quad (29)$$

where K is the number of classes ($K = 5$), p_k is the probability assigned to class k , and $\bar{p}$ is the mean probability across all classes. This probability-based metric provides a direct measure of classification confidence at the pixel level (Ramezan et al., 2019). A low standard deviation indicates that the model assigns similar probabilities across all classes, reflecting high classification certainty. Conversely, a high standard deviation indicates that the model assigns high probability to one class over others, which may represent either high confidence or potential overfitting, depending on the context. The resulting uncertainty maps, presented in Figure 38, illustrate the spatial pattern of classification confidence across the study area.

This comparative approach provides an additional, independent layer of validation beyond conventional accuracy metrics. By explicitly distinguishing zones of model agreement and disagreement, it supports a more nuanced interpretation of desertification patterns while also identifying areas where predictions carry higher uncertainty and should therefore be interpreted with caution. Furthermore, the spatial pattern of agreement and disagreement provides insight into the consistency and transferability of the modelling framework across heterogeneous eco-climatic conditions. Areas of persistent agreement indicate strong model generalisation, whereas recurring disagreements may reflect limitations in the input data, sensitivity to particular predictors, or intrinsic ambiguity in class boundaries.

Overall, this agreement-based uncertainty assessment enhances the interpretability and credibility of the modelling results, ensuring that the final desertification maps are not only accurate but also transparently expressed in terms of confidence and reliability.

3.4.2.3.9. Provincial Zonal Statistics:

To translate pixel-based desertification classifications into policy-relevant administrative insights, a zonal statistics analysis was conducted at the provincial (Wilaya) scale. The primary objective was to quantify the spatial distribution and net change in desertification severity across the 40 provinces of northern Algeria between the two reference years (2002 and 2022), focusing on change detection between reference years rather than continuous temporal dynamics.

It is important to note that this analysis compares desertification severity between two reference years (2002 and 2022) to assess net structural changes over a 20-year period. Although this two-date approach does not capture interannual variability or continuous temporal dynamics, it effectively identifies persistent long-term degradation patterns that are directly relevant for land management and environmental planning. This methodological approach is consistent with previous regional-scale desertification studies (Djeddaoui et al., 2017; Feng et al., 2022), which have demonstrated that strategically selected reference years are effective for detecting substantial land cover and degradation changes. Consequently, the observed differences should be interpreted as the cumulative effects of climatic and anthropogenic pressures over the study period rather than as a continuously monitored temporal trajectory.

The analysis was based on progressive desertification maps derived from the Random Forest classifier. These maps were post-processed to enforce monotonic temporal transitions, ensuring that no pixel exhibited a reversal in desertification severity between the two reference years. This post-processing step was applied to eliminate spurious class reversals arising from classification noise and interannual variability in spectral signatures. It does not suppress real ecological recovery where it occurs—pixels that improved (e.g., from 'Moderate' to 'Slight') were preserved. The constraint ensures that the detected degradation trends represent persistent net structural changes rather than artifacts of classification uncertainty (Feng et al., 2022). This constraint yields a conservative representation of degradation dynamics by eliminating spurious class oscillations. Administrative boundaries for the 40 provinces were obtained from a vector shapefile of northern Algeria and reprojected to match the coordinate reference system of the raster data, ensuring geometric consistency during spatial overlay operations.

The spatial resolution of the raster data was extracted from metadata, and converted to square kilometres as the following:

$$A_{pixel, Km^2} = \frac{A_{pixel}}{10^6} \quad (30)$$

For each province p , year y , and desertification class c , the total area was computed as:

$$A_{c,p,y} = N_{c,p,y} \times A_{pixel, km^2} \quad (31)$$

Where $N_{c,p,y}$ represents the number of pixels belonging to class c within province p for year y , and A_{pixel} pixel is the area of a single pixel.

The total degraded area was defined as the sum of the High and Severe desertification classes using the following equation:

$$A_{degraded,p,y} = A_{High,p,y} + A_{Severe,p,y} \quad (32)$$

Temporal change in degraded area was quantified using the following equation:

$$\Delta A_{degraded,p} = A_{degraded,p,t_2} - A_{degraded,p,t_1} \quad (33)$$

Positive values indicate an expansion of degraded land. The average annual rate of degradation over the two-decade interval was calculated as:

$$R_{degraded,p} = \frac{\Delta A_{degraded,p}}{20} \quad (34)$$

Where $R_{degraded,p}$ represents the annual degradation rate for province p , and t_1 and t_2 denote the initial and final years, respectively.

Provinces were subsequently ranked in descending order of the net change in degraded area $\Delta A_{degraded,p}$ to identify administrative units experiencing the most pronounced degradation over the 20-year period.

3.4.2.3.10. *Future Scenario Projection to 2030:*

Two multi-band raster datasets containing 16 environmental predictors for the reference years 2002 and 2022 were used as model inputs. These datasets represent baseline and recent environmental conditions, respectively, and were derived from remote sensing products and ancillary spatial data. All predictor layers were harmonised to a common spatial resolution and coordinate reference system to ensure consistency in subsequent analyses.

For each predictor band b and pixel (i,j) , the average annual rate of change between the two reference years was computed as:

$$trend_{b,i,j} = \frac{value_{b,i,j,2022} - value_{b,i,j,2002}}{20} \quad (35)$$

The projected value for 2030 was then estimated as:

$$value_{b,i,j,2030} = value_{b,i,j,2022} + trend_{b,i,j} \times 8 \quad (36)$$

Where 8 represents the number of years between 2022 and 2030.

Based on the linear trends observed in environmental predictors between the two reference years (2002 and 2022), a forward projection was developed to illustrate the potential distribution of desertification by 2030. This projection should be interpreted as an illustrative business-as-usual scenario rather than a deterministic forecast. It assumes that the net changes observed between 2002 and 2022 continue at a similar rate, without accounting for non-linear ecological responses, abrupt climatic changes, policy interventions, or socio-economic developments that could alter future degradation trajectories (D'Acunto et al., 2024). Consequently, the projected map is intended as a strategic planning tool for identifying areas at risk and prioritizing proactive land management interventions, rather than as a precise prediction of future environmental conditions.

To maintain physical plausibility, predictor values were constrained within predefined bounds. For instance, vegetation and moisture indices (NDVI, EVI, NDWI, MSAVI) were restricted to the range $[-1, 1]$, while fractional vegetation cover (FVC) and albedo were limited to $[0, 1]$. Values exceeding these thresholds were clipped accordingly to prevent extrapolation artefacts and ensure numerical stability in model predictions.

The projected multi-band predictor dataset for 2030 was used as input to the previously trained and validated Random Forest classifier. To efficiently handle large

raster datasets, predictions were implemented using a block-wise processing strategy, ensuring computational efficiency while preserving spatial continuity. For each processing block, predictor variables were extracted and reshaped into a two-dimensional feature matrix. Pixels containing missing values in any predictor were excluded from the classification process to ensure data integrity. The remaining observations were standardized using the same scaling parameters derived from the training dataset, thereby preventing data leakage and ensuring consistency between the training and prediction phases.

The Random Forest model was then applied to assign each pixel to one of five desertification severity classes (1 = None, 2 = Slight, 3 = Moderate, 4 = High, 5 = Severe). Predicted values were subsequently reassembled into a spatially continuous raster, with invalid pixels assigned as NoData. The final output preserved the spatial resolution, spatial extent, and coordinate reference system of the input data.

The projected map was visualised using a sequential colour scheme (white to red) representing increasing desertification severity. Administrative boundaries were overlaid, and standard cartographic elements (north arrow and scale bar) were included. To avoid misinterpretation, the map was explicitly labelled as an illustrative scenario, accompanied by a disclaimer stating that projections are based on the net change observed between the two endpoints (2002 and 2022) rather than continuous temporal dynamics, and do not account for potential future variability or non-linear ecological responses.

The resulting product provides a strategic spatial overview of areas potentially at risk under the observed two-decade environmental trajectory, supporting long-term land management and planning.

3.5. Sub-Regional Scale Analysis (Northwestern Algeria):

The regional anomaly analysis presented in Section 3.4 established a broad picture of vegetation–climate variability across Northern Algeria, but it did not directly examine how meteorological drought propagates into vegetation stress. The sub-regional analysis addresses this aspect by focusing on Northwestern Algeria, a particularly sensitive hydroclimatic transition zone linking the Mediterranean coast with the semi-arid High Plateaus. At this scale, the analysis brings together four complementary components: (i) the multi-timescale Standardized Precipitation Index (SPI) for characterising meteorological drought (Section 3.5.1); (ii) the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and their integration into the Vegetation Health Index (VHI) for assessing vegetation and thermal stress (Section 3.5.2); (iii) Mann–Kendall trend analysis for identifying persistent directional changes over time (Section 3.5.3); and (iv) correlation analysis for examining the relationship between precipitation variability and vegetation health, including potential lagged responses (Section 3.5.4). By combining these complementary indicators and statistical approaches, the analysis provides a more detailed assessment of how meteorological drought varies across Northwestern Algeria and how these conditions are reflected in vegetation stress at the sub-regional scale.

3.5.1. Meteorological Drought Indicator:

3.5.1.1. Standardized Precipitation Index (SPI):

The Standardized Precipitation Index (SPI) is a widely used meteorological drought indicator recommended by the World Meteorological Organization (WMO) for monitoring precipitation deficits across multiple temporal scales (Hayes et al., 2011; McKee et al., 1993). In this study, SPI was calculated to capture short-term (3-month), seasonal (6-month), and long-term (12-month) drought variability. Accumulated precipitation (P_t) was derived by aggregating daily CHIRPS v2.0 precipitation data over 3-, 6-, and 12-month windows, for each time step, precipitation totals were derived as the cumulative sum of daily rainfall values, as expressed in the following equation:

$$P_t = \sum_{i=1}^n R_i \quad (37)$$

Where R_i denotes daily precipitation and n is the number of days in the aggregation period.

To ensure computational efficiency and robust pixel-wise analysis within the GEE environment, SPI was approximated using a standardized precipitation anomaly (z-score) approach. This is a widely adopted and robust alternative to classical gamma distribution fitting in large-scale remote sensing studies (Stagge et al., 2015; Vicente-Serrano et al., 2010). The SPI values were subsequently derived by standardising accumulated precipitation using the long-term statistical parameters of the 2003–2023 study period:

$$SPI = \frac{\rho - \mu}{\sigma} \quad (38)$$

Where P is the accumulated precipitation, μ represents the long-term mean precipitation for the baseline period, and σ is the corresponding standard deviation. This normalization yields a dimensionless index where negative values indicate drier than normal conditions. Finally, SPI values were classified into drought severity categories based on the thresholds defined by (McKee et al., 1993) (Table 3).

Table 3. Drought classification scheme based on (SPI) thresholds (after McKee et al., 1993).

No.	Drought Class	SPI Range
1	Extreme drought	≤ -2.0
2	Severe drought	-1.99 to -1.50
3	Moderate drought	-1.49 to -1.00
4	Near normal	-0.99 to +0.99
5	Moderately wet	+1.00 to +1.49
6	Severely wet	+1.50 to +1.99
7	Extremely wet	$\geq +2.0$

3.5.2. Vegetation-Based Drought Indicators:

Vegetation-based drought indicators were employed to assess the response of vegetation to climatic stress by integrating satellite-derived vegetation and thermal data. These indices are particularly valuable as they capture the combined effects of moisture deficits and temperature stress on vegetation dynamics.

3.5.2.1. Vegetation Condition Index (VCI):

The Vegetation Condition Index (VCI), introduced by (Kogan, 1995a, 1995b), is a remote sensing-based indicator that evaluates vegetation condition by normalising NDVI values relative to their historical range for a given location. It effectively captures vegetation responses to environmental variability while minimising the influence of seasonal fluctuations.

VCI is expressed using the following equation:

$$VCI = 100 \times \frac{NDVI_{current} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (39)$$

Where:

- ($NDVI_{current}$) represents the NDVI value at a given time step;
- ($NDVI_{min}$) And ($NDVI_{max}$) correspond to the minimum and maximum NDVI values observed over the study period (2003–2023).

VCI values range from 0 to 100, with lower values indicating vegetation stress and higher values reflecting more favourable vegetation conditions.

In this study, VCI was computed using MODIS NDVI data at a spatial resolution of 250 m. NDVI values were first scaled using the standard factor (0.0001), after which monthly composites were generated. Pixel-wise minimum and maximum NDVI values were subsequently derived from the full study period to establish the normalisation bounds. It is important to note that while percentile-based normalization can reduce the impact of extreme outliers, the use of absolute historical min/max values was retained to strictly adhere to the original VCI/TCI formulation (Kogan, 1995a). Furthermore, the prior application of rigorous Quality Assurance (QA) masking effectively removed cloud-contaminated and anomalous pixels, ensuring that the derived min/max bounds reliably represent true environmental extremes rather than data artifacts.

3.5.2.2. Temperature Condition Index (TCI):

The Temperature Condition Index (TCI), also proposed by (Kogan, 1995a), represents the thermal counterpart of VCI and is used to assess vegetation stress induced by elevated surface temperatures. It is particularly relevant under drought conditions, where reduced soil moisture leads to increased land surface temperatures (Huang et al., 2020; Kogan, 1995a) and associated vegetation stress.

TCI is calculated using the following equation:

$$TCI = \frac{(LST_{max} - LST)}{(LST_{max} - LST_{min})} \quad (40)$$

Where:

- (LST) denotes the observed land surface temperature;
- (LST_{max}) and (LST_{min}) represent the maximum and minimum values recorded over the study period, respectively.

TCI values range from 0 to 100, with lower values indicating higher levels of thermal stress and higher values representing more favourable thermal conditions.

In this study, LST data at a spatial resolution of 1 km were derived from the MOD11A2 product. Digital numbers were converted into physical temperature values using a scale factor of 0.02. Monthly mean LST composites were subsequently generated from the 8-day products, and pixel-wise minimum and maximum values were extracted over the period 2003–2023 to establish the normalisation bounds.

TCI normalises LST values to express relative thermal stress conditions. Lower TCI values are generally associated with higher levels of temperature stress and more pronounced drought conditions (Bichi et al., 2024; Jalayer et al., 2023).

In addition, air temperature derived from the ERA5 dataset was utilised to characterise atmospheric conditions and to complement satellite-based thermal observations (Hersbach et al., 2020).

3.5.2.3. Vegetation Health Index (VHI):

The Vegetation Health Index (VHI) integrates vegetation condition and thermal stress into a single composite indicator, thereby providing a comprehensive assessment of drought impacts on vegetation (Kogan, 2001). By combining VCI and TCI, VHI captures both moisture-related stress and temperature-induced stress. VHI is computed using the following equation:

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \quad (41)$$

Where:

- (VCI) denotes the vegetation condition index;
- (TCI) represents the temperature condition index;
- (α) represents a weighting factor, set to 0.5 in this study.

The use of equal weighting reflects the assumption that vegetation and thermal stress contribute comparably to overall drought conditions. While it is acknowledged that in strictly water-limited environments, vegetation condition (VCI) is sometimes assigned a higher weight (e.g., $\alpha = 0.7$) to reflect moisture as the primary limiting factor (Bento et al., 2018), an equal weight ($\alpha = 0.5$) was applied in this study. This

decision was made to maintain consistency with the standard VHI formulation used in comparable regional studies, and to ensure that the severe thermal stress and heatwaves characteristic of the study area's summer months are adequately captured as an independent driver of vegetation degradation.

VHI values range from 0 to 100, with lower values indicating more severe drought conditions and higher values reflecting more favourable environmental conditions.

In this study, monthly VCI and TCI datasets were integrated to compute VHI at the pixel level for the period 2003–2023.

VHI Classification:

Table 4. Drought Severity Classification Scheme according to VHI values.

No.	Drought Class	VHI
1	Extreme drought	< 10
2	Severe drought	10 – 20
3	Moderate drought	20 – 30
4	Mild drought	30 – 40
5	No drought	> 40

3.5.3. Mann-Kendall Trend Analysis

The non-parametric Mann–Kendall (MK) test was used to identify statistically significant and persistent trends in the temporal records of VHI, TCI, VCI, and SPI at 3-, 6-, and 12-month timescales over the 2003–2023 study period. The MK test is widely applied in environmental research because it is relatively robust to extreme observations and does not require the data to follow a particular probability distribution (Abu Arra et al., 2024; Kourouma et al., 2022; Wang et al., 2020).

The test was applied to the annual time series of each index on a pixel-by-pixel basis across the study area. For each pixel, the analysis evaluated the null hypothesis (H_0), which assumes no monotonic trend in the time series, against the alternative hypothesis (H_1), which indicates the presence of a statistically significant monotonic trend. The results were expressed using the Mann–Kendall test statistic (S) and its corresponding p-value. A significance level of $\alpha = 0.05$ was adopted, and pixels with p-values below this threshold were considered to exhibit statistically significant trends (Genovese et al., 2025). The MK test statistic was calculated using the following relationship:

The test statistic, S , is computed as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (42)$$

Where, x_j and x_k are the annual values in years j and k , respectively

$$\text{sign}(x_j - x_k) = \begin{cases} +1, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (43)$$

To statistically assess the significance of the trend, it is necessary to calculate the probability associated with S and the sample size n . The formula used to compute the variance of S is expressed as follows:

$$\sigma^2 = \frac{\{(n-1)(2n+5) - \sum_{j=1}^p t_j(t_j-5)(2t_j-1)\}}{18} \quad (44)$$

Where:

- σ^2 = variance of S
- n = number of observations
- t_j = number of data points in the j^{th} tied group
- p = number of the tied group in the time series

Assuming the time series is random and independent, the statistic S is approximately normally distributed, and the following z-transformation equation is applied:

$$z = \begin{cases} \frac{S-1}{\sigma} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sigma} & \text{if } S < 0 \end{cases} \quad (45)$$

To quantify the magnitude of the detected trends, Sen's slope estimator was applied. For each pixel, annual values for the period 2003–2023 were extracted as a time series, and the slope was calculated as the median of all pairwise slopes between observations, expressed as Equation (10):

$$Q_i = \frac{x_j - x_i}{j - i}, \quad j > i \quad (46)$$

Where x_i and x_j represent the values at time steps i and j , respectively. This non-parametric estimator is robust to outliers and provides a reliable measure of the rate of change per unit time (Gutiérrez-Hernández & García, 2024). Positive values indicate increasing trends, while negative values indicate decreasing trends.

Spatial patterns of trends were visualized using Sen's slope maps, Mann–Kendall p-value maps, and trend classification maps. In addition, summary statistics were computed for each drought index to quantify the spatial extent and intensity of trends. Specifically, the total area exhibiting significant increases or decreases was calculated, along with the mean and standard deviation of Sen's slope values within these areas (Genovese et al., 2025).

The integration of multiple drought indices enabled the identification of regions experiencing significant temporal changes in precipitation, vegetation health, and

thermal stress. This approach provides a comprehensive assessment of spatio-temporal drought dynamics in Northwest Algeria over the period 2003–2023.

3.5.4. Correlation Analysis of Drought Indices:

To further examine how meteorological drought conditions translate into vegetation response, a Pearson correlation analysis was performed between the Standardized Precipitation Index (SPI) and the Vegetation Health Index (VHI).

The Pearson correlation coefficient (r) was computed as:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (47)$$

Where x_i and y_i represent paired observations of SPI and VHI, and $\bar{x}$ and $\bar{y}$ denote their respective means.

This analysis quantifies both the strength and direction of the linear relationship between precipitation anomalies and vegetation health, providing a direct measure of how rainfall variability is reflected in vegetation condition (Kogan, 1995a, 2001; McKee et al., 1993).

For this purpose, regional mean time series were extracted for SPI-3, SPI-6, SPI-12, and VHI from the respective datasets (Dai, 2011; Peters et al., 1991; Vicente-Serrano et al., 2010). The series were first temporally aligned by matching corresponding months and years. Short-term variability was then reduced by aggregating the data into annual means, providing a more stable and comparable basis for subsequent analysis. It is important to note that while the spatial pixel-level relationships analyzed via Spearman correlation are inherently non-linear, aggregating the data to regional annual means normalizes the distribution and linearizes the interannual trend, thereby satisfying the assumptions required for the Pearson correlation.

Correlation coefficients were calculated using annual observations ($n = 21$ years), with statistical significance evaluated through a two-tailed test at a significance level of $\alpha = 0.05$. Corresponding p-values were then derived to assess the robustness and reliability of the observed relationships. To support interpretation, scatter plots were produced to visualise the relationships between SPI and VHI. Linear regression lines were fitted to the data, with 95% confidence intervals included to reflect the associated uncertainty. The resulting correlation coefficients (r) and corresponding p-values were reported both in the text and directly within the graphical outputs.

This analysis sheds light on how meteorological drought signals translate into vegetation response across different temporal scales. In doing so, it offers a more nuanced understanding of drought dynamics within the study area.

3.6. Local Scale analysis:

While the preceding sub-regional analysis examined the climatic dimensions of drought across Northwestern Algeria, it did not directly capture the anthropogenic processes contributing to land degradation or the long-term dynamics of ecological

restoration at the landscape scale. The local-scale analysis therefore turns to the Moudjbara perimeter in Djelfa Province, a particularly vulnerable desert–steppe transition zone and the first area to be afforested under Algeria’s Green Dam programme. Its location and land-use history provide an opportunity to examine how land-cover transformations have evolved under the combined influence of climatic stress and human activities.

The methodological framework integrates four complementary components: (i) supervised classification and accuracy assessment of multi-temporal Landsat imagery to map land use and land cover (LULC) (Section 3.6.1); (ii) change detection and intensity analysis using the Land Change Modeler (Section 3.6.2); (iii) future LULC scenario modelling to 2029 using an Artificial Neural Network coupled with a Markov chain model (Section 3.6.3); and (iv) analysis of population and livestock trends as indicators of anthropogenic pressure (Section 3.6.4). Taken together, these approaches provide a landscape-scale assessment of LULC transformations and allow the long-term trajectory and sustainability of the Green Dam afforestation initiative to be examined in relation to both environmental and human pressures.

3.6.1. LULC classification:

Land use/land cover (LULC) maps were produced using a supervised classification approach, a method widely employed to detect land surface changes in multispectral satellite imagery (Bailly et al., 2007; Weng, 2002), the Maximum Likelihood Classifier (MLC) was implemented in ArcGIS 10.8.1. The algorithm assigns each pixel to the class with the highest probability based on the statistical distribution of its spectral signature, operating under the assumption that the input data follow a normal distribution (Alipbeki et al., 2020; X.-H. Liu et al., 2002; Richards & Jia, 2006).

The classification process began with the selection of representative training samples. These were manually digitised from high-resolution Google Earth imagery to ensure accurate delineation of land cover types. For the 1972 Landsat MSS imagery, which has a spatial resolution of 60 m, training polygons were selected using four complementary criteria. First, spectral separability was considered to ensure that the selected samples represented distinguishable land-cover classes. Second, the polygons were distributed across the study area to capture the spatial variability within each class. Third, the selection process was informed by available historical knowledge of land cover, including records relating to the Green Dam plantations and the distribution of natural forest. Finally, where available, historical aerial photographs and other ancillary data were used to cross-check and validate the interpretation of the training samples. In addition, for each class, at least 20 training polygons were defined, providing sufficient coverage to capture within-class variability.

A total of five LULC classes were defined: degraded steppes, urban areas, croplands, dense plantations and natural forests, and open plantations. Owing to spectral similarity, natural forests and dense Aleppo pine plantations could not be reliably distinguished and were therefore combined into a single class. This class aggregation

helped improve classification accuracy and limit ambiguity in pixel assignment, an important consideration in semi-arid environments where land cover tends to be highly heterogeneous.

Following classification, a rigorous accuracy assessment was undertaken to evaluate the reliability of the resulting LULC maps. Accuracy assessment constitutes a critical stage in land use/land cover (LULC) classification, particularly when the resulting maps are intended for change detection and spatiotemporal analysis. It offers a quantitative evaluation of classification reliability and provides a necessary basis for validating subsequent analyses.

Accuracy was evaluated using a confusion matrix approach, from which Overall Accuracy (OA) and the Kappa coefficient were derived. Overall Accuracy (OA) represents the proportion of correctly classified samples relative to the total number of validation points (Congalton, 1991; Flasse, 2005; Tilahun & Teferie, 2015).

While the Kappa coefficient has historically been used in accuracy assessment, recent literature has demonstrated its unsuitability as a primary measure of classification accuracy. (Foody, 2020) argues that Kappa is not an index of accuracy but rather a measure of agreement beyond chance which is irrelevant in accuracy assessment and is inappropriately modelled for typical remote sensing applications. Consequently, Kappa is reported here for comparative purposes only, while Overall Accuracy is emphasised as the primary accuracy metric.

Classification accuracy was evaluated using a confusion matrix approach. For each classified map, more than 150 random validation points were generated across the study area in ArcGIS 10.8.1. The validation samples were allocated across the five LULC classes to ensure adequate representation of each category.

Reference data were derived through visual interpretation of high-resolution Google Earth imagery, selected to align as closely as possible with the acquisition dates of the Landsat scenes. This approach helped maintain temporal consistency between the classified outputs and the reference data.

The accuracy metrics derived from the confusion matrices are presented in Table 9. Overall Accuracy ranged from 75.5% to 94%, with the 1989 map exhibiting the lowest accuracy. While 75.5% is below the commonly cited 85% threshold for contemporary land-cover mapping (Foody, 2008; Pontius Jr & Millones, 2011), several factors contextualise this value. First, the 1989 map represents the earliest temporal snapshot and was derived from Landsat TM imagery with inherent spectral limitations. Second, the primary purpose of this map is to establish the initial landscape condition prior to the implementation of the Green Dam programme, rather than to serve as a standalone high-accuracy product. Third, the inclusion of additional temporal snapshots (1999, 2009, and 2019) with progressively higher accuracies (89%, 87%, and 94%, respectively) provides a consistent trajectory of change that mitigates the impact of the single lower-accuracy map. Taken together, these metrics provide a robust assessment of classification performance and are routinely applied in remote sensing studies to evaluate the reliability of LULC maps.

3.6.2. LULC Change Analysis:

Understanding land use/land cover (LULC) dynamics requires the use of multi-temporal datasets to quantify not only the magnitude and spatial distribution of change, but also the processes driving land transformation. In this study, a chronological sequence of LULC maps was analysed to track changes in the Moudjbara region and to examine how the Green Dam project has evolved over time.

LULC change analysis was carried out using the Land Change Modeler (LCM) in Idrisi TerrSet 18.7 (Clark Labs, Worcester, MA, USA) (Leta et al., 2021; Mas et al., 2014), together with the OpenLand package in R 4.0.3. LCM is well established for analysing land transitions and exploring potential future scenarios (Exavier & Zeilhofer, 2021), while OpenLand offers tools for intensity analysis and the production of standardised graphical outputs.

Change detection was carried out across four time intervals: 1972–1989, 1989–1999, 1999–2009, and 2009–2019. The analysis was designed to quantify LULC transitions within each period, examine how both the magnitude and rate of change evolved over time, and compare observed change rates with uniform benchmarks based on an assumption of evenly distributed change. Particular attention was given to tracking the spatial progression of the Green Dam project across these intervals.

Particular attention was directed toward pine plantations, where gains, losses, and resulting net changes were quantified for each time interval. Tracking these shifts over time makes it possible to move beyond simple mapping and examine how vegetation evolves under pressure, providing a more detailed picture of both vegetation dynamics and the progression of land degradation within the study area (Decuyper et al., 2022; S. Kumar et al., 2020).

To quantify the magnitude and rate of LULC change across the four study intervals (1972–1989, 1989–1999, 1999–2009, and 2009–2019), intensity analysis was employed using the OpenLand package in R (Exavier & Zeilhofer, 2021). This framework enables the comparison of observed change intensities against a benchmark of uniform change, thereby identifying periods of accelerated or decelerated land transformation (Aldwaik & Pontius, 2012).

The total change intensity for each time interval $[Y_t, Y_{t+1}]$ is calculated as the percentage of the landscape that changed between the two time points:

$$S_t = \frac{\sum_{j=1}^J (\sum_{i=1}^J C_{tij} - C_{tjj})}{\sum_{j=1}^J \sum_{i=1}^J C_{tij}} \times 100 \quad (48)$$

where J is the number of LULC classes, C_{tij} is the area transitioning from class i to class j during interval t , and C_{tjj} represents the area that remained in class j (persistence). The numerator sums all transitions (excluding persistence), while the denominator represents the total landscape area.

$$A = \frac{\sum_{t=1}^{T-1} (\sum_{j=1}^J \sum_{i=1}^J C_{tij} - \sum_{j=1}^J C_{tjj})}{\sum_{t=1}^{T-1} (Y_{t+1} - Y_t) \times \sum_{j=1}^J \sum_{i=1}^J C_{tij}} \quad (49)$$

where T is the number of time points (years), and $(Y_{t+1} - Y_t)$ is the duration of interval t in years. The numerator sums all transitions across all intervals, and the denominator multiplies the total landscape area by the sum of interval durations. The resulting U value represents the percentage of the landscape that would change per year under a hypothetical scenario of constant change intensity.

If the observed total change intensity $S_t > U$, the interval is classified as fast (change occurred more rapidly than the uniform benchmark). If $S_t < U$, the interval is classified as slow.

To characterize the long-term evolution of open plantations and dense plantations/natural forests, a quadratic polynomial function was fitted to the time-series area data (1972, 1989, 1999, 2009, and 2019). This approach captures the non-linear trajectory of plantation areas, reflecting periods of expansion, stabilization, and decline that cannot be adequately represented by linear models.

The quadratic polynomial is expressed as:

$$A(t) = at^2 + bt + c \quad (50)$$

where $A(t)$ represents the area (in hectares) at time t, and a, b, and c are the fitted coefficients. The coefficient a determines the curvature of the trajectory: a negative a indicates a concave (peak-and-decline) pattern, while a positive a suggests a convex (valley-and-recovery) pattern. The goodness-of-fit was assessed using the coefficient of determination (R^2).

This trajectory analysis complements the spatial modelling framework (Section 3.6.3) by providing a temporal context for plantation dynamics. While the polynomial function describes the historical evolution of plantation areas, the ANN-Markov modelling was reserved for spatially explicit future projections, as the latter accounts for land-use transition probabilities and driving factors..

3.6.3. Future Scenario Modelling:

To explore the future evolution of LULC, with a particular focus on pine plantations, a spatially explicit modelling framework was implemented using the Land Change Modeler (LCM).

The prediction of LULC changes for the year 2029 was carried out through a multi-step procedure. In the initial stage, all transitions involving pine plantations, including both dense and open stands, toward other land cover types such as degraded steppes, croplands, and urban areas were consolidated into a single sub-model. This grouping reflects the assumption that these transitions are largely governed by similar anthropogenic pressures rather than distinct processes.

In the second stage, a set of explanatory variables was selected to model these transitions, including the Digital Elevation Model (DEM), distance to croplands, distance to steppes, distance to roads, and distance to urban areas. The relevance of each variable was then evaluated using Cramer's V coefficient, allowing the most influential drivers of land cover change to be identified and retained for subsequent modelling.

In the third stage, transition potentials were estimated using an Artificial Neural Network (ANN) based on a Multi-Layer Perceptron (MLP). This approach allows the modelling process to move beyond simple relationships, capturing the complex and non-linear interactions that often govern land cover transitions.

In the fourth stage, future land cover changes were simulated using a Markov chain model, which estimates transition probabilities from observed historical change patterns. The model was calibrated using the 1999–2009 period, and its predictive performance was subsequently evaluated by comparing the outputs with the 2019 LULC map.

In the final stage, once model performance and predictive accuracy had been evaluated, the calibrated model was applied using the 2009 and 2019 LULC maps to simulate the spatial distribution of land cover for the year 2029.

3.6.4. Anthropogenic Pressure Indicators:

To complement the LULC change analysis and future scenario modelling, temporal trends in human population and livestock numbers were incorporated as proxies of anthropogenic pressure in the Green Dam region. These variables make it possible to reconstruct historical shifts in land use and, more importantly, to infer the intensity of human pressure exerted on pine plantations and steppe ecosystems.

Demographic data for Djelfa Province were obtained from the Office for National Statistics (ONS), while livestock data, primarily sheep and cattle, were sourced from the Ministry of Agriculture and Rural Development (MARD). These datasets were analysed to trace temporal trends in population growth and livestock expansion, two factors that are closely associated with increasing land-use pressure, overgrazing, and subsequent vegetation degradation.

Future estimates for the year 2030 were also derived. Human population was projected using a mean annual growth rate of 3.3% observed over the period 2008–2018, whereas livestock numbers were estimated using a power function. These projections extend the analysis beyond observed trends, providing additional context for assessing the likely continuation of anthropogenic pressure on the Green Dam system.

4. Results:

4.1. Drought Variability and Vegetation Response (2011–2022):

4.1.1. Spatio-temporal Patterns in Seasonal NDVI:

The spatio-temporal dynamics of vegetation activity across northern Algeria were examined using NDVI over the growing season (November–June) for the period 2011–2022 is presented in Figure 7. Rather than serving only as a descriptive indicator, NDVI provides a consistent proxy for vegetation greenness and photosynthetic activity, making it possible to track both interannual variability and the spatial heterogeneity of ecosystem productivity under semi-arid conditions.

Annual mean NDVI maps reveal a clear spatial gradient across the study area. Higher values consistently occur in the northern and coastal regions, particularly in provinces such as Skikda, Tizi-Ouzou, Jijel, Annaba, El Tarf, Béjaïa, Tipaza, and Algiers, where climatic conditions are comparatively favourable. In these zones, vegetation cover tends to be denser and more stable over time. In contrast, the southern and steppe regions covering a substantial share of the study area are dominated by lower NDVI values, reflecting sparse vegetation and greater exposure to environmental stress. This north–south gradient persists throughout the study period, although its intensity fluctuates from year to year.

Interannual variability is evident not only in the magnitude of NDVI values but also in their spatial distribution. The year 2013 recorded the highest maximum NDVI (0.95), while in other years the maximum ranged between 0.87 and 0.94, suggesting that the upper limit of vegetation greenness remained relatively stable. The more informative signal lies in shifts in the median and overall distribution, which reveal how vegetation conditions varied across the landscape from year to year.

To further examine temporal variability, annual NDVI distributions were evaluated against a long-term baseline (2000–2010). Boxplot analysis shows a consistently right-skewed distribution (Figure 8), indicating that low NDVI values dominate across the region. Median NDVI remains below 0.25 in all years, which is consistent with the generally sparse vegetation cover typical of semi-arid environments. That said, the pattern is not entirely static years such as 2013, 2018, and 2022 display noticeably higher median values relative to the baseline, pointing to intervals of comparatively improved vegetation conditions.

Periods of environmental stress are reflected not only in lower NDVI values but also in a wider spread of the distribution, pointing to greater spatial variability. In contrast, years with more favourable conditions tend to show tighter, more compact distributions, suggesting a more uniform vegetation response across the landscape. Spatially, the strongest fluctuations are concentrated in the interior high plains and steppe regions, where vegetation responds rapidly to climatic variability, particularly deficits in precipitation.

Overall, the observed spatio-temporal patterns indicate that vegetation dynamics in northern Algeria are strongly governed by climatic variability, with clear contrasts

between relatively favourable and stress-dominated years. The persistence of low median NDVI values, alongside episodic improvements in specific years, highlights the fragile equilibrium of vegetation systems under semi-arid conditions. These results provide a necessary baseline for the subsequent analysis of NDVI anomalies and drought severity presented in the following sections. It is important to distinguish between the absolute NDVI values presented here and the NDVI anomaly-based drought analysis presented in Section 4.1.2. Absolute NDVI represents the actual vegetation greenness and density at a given time, but it does not indicate whether vegetation conditions are anomalous relative to the expected baseline. For example, naturally sparse steppe ecosystems may exhibit low absolute NDVI values under normal conditions, whereas densely vegetated areas may maintain relatively high NDVI values during drought despite experiencing a substantial decline relative to their long-term average. The NDVI anomaly analysis in Section 4.1.2 addresses this limitation by quantifying deviations from baseline conditions, thereby providing a more reliable measure of vegetation stress that accounts for the natural variability in vegetation density across the study area.

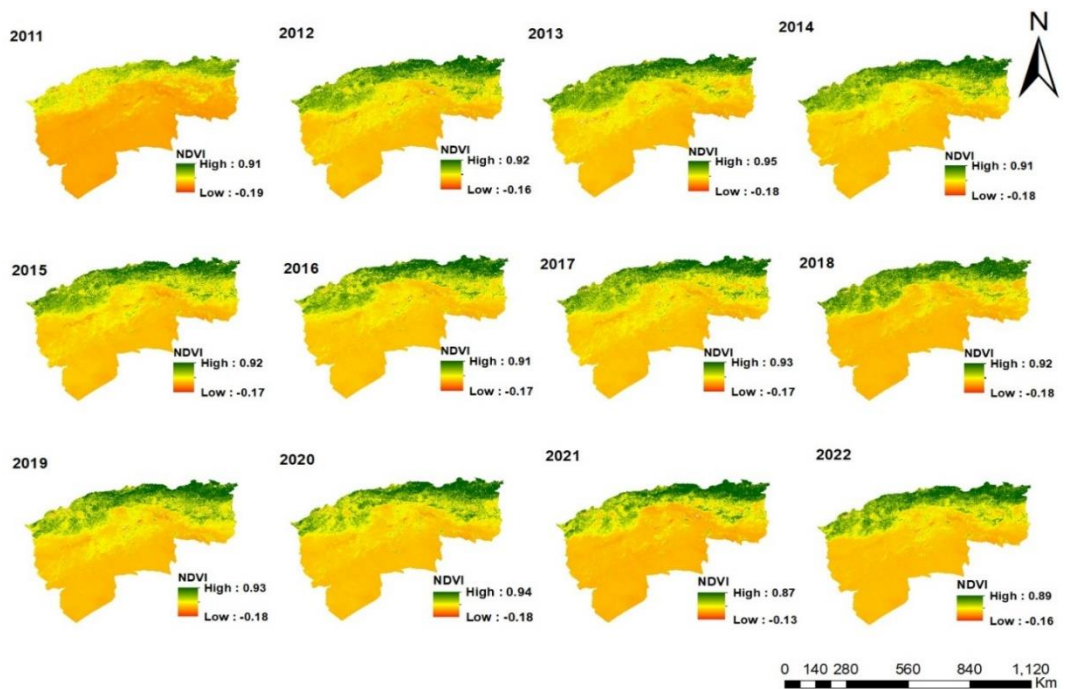


Figure 7. Spatial distribution of the mean NDVI for each year's growing season from 2011 to 2022.

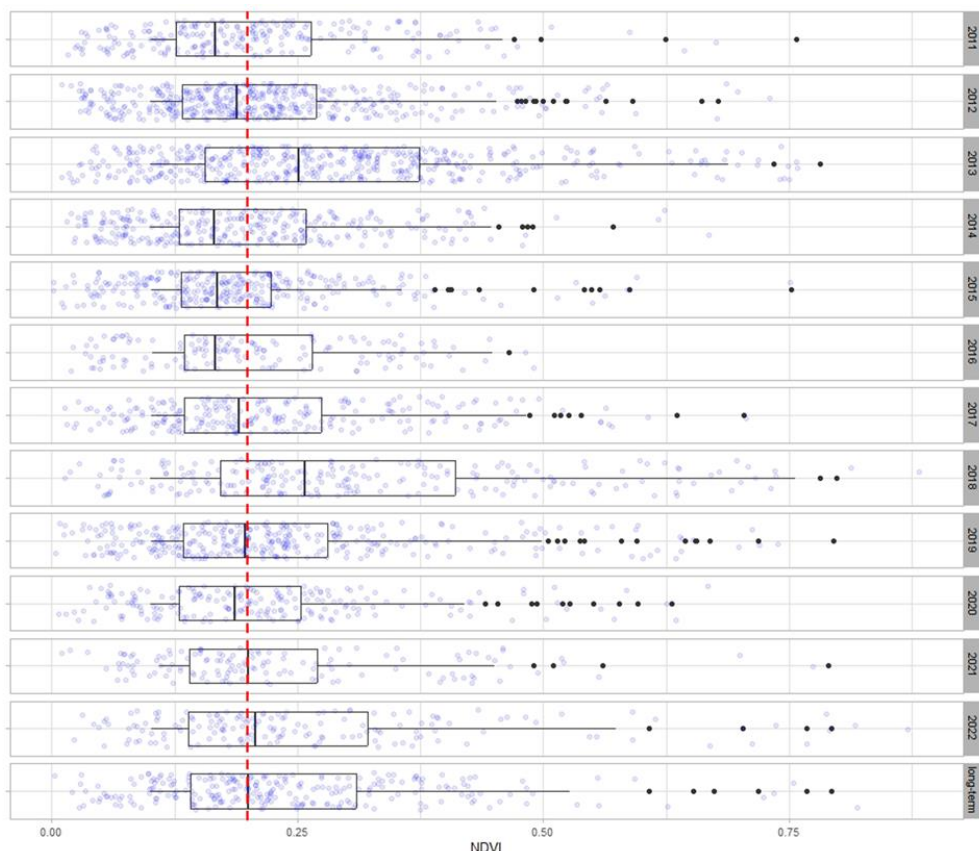


Figure 8. Temporal variation in seasonal mean NDVI from 2011 to 2022 compared to the long-term NDVI (the red-dashed line denotes a long-term median NDVI value).

4.1.2. NDVI Anomaly-Based Drought Severity:

Assessing drought severity through NDVI anomalies reveals marked temporal and spatial variability across northern Algeria over the 2011–2022 period is illustrated in Figure 10 . By expressing vegetation conditions relative to a long-term baseline (2000–2010), NDVI anomalies move beyond raw greenness values and directly capture vegetation stress, making it possible to trace both the intensity and distribution of drought across time and space.

While Section 4.1.1 described the absolute spatial patterns of vegetation greenness, this section examines vegetation stress using NDVI anomalies, which quantify deviations from long-term baseline conditions. This distinction is important because absolute NDVI values primarily reflect the inherent vegetation density of a location, which is influenced by climate, soil, and land-cover characteristics, whereas NDVI anomalies indicate whether vegetation conditions are above or below their expected level at a given location and time. For example, although 2018 exhibited relatively favorable absolute NDVI values in naturally vegetated areas (Section 4.1.1), the anomaly analysis shows that many of these areas experienced negative anomalies,

indicating vegetation stress relative to their long-term averages. This apparent contrast demonstrates the complementary value of absolute and anomaly-based metrics: absolute NDVI describes the spatial distribution and relative density of vegetation, whereas NDVI anomalies provide a measure of departure from normal conditions and are therefore more suitable for assessing drought-related vegetation stress.

The results reveal clear interannual fluctuations in drought occurrence. Among the analysed years, 2012 and 2013 stand out as the least affected, with more than 70% of the study area remaining under non-drought conditions. This pattern aligns with the relatively strong vegetation performance observed earlier, reflected in higher NDVI values. A different picture emerges in the later years: 2016, 2021, and 2022 show a clear deterioration in vegetation conditions and represent the most pronounced drought episodes within the study period. In 2016, around 39.93% of the study area fell under slight drought conditions, with a further 20.7% affected by moderate drought. Severe drought, though less extensive, still covered 5.79% of the region, signalling a clear deterioration in vegetation health and increasing water stress. Conditions worsened in 2021, when the extent of severe drought nearly doubled, reaching 11.06% of the study area and pointing to a marked escalation in drought intensity.

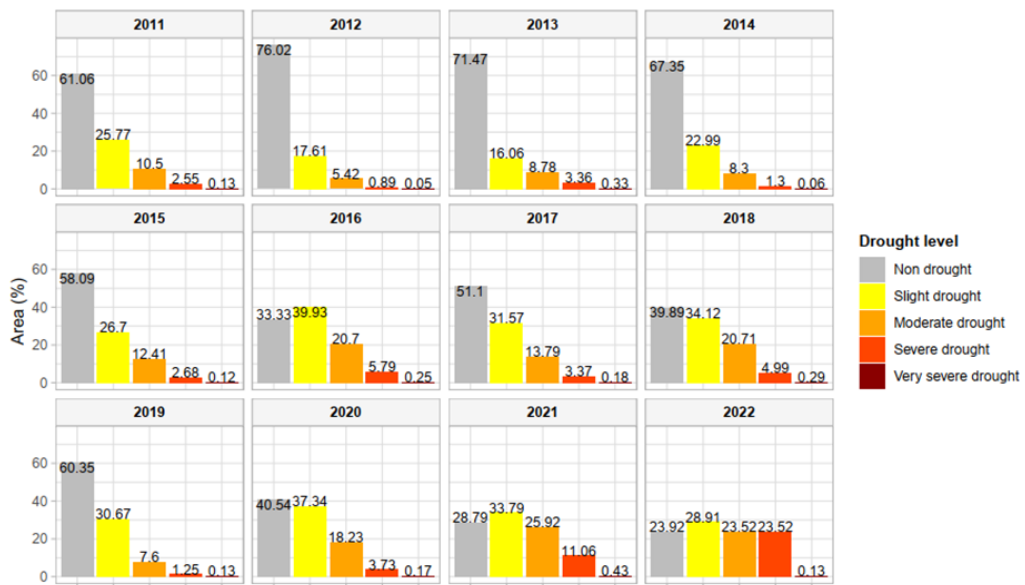


Figure 9. Percentage surface area of drought in northern Algeria from 2011 to 2022.

The year 2022 marks a clear turning point in drought conditions. Only 23.92% of the study area remained under non-drought conditions, while 76.08% experienced drought ranging from slight to severe. This shift signals a widespread deterioration of vegetation conditions, placing 2022 among the most extreme drought years in the

record, with extensive vegetation stress and a noticeable decline in ecosystem productivity.

Spatially, drought patterns show clear regional differentiation rather than a uniform spread. In 2011, drought was mainly confined to the western and central parts of the study area. By contrast, in 2013 and 2017 the signal shifts eastward, with stronger impacts in the eastern and south-eastern regions. The year 2018 stands out, as drought conditions extended across almost the entire southern sector. More broadly, the years 2016, 2018, 2021, and 2022 are marked by near-complete spatial coverage of drought, although the intensity still varies from one region to another.

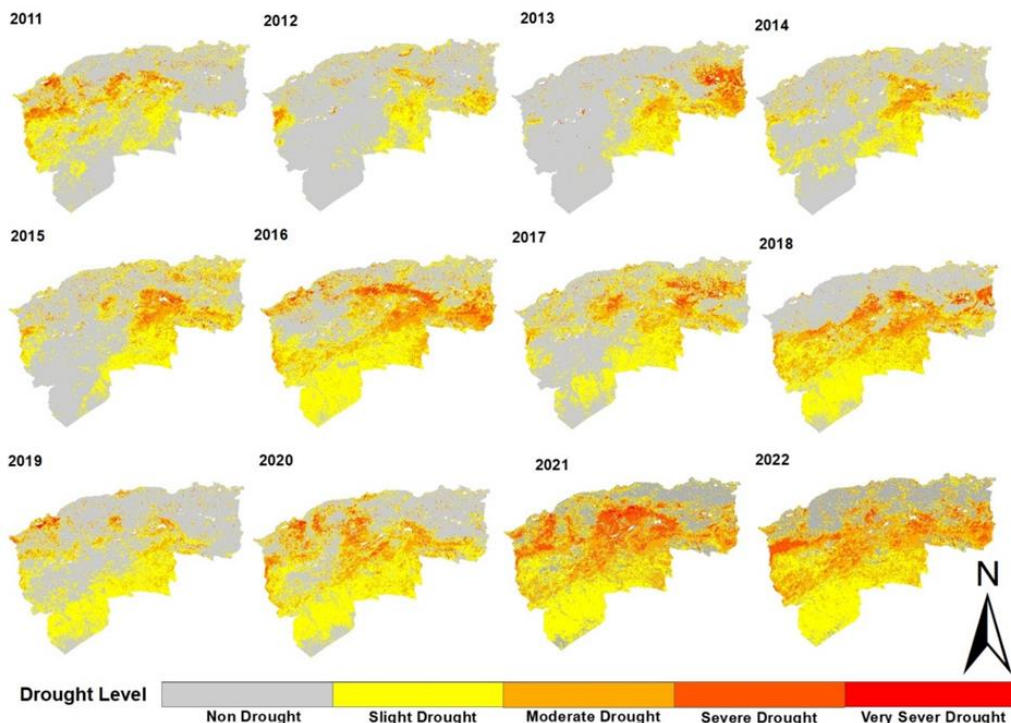


Figure 10. The spatial distribution of drought in northern Algeria from 2011 to 2022.

4.1.3. Temporal Variations in NDVI, Rainfall, and Temperature Anomalies:

The temporal dynamics of vegetation and climatic variability were explored through a joint analysis of NDVI, rainfall, and temperature anomalies over the 2011–2022 period (Figure 11). Bringing these variables together makes it possible to move beyond simple trends and examine how vegetation responds to shifting climatic conditions, while also highlighting recurring patterns and anomalous years in ecosystem behaviour.

The NDVI anomaly time series shows clear interannual variability rather than a steady trend. In most years, anomalies remain positive, indicating vegetation conditions above the long-term average. This pattern breaks in 2016, 2020, 2021, and

2022, where negative anomalies dominate, marking periods of pronounced vegetation stress and reduced ecosystem performance.

The NDVI anomaly time series exhibits interannual variability with apparent quasi-periodic fluctuations. While the 12-year study period is relatively short for establishing definitive cyclical patterns, the data suggest recurring fluctuations that warrant further investigation with longer time series. The first phase (2011–2013) shows a steady increase, culminating in a peak in 2013. This is followed by a decline between 2014 and 2016, when anomalies turn negative, indicating deteriorating vegetation conditions. A recovery phase emerges from 2017 to 2019, during which vegetation performance improves, before another downturn begins in 2020, reaching its lowest point in 2021.

A generally consistent relationship is observed between NDVI and rainfall anomalies, indicating precipitation as a primary driver of vegetation dynamics in northern Algeria. Periods of positive rainfall anomalies are typically associated with improved vegetation conditions, whereas rainfall deficits correspond to reduced NDVI values. However, this relationship is not uniform across all years; in particular, 2014 and 2021 show a divergence between NDVI and rainfall anomalies, suggesting that additional environmental or anthropogenic factors also influence vegetation response. In contrast, the relationship between NDVI and temperature anomalies is less consistent and more complex. Temperature variations do not show a clear or systematic correspondence with vegetation dynamics, suggesting that temperature alone is not a dominant driver of vegetation variability in the region. Instead, its influence is likely expressed in interaction with other stressors, particularly moisture availability, which more directly governs vegetation response in semi-arid environments.

Overall, the integrated analysis reveals that precipitation is a key driver of vegetation dynamics in northern Algeria, although its influence is not uniform across all years. The relationship between NDVI and precipitation anomalies varies interannually, with years such as 2011, 2014, and 2021 demonstrating deviations from expected correlations (as discussed in Section 4.1.4). This variability indicates that vegetation response is governed by a complex interaction of precipitation, temperature, and potentially lag effects or anthropogenic factors, rather than precipitation alone.

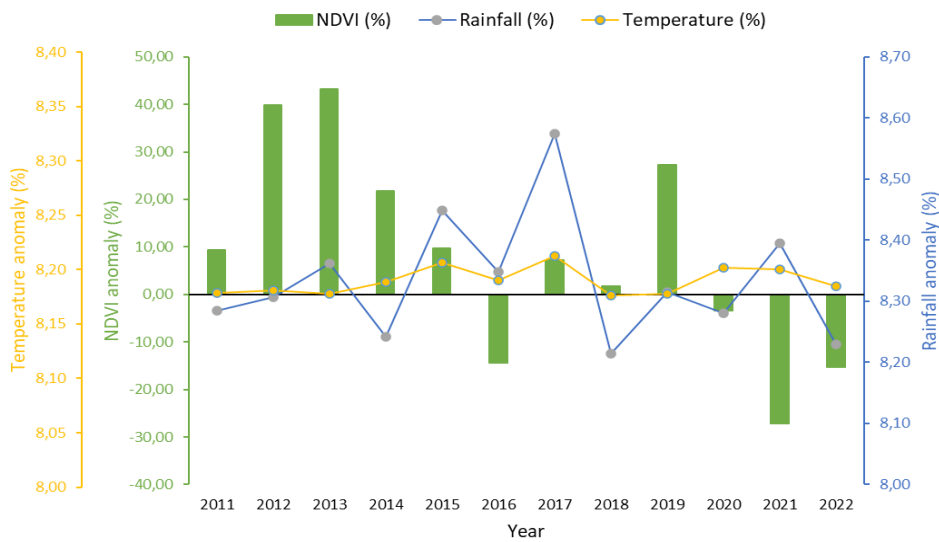


Figure 11. Seasonal variations in NDVI, rainfall, and temperature anomalies from 2011 to 2022.

4.1.4. NDVI–Climate Relationships; Correlation patterns and interannual variability.

The relationships between NDVI anomalies and climatic variables were quantified using Spearman’s rank correlation to evaluate both the strength and direction of association. The results indicate a statistically significant relationship ($p < 0.05$) between NDVI anomalies and climatic anomalies; however, the magnitude of these relationships varies across the study period (Figure 12).

Overall, NDVI shows a weak but predominantly positive relationship with rainfall anomalies, with correlation coefficients ranging between 0.10 and 0.37. This indicates that higher precipitation is generally associated with increased vegetation activity; however, the relatively low correlation strength highlights the influence of additional non-climatic factors and the inherent variability characteristic of semi-arid ecosystems. In contrast, NDVI exhibits a consistently negative relationship with temperature anomalies over the study period. Correlation coefficients range from near-zero values ($r_s = -0.01$) to moderately strong negative relationships (up to $r_s = -0.47$), suggesting that higher temperatures are generally associated with reduced vegetation greenness, likely through increased evapotranspiration and accelerated soil moisture depletion.

The results indicate that precipitation is the main climatic driver of vegetation variability in the study area, while temperature acts primarily as an amplifying stress factor during warmer periods. The interannual variability in correlation strength further suggests that vegetation response is not strictly linear, but is shaped by interactions among climatic variables as well as ecosystem memory effects.

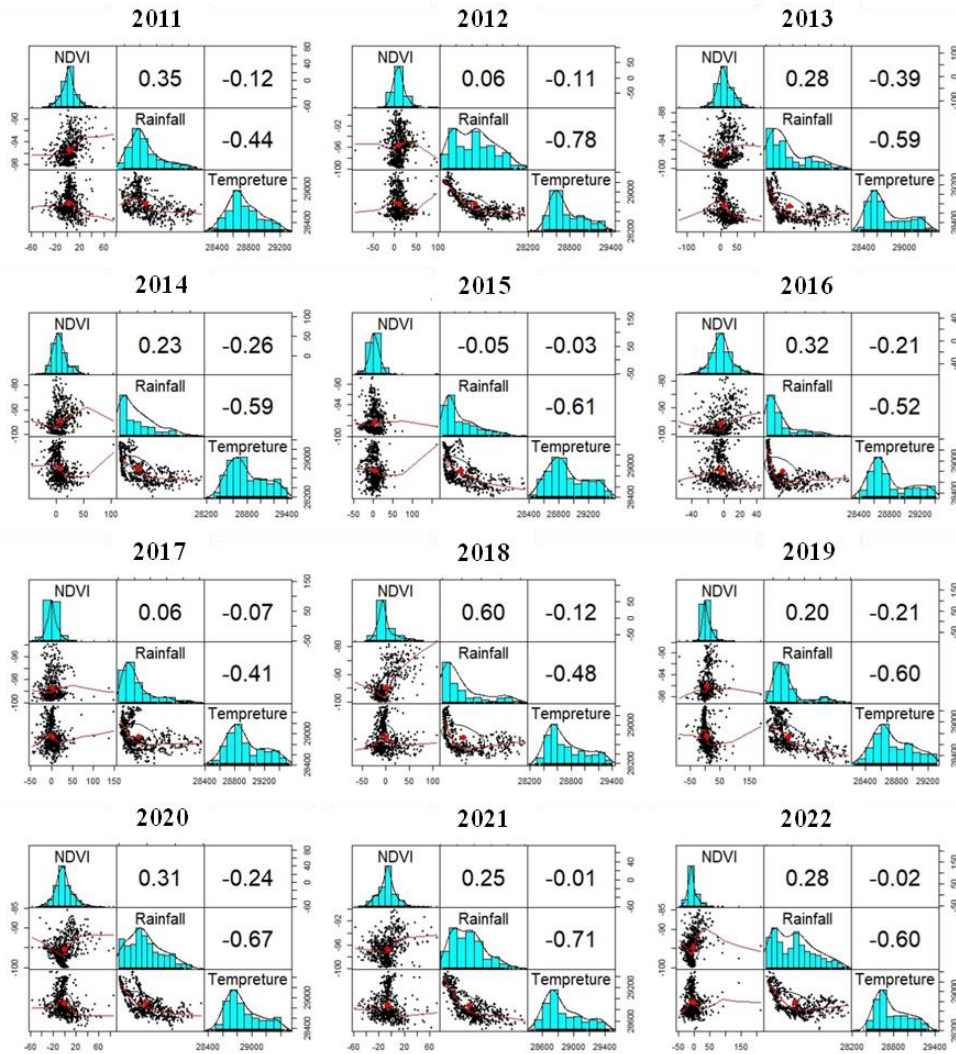


Figure 12. Spearman correlation coefficients (r_s) of NDVI, rainfall, and temperature anomalies from 2011 to 2022.

4.2. Multi-Index Drought Assessment in Northwestern Algeria (2003–2023):

4.2.1. cSPI-Derived Meteorological Drought Patterns:

SPI was employed to characterize meteorological drought variability across northwestern Algeria at multiple temporal scales (3-, 6-, and 12-month) over the 2003–2023 period. This multi-scalar approach enables the detection of short-term precipitation fluctuations, seasonal anomalies, and longer-term hydroclimatic transitions, providing a comprehensive view of drought dynamics.

4.2.1.1. SPI-3: Short-Term Precipitation Variability:

To clarify the temporal representation of the results, SPI-3 and SPI-6 were calculated at monthly time steps using a 30-year baseline period (1990–2020), following WMO recommendations. For each year, the 12 monthly SPI-3 and SPI-6 values were averaged to derive annual values representing the overall short-term (3-month) and medium-term (6-month) drought conditions, respectively. This annual aggregation facilitates the comparison of drought conditions among years while preserving the multi-timescale characteristics of the SPI framework. The SPI-3 results (Figure 13) reveal pronounced interannual and intra-annual variability in short-term precipitation conditions, marked by frequent alternation between wet and dry anomalies. Several years, including 2003, 2004, 2007, 2008, and 2012, were characterized by predominantly positive SPI values, indicating moderately to extremely wet conditions, particularly across the coastal and northern parts of the study area. Among these, 2012 stands out as the wettest year, with extensive areas experiencing severe to extremely wet conditions. In contrast, dry conditions were more spatially extensive during 2009, 2015, 2017, 2019, 2020, 2021, 2022, and 2023, with the period from 2019 to 2023 marked by recurrent and increasingly widespread precipitation deficits. The years 2005, 2006, 2010, 2011, 2013, and 2018 were characterized predominantly by near-normal conditions. Overall, the results reveal a highly episodic pattern of short-term precipitation variability, with wet conditions occurring intermittently, whereas dry conditions became more frequent and spatially extensive during the latter part of the study period, particularly across the interior and southern regions.

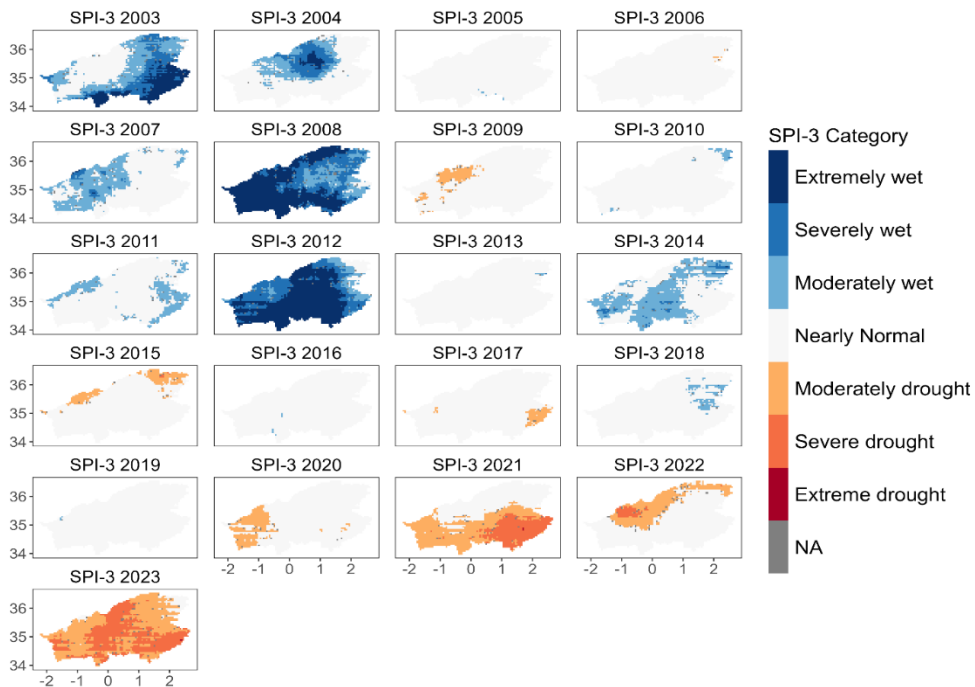


Figure 13. Spatial distribution of SPI3 (2003-2023).

4.2.1.2. SPI-6: Seasonal Hydroclimatic Conditions:

Consistent with the methodology described for SPI-3, the annual SPI-6 values presented in this section represent the average of 12 monthly SPI-6 calculations over the baseline. The SPI-6 results (Figure 14) reduce short-term variability and highlight hydroclimatic persistence at the seasonal scale. The period from 2003 to 2014 exhibits significant interannual variability, alternating between wet and dry phases. Notable wet episodes are observed in 2008, 2012, and 2014, which exhibit widespread spatial coverage of moderate to extreme wet conditions, whereas years such as 2005, 2006, 2010, 2011, and 2013 display negative anomalies.

A clear hydroclimatic shift is observed after 2015, marking the onset of a prolonged dry phase that extends through 2023. This period is characterised by predominantly moderate to severe drought conditions, with the most severe episodes occurring during 2015, 2017, and 2020–2023, while 2016 and 2019 showed relatively less severe or near-normal conditions in some areas. The years 2021 and 2023 emerge as major drought episodes, with widespread spatial coverage of severe to extreme precipitation deficits. While spatial heterogeneity persists, drought conditions become increasingly persistent and more regionally synchronised after 2015, indicating a transition toward sustained seasonal water stress.

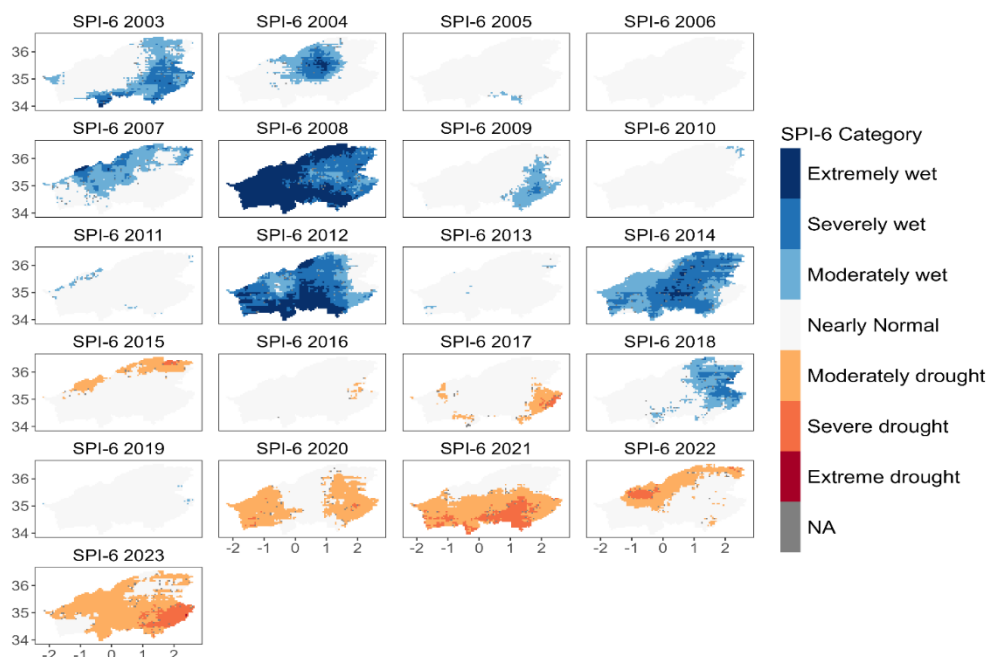


Figure 14. Spatial distribution of SPI6 (2003-2023).

4.2.1.3. SPI-12: Long-Term Hydroclimatic Evolution:

The SPI-12 analysis (Figure 15) captures long-term precipitation anomalies and clearly highlights a decadal-scale hydroclimatic regime shift. The period 2003–2014 is dominated by persistently wet conditions, with moderate to strong positive anomalies and peak wet years occurring in 2007, 2009–2011, and 2013. During this phase, above-average precipitation is both spatially widespread and relatively stable over time, indicating a sustained period of favourable hydroclimatic conditions. From 2015 onward, a persistent long-term drought regime becomes evident and extends through 2023. This transition is characterised by a gradual intensification of drought conditions, shifting from moderate drought in 2015 and 2017 to severe and extreme conditions during 2019–2023. The year 2023 stands out as the most severe drought episode of the entire period, affecting a large portion of the region. Although 2018 appears as a temporary wet anomaly within this sequence, it does not disrupt the overall drying trend.

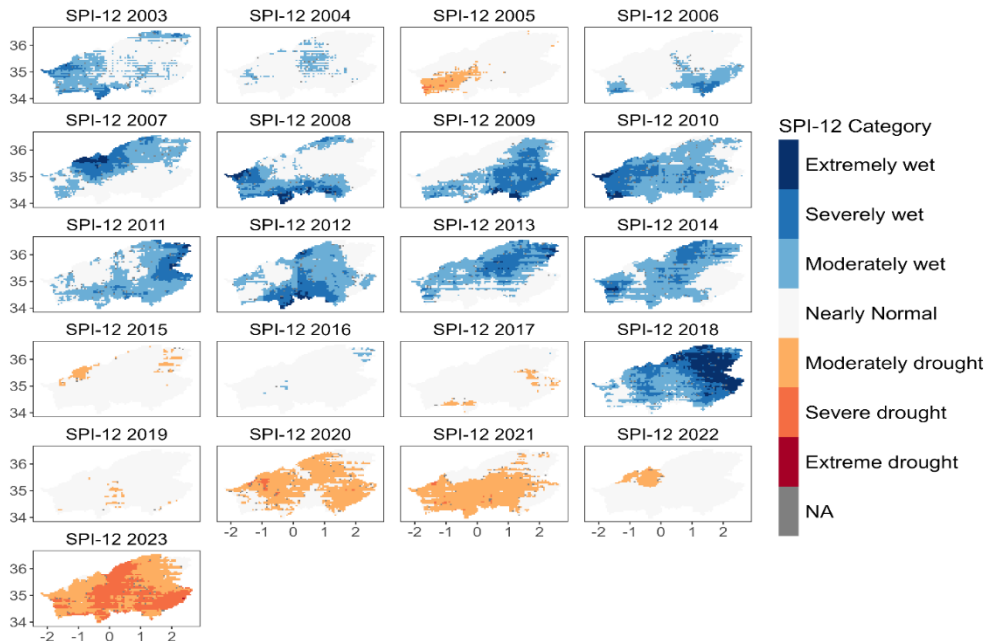


Figure 15. Spatial distribution of SPI12 (2003-2023).

4.2.1.4. Hydroclimatic Regime Shift in Northwestern Algeria (2003–2023):

Overall, the multi-scale SPI analysis reveals a clear hydroclimatic transition in northwestern Algeria, shifting from a predominantly wet regime (2003–2014) to a sustained dry regime (2015–2023). The increasing frequency, duration, and spatial extent of drought conditions after 2015 point to a structural shift in precipitation patterns rather than isolated climatic variability. While short-term fluctuations remain

evident, the dominant long-term signal is one of progressive drying, with significant implications for ecosystem stability, water availability, and the intensification of land degradation processes in the region.

4.2.2. Vegetation and Thermal Stress Dynamics (VCI, TCI, VHI):

To characterise vegetation condition and drought severity across northwestern Algeria, three complementary indices were analysed over the 2003–2023 period: the Vegetation Condition Index (VCI), the Temperature Condition Index (TCI), and the Vegetation Health Index (VHI). Considered together, these indices provide a multi-dimensional perspective, capturing vegetation response to both moisture availability and thermal stress rather than relying on a single indicator.

4.2.2.1. Vegetation Condition Spatial Patterns (VCI):

The spatial distribution of VCI across northwestern Algeria is mapped in Figure 16. This visualization reveals a persistent contrast between the humid coastal and sub-humid mountainous regions and the semi-arid interior provinces. Coastal areas including Mostaganem, Chlef, Ain Defla, Oran, and Ain Témouchent consistently exhibit higher VCI values, indicating relatively stable vegetation conditions and sustained biomass productivity. In contrast, interior provinces such as Saïda, Tiaret, Sidi Bel Abbès, and Mascara display systematically lower VCI values, reflecting greater sensitivity to climatic variability and recurrent vegetation stress.

Interannual variability is clearly evident. Favorable vegetation conditions occur in years such as 2005, 2010, and particularly 2017, when high VCI values are widespread, indicating above-average moisture availability. In contrast, years such as 2008, 2012, 2018, and 2022 show pronounced declines in VCI, extending even into typically resilient areas, which underscores the severity of drought conditions during these periods.

4.2.2.2. Thermal Stress Patterns (TCI):

The TCI analysis delineates the spatial distribution of thermal stress and its influence on vegetation dynamics. Higher TCI values indicating lower thermal stress are typically concentrated in coastal and elevated regions such as Mostaganem, Chlef, Ain Defla, and Tissemsilt. In contrast, interior and steppe zones, including Tiaret, Saïda, Sidi Bel Abbès, and southern Mascara, consistently exhibit lower TCI values, reflecting elevated land surface temperatures and increased evaporative demand.

Temporal analysis indicates a clear increase in both the frequency and spatial extent of thermal stress over the study period. Major stress events are evident in 2012, 2020, and especially 2022, the latter representing the most severe thermal anomaly, with widespread impacts across interior provinces and a strong correspondence with observed vegetation decline (Figure 17).

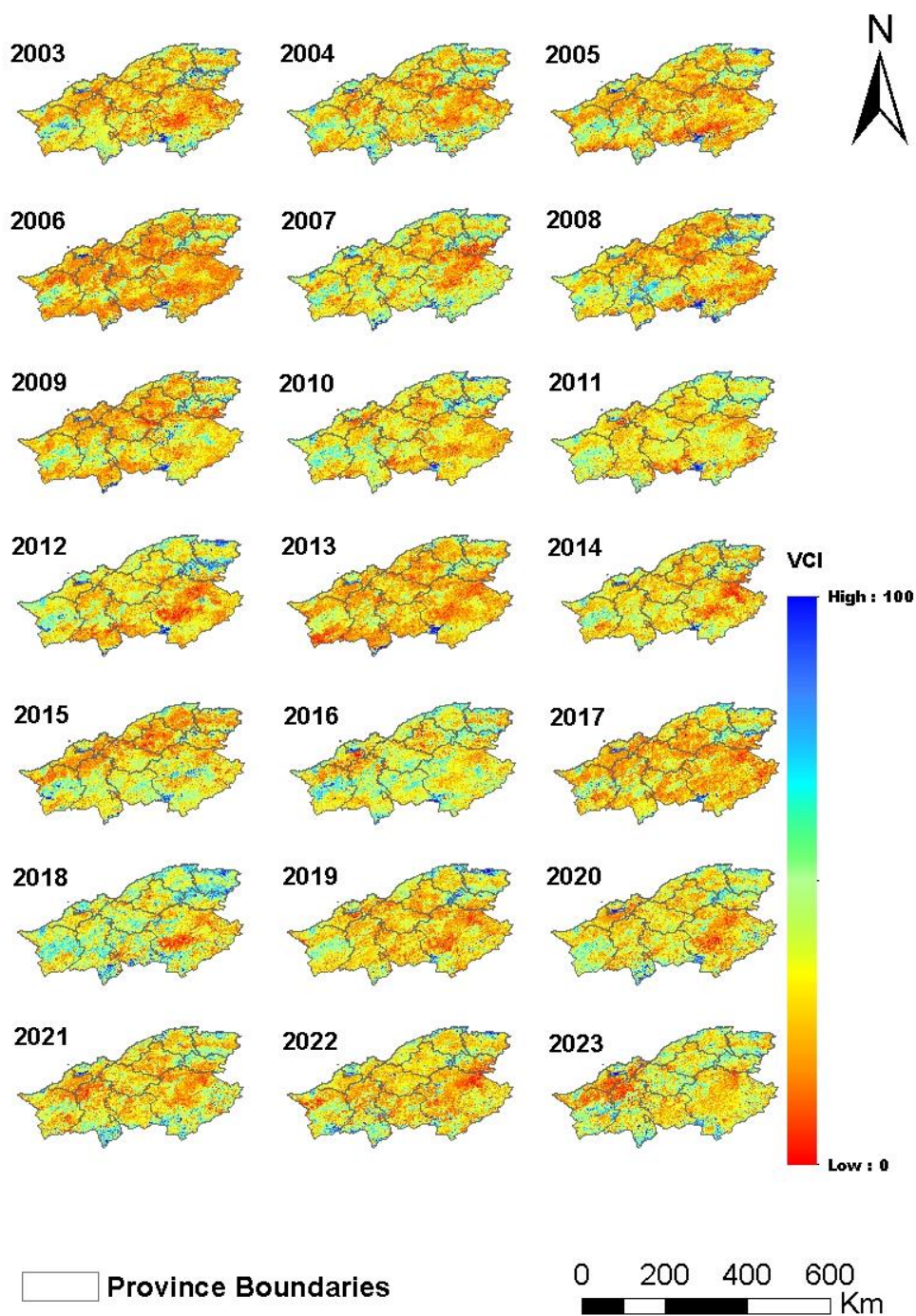


Figure 16. Spatial distribution of the VCI for the period 2003-2023.

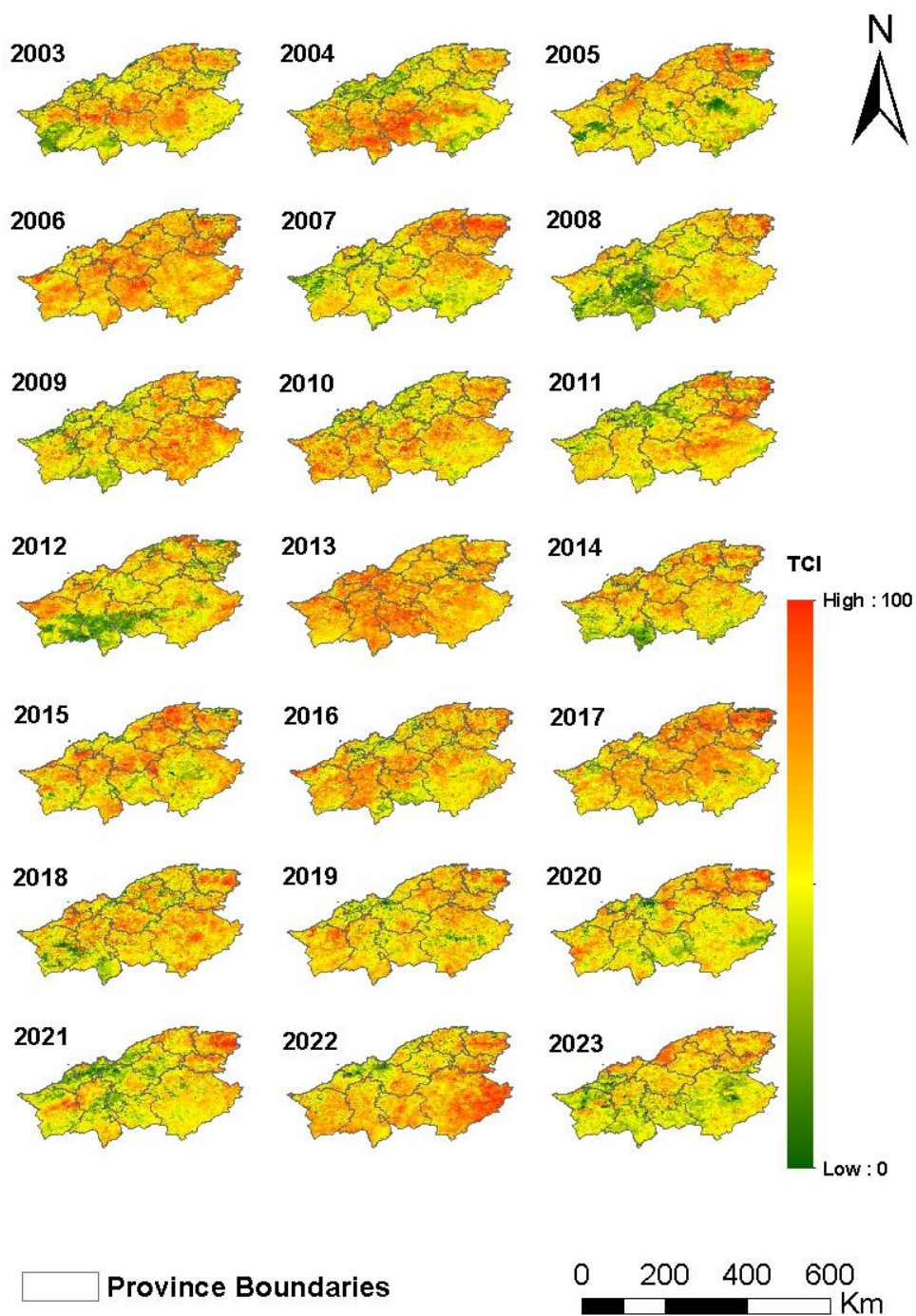


Figure 17. Spatial distribution of the TCI during 2003-2023.

4.2.2.3. Integrated Drought Severity (VHI):

The VHI integrates vegetation and thermal signals, offering a more comprehensive indicator of drought severity (Figure 18). Its spatial patterns closely align with those observed for VCI and TCI, reinforcing the strong coupling between moisture deficits and thermal stress in shaping vegetation response. It is noteworthy that the spatial patterns of VCI and VHI show varying degrees of similarity among years. In 2014 and 2018, VCI and VHI exhibited highly similar spatial distributions, suggesting that vegetation condition was the dominant component influencing the spatial pattern of VHI during these years. In contrast, during other years, particularly those associated with severe drought conditions, VHI diverged substantially from VCI. This divergence indicates that thermal stress, represented by TCI, contributed substantially to the spatial variability of VHI and modified the drought signal captured by VCI alone. By integrating vegetation and thermal conditions, VHI therefore provides a more comprehensive representation of vegetation drought stress than either VCI or TCI individually, particularly during periods when temperature anomalies exert an additional influence on vegetation health. A pronounced spatial gradient is evident, with interior and southern provinces such as Saïda, Tiaret, and Mascara experiencing recurrent moderate to severe drought conditions, while coastal and mountainous regions remain comparatively resilient. (Figure 18) illustrates the spatial distribution of drought severity across Northwestern Algeria from 2003 to 2023. Rather than indicating a continuous linear deterioration, the maps reveal a highly episodic pattern of drought occurrence, reflecting the substantial interannual variability of hydroclimatic conditions across the region. Severe and extreme drought conditions are concentrated in specific years, particularly 2006, 2011, 2016, 2021, and 2023. However, a clear temporal shift is evident: whereas the early 2000s were characterized by alternating wet and dry conditions, the frequency and spatial extent of severe drought episodes increased during the latter part of the study period, particularly after 2015. This pattern of episodic intensification is consistent with the broader drying tendency identified through the multi-scale SPI analysis and suggests an increasing prevalence of seasonal water stress across Northwestern Algeria.

It is important to note that the interpretation of drought conditions differs between the various analyses due to the different baseline periods and dimensions of drought they capture. The NDVI anomaly was calculated using a pre-drought baseline period (2000–2010), while the associated rainfall and temperature anomalies used a 30-year climatological baseline (1990–2020). In contrast, the SPI, VCI, TCI, and VHI were calculated using the full study period (2003–2023) as their baseline. Consequently, the classification of a given year reflects the specific baseline and the dimension of drought being assessed. For example, 2012 exhibited a positive precipitation anomaly relative to the 1990–2020 baseline (indicating wetter-than-average conditions) but also experienced elevated temperatures. This combination resulted in vegetation stress (as shown by the NDVI anomaly and VHI), highlighting the role of thermal stress in exacerbating drought impacts even during periods of above-average precipitation a phenomenon known as a 'hot drought' (K. E. Trenberth et al., 2014; Vicente-Serrano et al., 2014). This apparent discrepancy underscores the value of multi-index drought assessment, as different indices and baselines capture

complementary information, providing a more comprehensive understanding of drought dynamics.

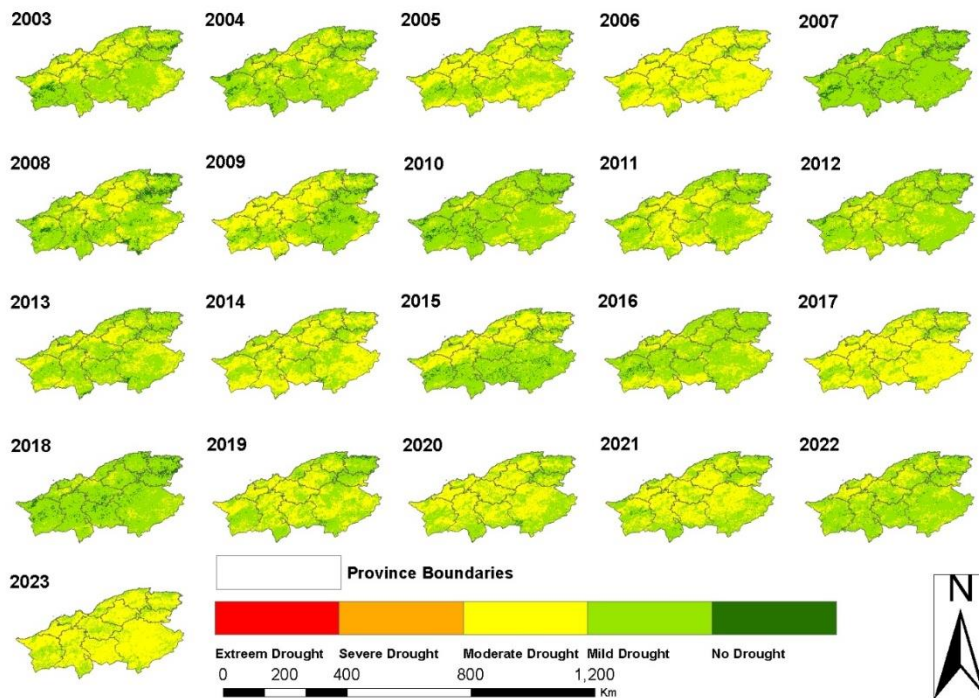


Figure 18. Spatial Distribution of Drought Severity in Northwest Algeria (2003–2023).

Recurrent Stress in Interior Provinces:

The combined analysis of VCI, TCI, and VHI reveals a structurally consistent pattern of drought vulnerability across northwestern Algeria. Interior and steppe regions are systematically exposed to both reduced vegetation condition and heightened thermal stress, leading to more frequent and intense drought impacts. In contrast, coastal and mountainous areas benefit from comparatively favourable climatic conditions and exhibit greater ecological resilience. Importantly, the concurrence of low VCI and low TCI values during key drought years, particularly 2012 and 2022 indicates that vegetation stress is not driven solely by precipitation deficits, but is strongly amplified by thermal anomalies. This coupled influence helps explain both the spatial expansion and the heightened severity of drought conditions observed in the VHI maps.

Overall, the multi-index approach confirms that drought dynamics in the region are governed by the interaction between moisture availability and temperature extremes, with interior provinces consistently emerging as hotspots of vegetation stress.

4.2.3. Multi-Temporal Analysis of Drought Conditions and Vegetation Response:

To quantify long-term changes in meteorological and vegetation drought conditions (Figure 19), temporal trends in SPI (3-, 6-, and 12-month), VCI, TCI, and VHI were evaluated using the non-parametric Mann–Kendall (MK) test alongside Sen’s slope estimator for the 2003–2023 period. This combination enables the detection of monotonic trends and their magnitude while remaining robust to non-normal data distributions and outliers, making it well suited for hydroclimatic time series analysis.

4.2.3.1. Temporal Evolution of Meteorological Drought (SPI):

The temporal dynamics of SPI at multiple time scales (Figure 19 a–c) reveal distinct patterns of variability and long-term change. SPI-3 captures high-frequency fluctuations, characterised by rapid alternation between wet and dry conditions. Notable drought episodes are observed during 2007–2009, 2011–2012, and intermittently between 2015 and 2022, reflecting short-term precipitation variability and episodic drought occurrence. In contrast, SPI-6 and SPI-12 highlight more persistent hydroclimatic signals. Both indices indicate a transition from predominantly wet conditions during 2003–2014 to a sustained drying phase after 2015. The period 2021–2023 emerges as the most severe drought interval across all time scales, consistent with the spatial SPI patterns described previously.

The Mann–Kendall analysis confirms a statistically significant negative trend in both SPI-6 and SPI-12, indicating a progressive shift toward drier conditions. Sen’s slope estimates further quantify this tendency, showing a consistent decline in precipitation anomalies over time. Together, these results provide robust statistical evidence of a long-term hydroclimatic drying trend in the study area.

4.2.3.2. Vegetation and Thermal Stress Trends (VCI, TCI, VHI):

The vegetation-based indices (Figure 19 d–f) show pronounced interannual variability while also reflecting systematic responses to climatic forcing. The VCI time series exhibits recurrent declines below the moderate stress threshold (<40) during major drought episodes (2007–2008, 2011–2012, and 2021–2022), interspersed with temporary recovery phases associated with wetter conditions (e.g., 2009–2010 and 2019–2020).

The TCI series exhibits strong temporal variability linked to thermal stress. Low values (<40) during major drought episodes indicate elevated land surface temperatures and intensified heat stress, whereas higher values (>60) correspond to reduced thermal stress and more favourable conditions for vegetation growth.

The VHI, which integrates both vegetation and thermal signals, shows comparatively smoother temporal dynamics while still clearly capturing prolonged drought phases particularly during 2004–2006, 2007–2008, 2011–2012, and 2020–2023. These intervals reflect sustained vegetation stress driven by the combined effects of moisture deficits and elevated thermal pressure.

Trend analysis indicates a declining tendency in both VCI and VHI, consistent with increasing drought severity, while TCI also exhibits a negative trend, reflecting intensifying thermal stress over time. The Mann–Kendall test confirms that these trends are statistically significant across several parts of the study area, and Sen’s slope further quantifies this pattern, highlighting the gradual but persistent intensification of vegetation stress.

4.2.3.3. Coupled Trends and Drought Intensification:

The combined analysis of meteorological and vegetation indices reveals a coherent signal of increasing drought intensity. The negative trends observed in SPI correspond closely with declining vegetation condition (VCI, VHI) and rising thermal stress (TCI), indicating a strong coupling between atmospheric forcing and land surface response.

Importantly, the post-2015 period is marked not only by a higher frequency of drought events but also by their increased duration and a diminished recovery capacity between episodes. This pattern points to more than just intensified variability, it indicates a shift toward persistent, structurally embedded drought conditions within the regional hydroclimatic system.

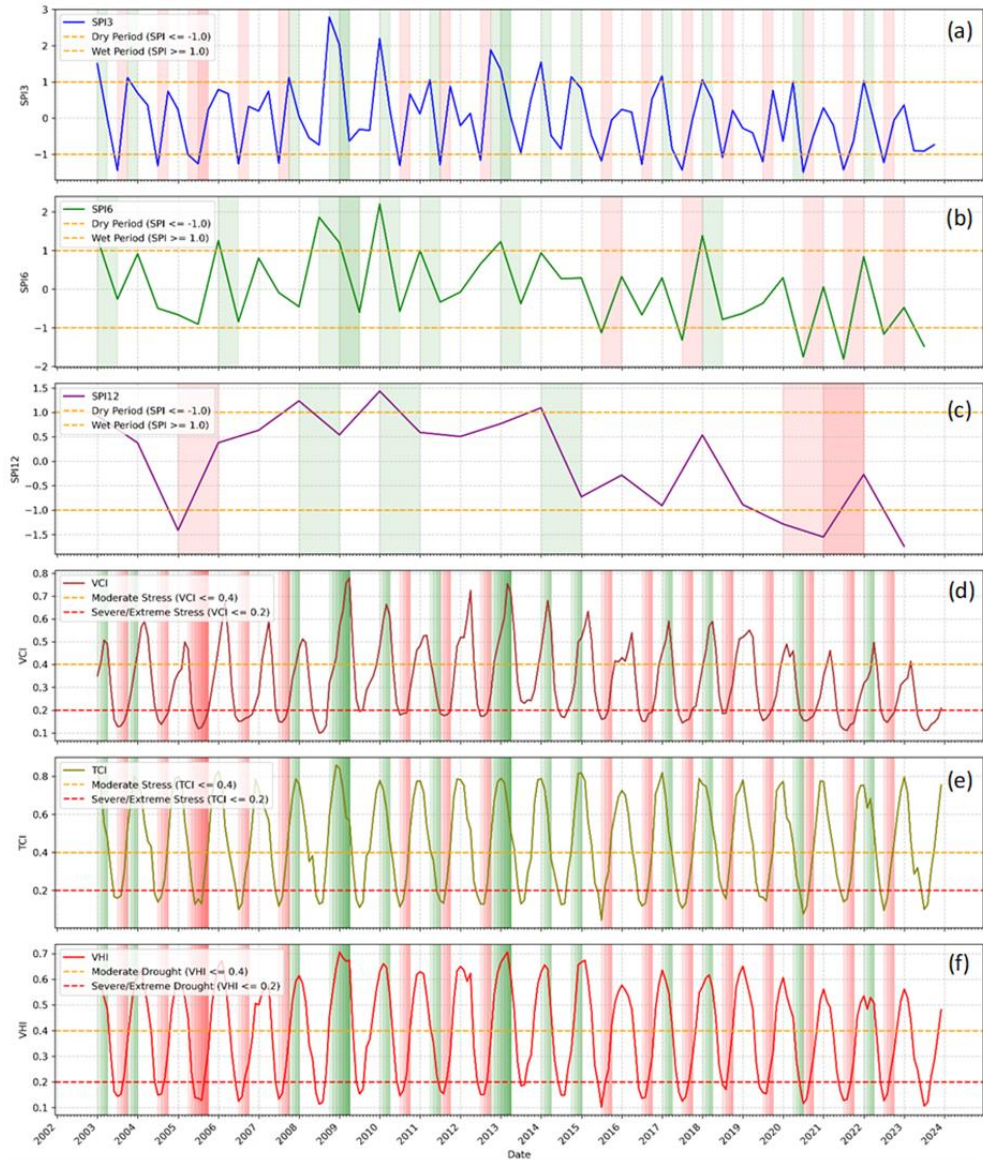


Figure 19. Temporal evolution of meteorological (SPI-3, SPI-6, SPI-12) and vegetation-based (VCI, TCI, VHI) drought indices across Northwest Algeria (2003–2023). Dashed lines indicate thresholds for moderate and severe drought/stress.

4.2.4. Spatiotemporal Trends in Drought Indices:

The spatiotemporal evolution of drought conditions across northwestern Algeria was evaluated using the Mann–Kendall (MK) test and Sen’s slope estimator applied to both meteorological indices (SPI-3, SPI-6, SPI-12) and vegetation-based indices (VCI, TCI, VHI) over the 2003–2023 period.

4.2.4.1. Meteorological Drought Trends (SPI):

The SPI-based trend analysis reveals a spatially coherent and statistically robust drying signal across all temporal scales, with no evidence of significant wetting trends across the study area (Figure 20; Table 7). Short-term variability (SPI-3) exhibits the widest spatial extent of significant drying, affecting approximately 56% of the region ($p < 0.05$), with a mean Sen's slope of -0.10 yr^{-1} . Similar patterns are observed at the seasonal scale (SPI-6), where about 55% of the area shows significant negative trends with a comparable mean slope (-0.10 yr^{-1}).

At the longer temporal scale, SPI-12 shows a reduced spatial extent of statistically significant trends (39%), although the magnitude of drying remains comparable (mean Sen's slope = -0.11 yr^{-1}). This lower spatial coverage reflects the integrative nature of long-term precipitation signals, which tend to smooth short-term variability while still preserving persistent hydroclimatic changes.

Overall, the consistent occurrence of significant negative trends across all SPI timescales indicates a progressive intensification of meteorological drought conditions. This signal becomes particularly pronounced after 2015, further reinforcing the evidence of a regional-scale shift toward drier climatic conditions identified in the previous sections.

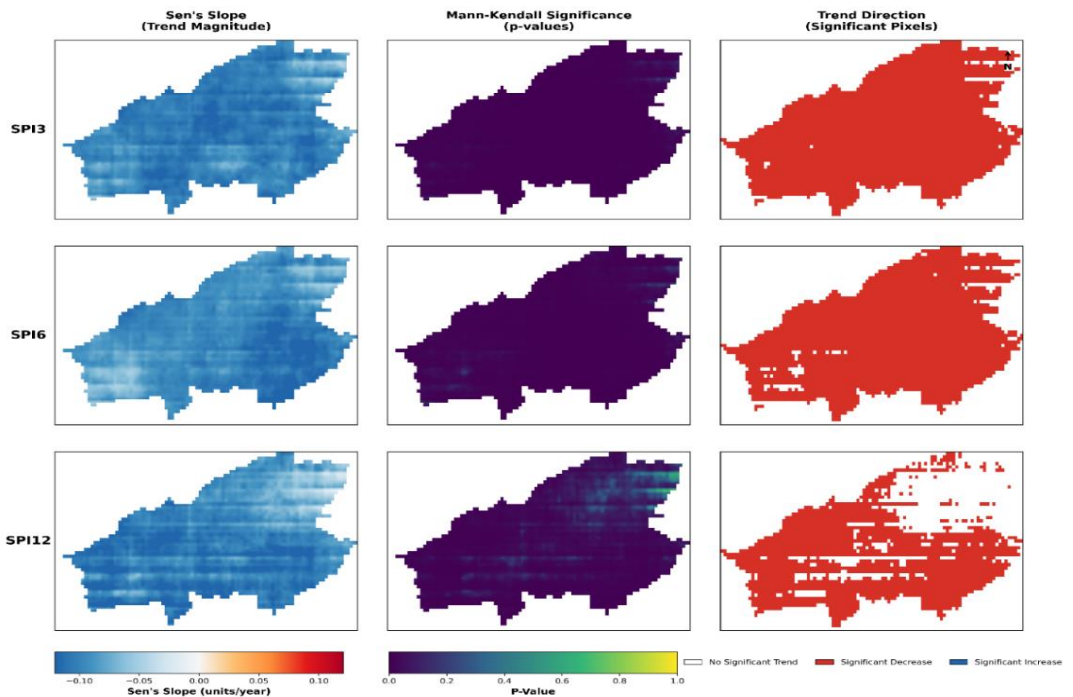


Figure 20. Spatiotemporal trend analysis of meteorological drought indices (SPI-3, SPI-6, SPI-12) across Northwest Algeria (2003–2023).

Table 7. Summary of Mann-Kendall Trend Analysis for Drought Indices (2003–2023).

Index	Trend Type		Significant Pixels (n)	Spatial Coverage (%)	Mean Sen's Slope (units · year ⁻¹)	SD of Sen's Slope	Interpretation
SPI-3	Significant (Drying)	Decrease	2,907	55.97	−0.1001	0.0123	Drying
	Significant (Wetting)	Increase	0	0.00	0.00	NA	NA
SPI-6	Significant (Drying)	Decrease	2,848	54.83	−0.0957	0.0144	Drying
	Significant (Wetting)	Increase	0	0.00	0.00	NA	NA
SPI-12	Significant (Drying)	Decrease	2,043	39.33	−0.1062	0.0124	Drying
	Significant (Wetting)	Increase	0	0.00	0.00	NA	NA

4.2.4.2. Vegetation and Thermal Stress Trends (VCI, TCI, VHI):

In contrast to the SPI results, vegetation-based indices display weaker and more spatially heterogeneous trend signals (Figure 21; Table 8). The TCI shows an almost complete absence of statistically significant trends, with less than 1% of pixels exhibiting significant changes ($p < 0.05$). It is important to note that TCI is an inverse index, where lower values indicate higher thermal stress. Therefore, the significant decrease in TCI (-0.0029 yr^{-1} over 0.94% of the area) indicates increasing thermal stress (warming), while the significant increase ($+0.0026 \text{ yr}^{-1}$ over 0.09% of the area) indicates decreasing thermal stress (cooling). This indicates that, despite pronounced interannual variability, long-term monotonic changes in thermal conditions are limited or spatially inconsistent across the study area. However, the predominance of warming trends over cooling trends (0.94% vs. 0.09%) confirms a net increase in thermal stress, which is consistent with the broader regional warming trend.

The VCI exhibits a mixed pattern of change, with 3.4% of the study area showing significant declines in vegetation condition and 2.7% displaying significant improvement. The near balance between negative and positive trends, together with similar Sen's slope magnitudes (approximately $\pm 0.006 \text{ yr}^{-1}$), suggests that vegetation dynamics are not governed solely by large-scale climatic trends, but are also strongly modulated by local environmental factors such as land cover heterogeneity, topographic controls, and human activities.

The VHI, integrating both vegetation and thermal stress signals, provides a more comprehensive indication of overall ecosystem response. A statistically significant decline in vegetation health is observed over 4.9% of the study area, compared with only 0.5% showing improvement. This clear imbalance points to a net deterioration in vegetation health, although the spatial extent of significant trends remains limited compared to meteorological indicators.

4.2.4.3. Synthesis of Spatiotemporal Trends:

The comparison between meteorological and vegetation-based indices reveals a clear asymmetry in drought dynamics. Meteorological drought shows a strong, spatially coherent, and statistically significant drying trend, whereas vegetation responses are more localized, heterogeneous, and less consistently expressed as long-term trends.

This divergence suggests that vegetation systems exhibit a degree of resilience or buffering capacity, potentially mediated by ecological adaptation, soil moisture storage, and anthropogenic land management practices. However, the predominance of negative trends in VHI indicates that, despite this buffering capacity, the cumulative effects of sustained drying are increasingly manifested in vegetation health deterioration.

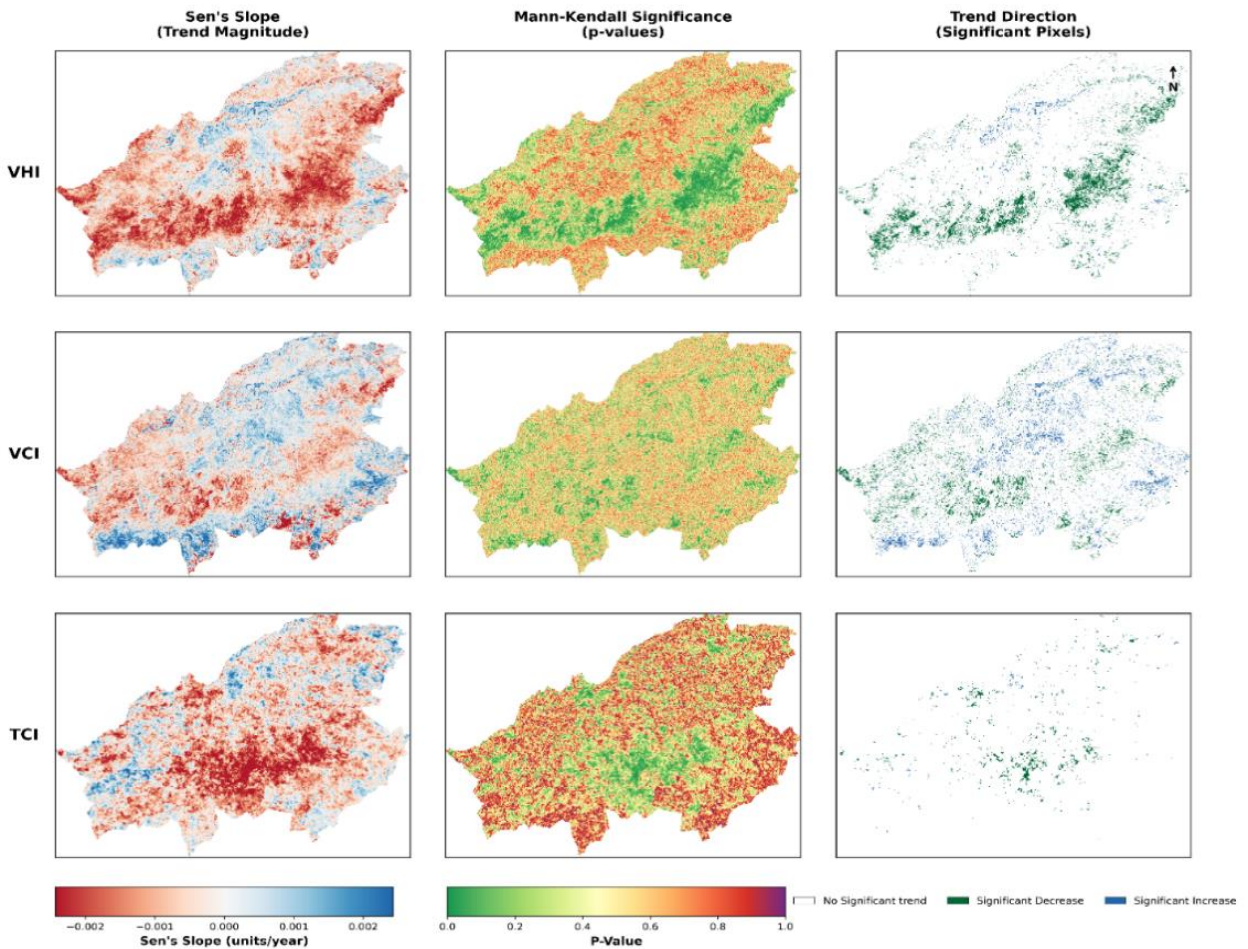


Figure 21. Spatiotemporal trend analysis of vegetation-based drought indices (VHI, VCI, TCI) across Northwest Algeria (2003–2023).

Table 8. Summary of Mann-Kendall Trend Analysis for Remote Sensing Drought Indices (2003–2023).

Index	Trend Type		Significant Pixels (n)	Spatial Coverage (%)	Mean Sen's Slope (units · year ⁻¹)	SD of Sen's Slope	Interpretation
TCI	Significant (Cooling)	Decrease	23,962	0.94	−0.0029	0.0007	Warming
	Significant (Warming)	Increase	2,402	0.09	+0.0026	0.0006	Cooling
VCI	Significant (Vegetation Stress)	Decrease	87,111	3.40	−0.0058	0.0023	Vegetation Stress
	Significant (Vegetation Health)	Increase	69,801	2.72	+0.0057	0.0022	Vegetation Health
VHI	Significant (Degradation)	Decrease	125,261	4.89	−0.0060	0.0014	Degradation
	Significant (Improvement)	Increase	13,182	0.51	+0.0057	0.0016	Improvement

4.2.5. Multi-timescale Coupling Between Meteorological Drought (SPI) and Vegetation Health (VHI):

The relationship between meteorological drought and vegetation condition was evaluated through correlation analysis between SPI at multiple temporal scales (SPI-3, SPI-6, and SPI-12) and the Vegetation Health Index (VHI) over the 2003–2023 period (Figure 22). This multi-scale approach enables the assessment of vegetation sensitivity to short-term, medium-term, and long-term precipitation variability.

The results indicate a consistent positive relationship between SPI and VHI across all temporal scales, confirming that vegetation conditions improve during wet periods and deteriorate under precipitation deficits. However, the strength and statistical significance of this relationship vary depending on the temporal aggregation of rainfall anomalies.

At the short-term scale (SPI-3), a moderate and statistically significant correlation is observed ($r = 0.567$, $p = 0.007$), indicating a rapid vegetation response to short-term precipitation fluctuations. This reflects the high sensitivity of surface vegetation activity to immediate moisture availability, particularly in semi-arid environments where soil water storage capacity is limited.

A comparable but slightly weaker relationship is observed at the seasonal scale (SPI-6 vs. VHI, $r = 0.509$, $p = 0.019$), suggesting that vegetation health is also strongly influenced by precipitation anomalies aggregated over several months. This highlights the role of accumulated rainfall deficits in driving seasonal vegetation stress. In contrast, the relationship between SPI-12 and VHI weakens and becomes statistically non-significant ($r = 0.364$, $p = 0.115$). This reduction in correlation

strength at longer timescales indicates a partial decoupling between vegetation response and long-term precipitation variability, which partially decouple vegetation response from long-term precipitation variability.

The results suggest that vegetation dynamics in northwestern Algeria are primarily influenced by short- to medium-term precipitation variability, as indicated by the statistically significant relationships observed for SPI-3 and SPI-6. By contrast, the relationship with SPI-12 was weaker and not statistically significant ($r = 0.364$, $p = 0.115$), suggesting a less direct response to longer-term precipitation variability. This pattern should not be interpreted as a complete decoupling of vegetation from long-term moisture conditions. Rather, it may reflect the greater importance of seasonal water availability and the buffering effect of soil moisture storage in this semi-arid environment (Ren et al., 2024). The observed scale-dependent response highlights differences in vegetation sensitivity across temporal scales, with vegetation responding more strongly to short- and medium-term moisture variability than to longer-term climatic forcing.

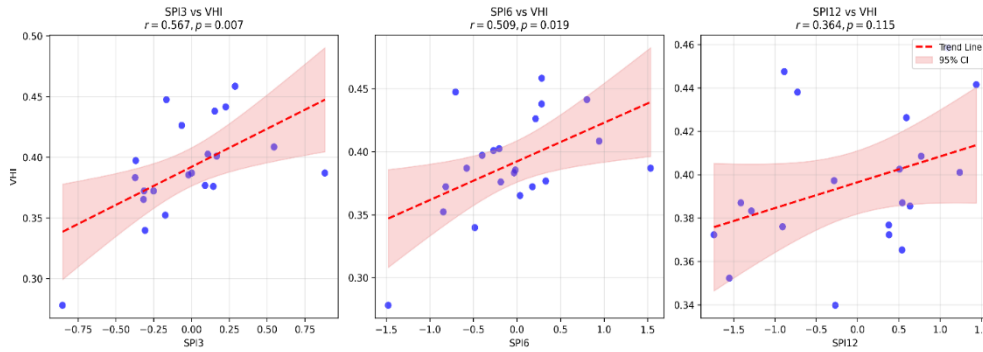


Figure 22. Scatter plots showing the relationship between SPI (3-, 6-, and 12-month timescales) and VHI based on annual aggregated time series (2003–2023). Each point represents a yearly observation. Dashed lines indicate linear regression fits, and shaded areas represent the 95% confidence intervals. Pearson correlation coefficients (r) and associated p -values are shown for each relationship.

4.3. Local-Scale Land-Use Dynamics and the Green Dam (Djelfa Province):

4.3.1.1. Classification Accuracy Assessment:

The reliability of the land use/land cover (LULC) classifications was assessed across all five temporal snapshots (1972, 1989, 1999, 2009, and 2019), with results presented in (Table 9). Overall classification accuracy ranged from 75.5% to 94%, while Kappa coefficients varied between 64.1% and 89.9%, indicating moderate to excellent levels of agreement.

The highest classification performance was achieved for the 2019 map (overall accuracy = 94%; Kappa = 89.9%), reflecting improvements in data quality and classification consistency. In contrast, the 1989 map exhibited the lowest accuracy

(75.5%; Kappa = 64.1%), likely due to limitations in data resolution and reduced spectral separability. Despite this variability, all classifications satisfy acceptable thresholds for LULC change analysis, ensuring the reliability of subsequent interpretations.

Table 9. Assessment of classification accuracy. Overall Accuracies (UA) and Kappa statistics (UP) of the five LULC maps, PA, producer's accuracy (%); UC, user's accuracy (%).

Classes	1972		1989		1999		2009		2019	
	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA
Dense plantations & Natural forest	80	88.8	10	100	80	100	80	100	100	100
Open plantations			78.3	74.6	91.6	89.7	80.4	94.2	100	100
Degraded steppes	90	96.7	70	43.7	91.1	92	90.6	89.8		100
Urban			76.8	100	80	66.6	80	33.3	100	98.9
Crops	70	41	60	26	80	80	100	83.3	100	100
Overall accuracy	0.88		0.75		0.89		0.87		0.94	
Overall Kappa	0.64		0.64		0.82		0.80		0.89	

4.3.1.2. Spatiotemporal Dynamics of LULC (1972–2019):

The spatial distribution and temporal evolution of five LULC classes, degraded steppes, croplands, urban areas, dense plantations and natural forests, and open plantations are illustrated in Figure 23, with corresponding quantitative changes summarized in Table 10.

The results reveal a non-linear, policy-driven trajectory of land transformation over the 47-year period. In 1972, the landscape was overwhelmingly dominated by degraded steppes. By 1989, a substantial portion of these areas had been converted into open plantations, reflecting large-scale afforestation efforts associated with the Green Dam project. This shift is clearly evidenced by the emergence of open plantations from non-existence in 1972 to 10,345 ha in 1989. However, this expansion was not sustained. Open plantations declined between 1989 and 1999 (–19.9%), followed by a partial recovery between 1999 and 2009 (+33.6%), and a marked decrease between 2009 and 2019 (–43%), reaching 6,303 ha. A similar trajectory is observed for dense plantations and natural forests, which increased steadily from 1972 to 1999 (585 ha to 1,615.65 ha), before declining to 626.6 ha in 2019.

Urban areas exhibit continuous and rapid expansion, increasing from 0 ha in 1972 to 910.4 ha in 2019, with particularly strong growth between 1999 and 2009 (+412%). Cropland dynamics show moderate variability, characterized by an initial decline (1972–1989), followed by expansion up to 2009, and relative stabilization thereafter. Degraded steppes exhibit the most complex trajectory. A sharp decline is observed during the first period (1972–1989; –44.08%), corresponding to large-scale afforestation efforts. This is followed by alternating phases of expansion and contraction, culminating in a net increase of +36.81% between 2009 and 2019, indicating a re-expansion of degraded landscapes.

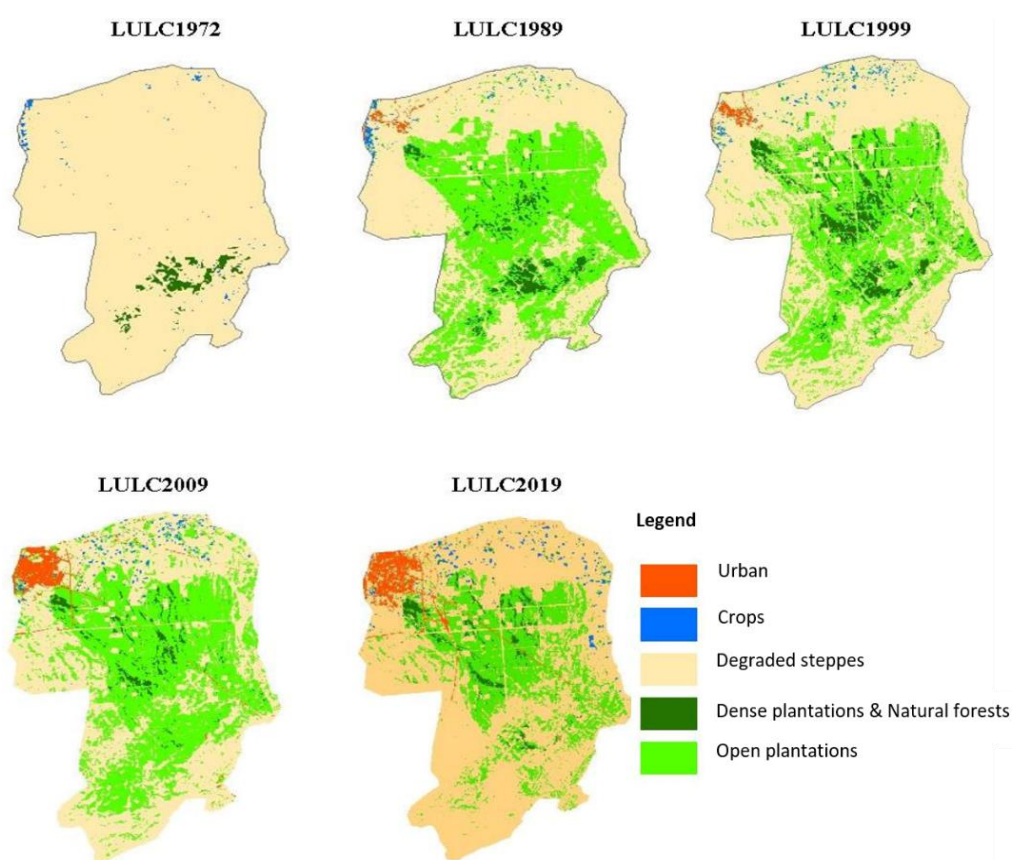


Figure 23. LULC classified maps of the Moudjbara region for the five studied years (1972, 1989, 1999, 2009, and 2019).

Table 10. LULC analysis in Green Dam region (Djelfa Province):

LULC class	1972		1989		1999		2009		2019	
	Area (ha)		Area (ha)	C(%)	Area (ha)	C(%)	Area (ha)	C(%)	Area (ha)	C(%)

Crops	157.01	132.91	-15.35	174.17	+31.05	236.36	+35.71	235.55	-0.34
Degraded steppes	24626.62	13770.76	-44.08	15139.31	+9.94	12640.89	-16.5	17293.83	+36.81
Dense plantations & Naatural forests	585.48	1003.26	+71.36	1615.65	+61.04	641.35	-60.3	626.62	-2.3
Open plantations	0	10344.99	+10344.99	8288.23	-19.88	11073.97	+33.61	6302.66	-43.09
Urban	0	117.2	+117.20	151.75	+29.48	776.54	+411.73	910.46	+17.25

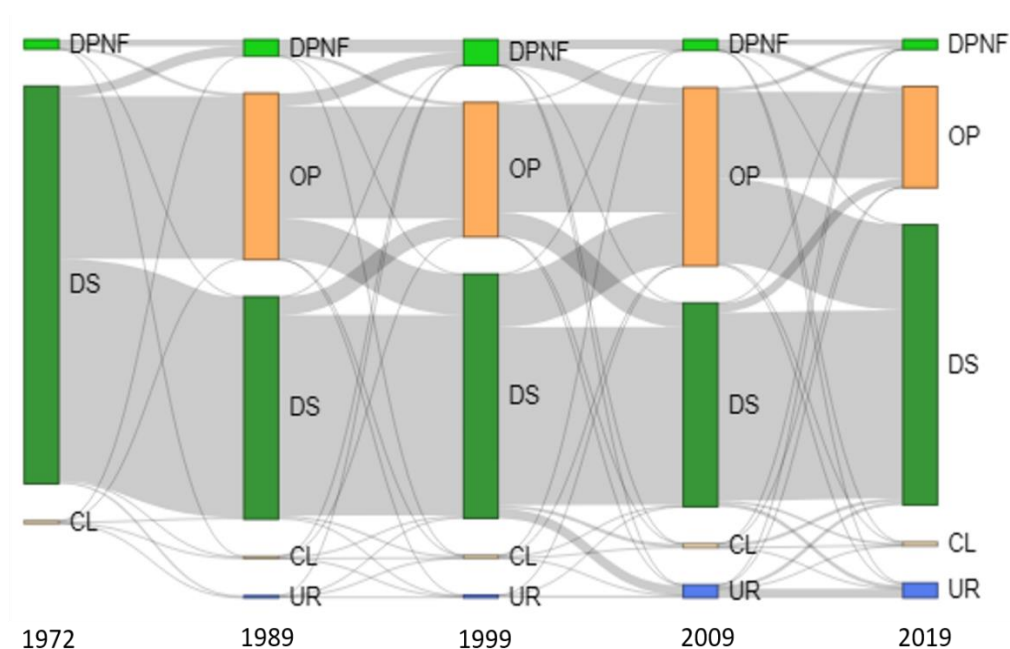


Figure 24. Sankey diagram illustrating LULC changes between 1972 and 2019 in the Moudjbara region; all links and nodes are displayed proportionately to absolute hectares. DPNF, dense plantations and natural forests; OP, open plantations; DS, degraded steppes; CL, crops; and UR, urban.

4.3.1.3. Intensity and Rate of Land-Use Change:

The temporal dynamics of LULC change were further assessed using intensity analysis (Figure 25), which reveals substantial variability in both the magnitude and rate of change across the four study intervals. The largest overall transformation occurred during the first period (1972–1989), which also represents the longest interval (17 years) and corresponds to the peak implementation phase of the Green

Dam project. In contrast, the period 1989–1999 shows the lowest magnitude of change, suggesting a phase of relative landscape stabilization

When normalized to annual rates, the results indicate that land-use change intensity was lowest during 1989–1999 and increased markedly after 1999. This acceleration suggests a transition toward more dynamic land-system processes in recent decades, potentially driven by the combined effects of environmental variability and anthropogenic pressures.

The intensity analysis provides a quantitative basis for identifying periods in which the rate of land transformation accelerated and for distinguishing phases of rapid intervention from subsequent periods of degradation. The results show that the 1972–1989 interval experienced the greatest overall magnitude of change, coinciding with the main implementation phase of the Green Dam project. By contrast, the 1989–1999 period recorded the lowest change intensity, suggesting a phase of relative landscape stability. Change intensity increased again after 1999, pointing to a renewed acceleration in land-cover transformations that may be associated with the combined effects of climatic stress and anthropogenic pressures.

The difference between total change and annual intensity indicates that land transformation in the region is not temporally homogeneous, but rather comprises distinct phases of rapid intervention followed by relative stabilization or degradation. This temporal non-stationarity is critical for evaluating the long-term sustainability of large-scale afforestation programs such as the Green Dam.

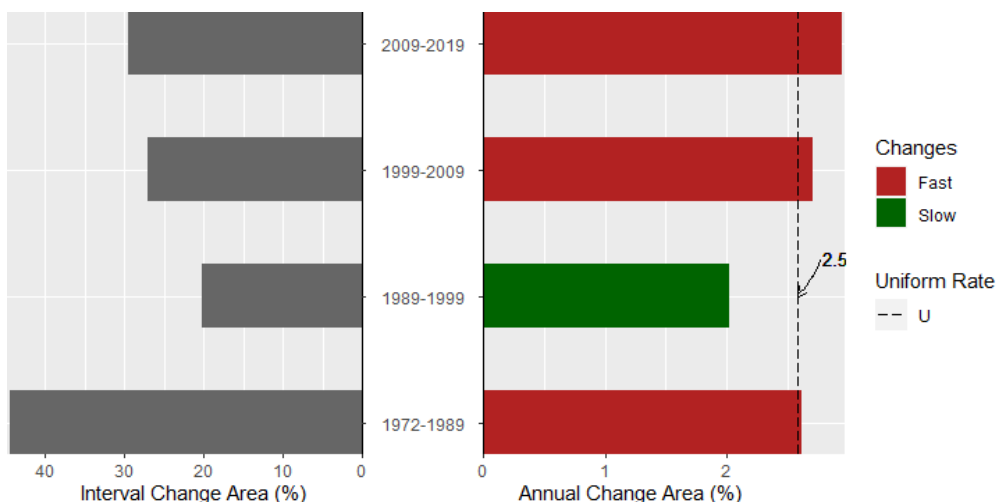


Figure 25. Time-intensity analysis for the four studied time intervals (1972–1989, 1989–1999, 1999–2009, and 2009–2019) showing how the size and speed of change vary across time intervals. Bars that extend to the left of zero show the area of overall change in each interval, while bars that extend to the right of zero show the intensity of the annual area of change within each time interval. Uniform rate (U) refers to the

rate that would occur if the annual changes were spread evenly over the entire time extent.

4.3.1.4. Green Dam Trajectory and Future Dynamics:

The Green Dam system in the Moudjbara region is primarily represented by open plantations and, to a lesser extent, dense plantations and natural forests. The spatiotemporal evolution of these classes reflects the long-term trajectory of afforestation initiatives and their subsequent transformation under combined environmental and anthropogenic pressures.

Trajectory and Structural Instability of the Green Dam:

The analysis of LULC transitions (Figures 26 and 27) reveals a non-linear, phase-dependent evolution of the Green Dam over the past five decades.

During the initial phase (1972–1989), large-scale afforestation efforts resulted in a substantial expansion of open plantations, which increased by approximately 10,000 ha, primarily at the expense of degraded steppes. Concurrently, dense plantations and natural forests experienced a modest net gain (~600 ha), indicating partial structural consolidation of the afforested landscape.

This expansion phase was followed by a period of partial decline and reorganization (1989–1999), during which open plantations lost approximately 2,000 ha, largely reverting to degraded steppes. In contrast, dense plantations and natural forests recorded a net gain of around 600 ha, suggesting localized densification and stand maturation processes. The period 1999–2009 marks a temporary recovery phase, with open plantations gaining approximately 2,700 ha, largely at the expense of degraded steppes. However, this recovery is accompanied by a decline in dense plantations (~900 ha), indicating internal redistribution rather than a net improvement in ecosystem structure.

A pronounced degradation phase is observed between 2009 and 2019, during which open plantations declined by more than 4,000 ha, predominantly reverting to degraded steppes. This reversal underscores the instability of afforested areas under prevailing environmental conditions.

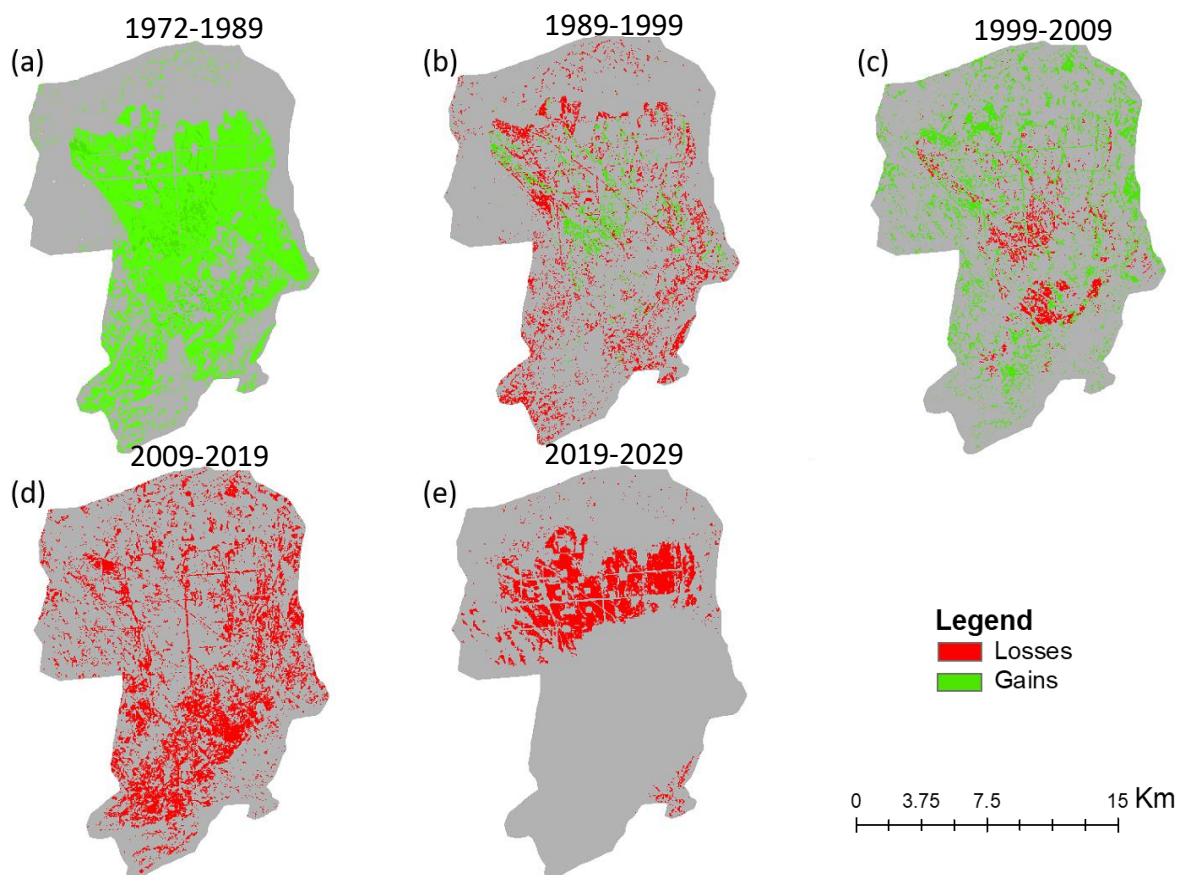


Figure 26. Gains and losses in open plantations, and dense plantations and natural forests in the Moudjbara region during the studied time intervals, (a) 1972–1989, (b) 1989–1999, (c) 1999–2009, (d) 2009–2019, and (e) 2019–2029.

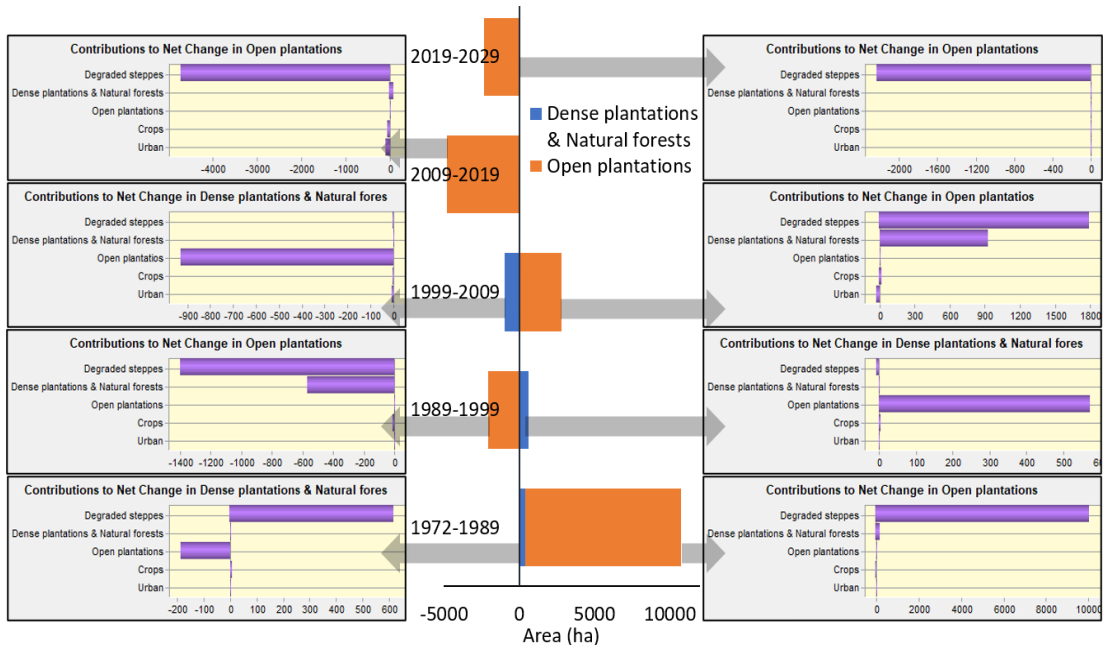


Figure 27. Contribution to net change (gain and loss) in open plantations, and dense plantations and natural forests during the five studied time intervals in the Moudjbara region.

4.3.1.5. Future Projection (2019–2029):

The Land Change Modeler projections indicate a continued decline in open plantations, with an expected loss of more than 2,000 ha by 2029, primarily transitioning into degraded steppes (Figure 26). The temporal trajectory (Figure 28) confirms a non-linear evolution, best described by a quadratic trend, with a clear peak followed by an accelerated decline phase.

The results indicate that if the present dynamics continue, the Green Dam system will gradually decrease, and open plantations in the Moudjbara region might eventually disappear in the long term. In contrast, natural forests and dense plantations show a relatively stable dynamics, which indicates a greater structural resilience than open plantations.

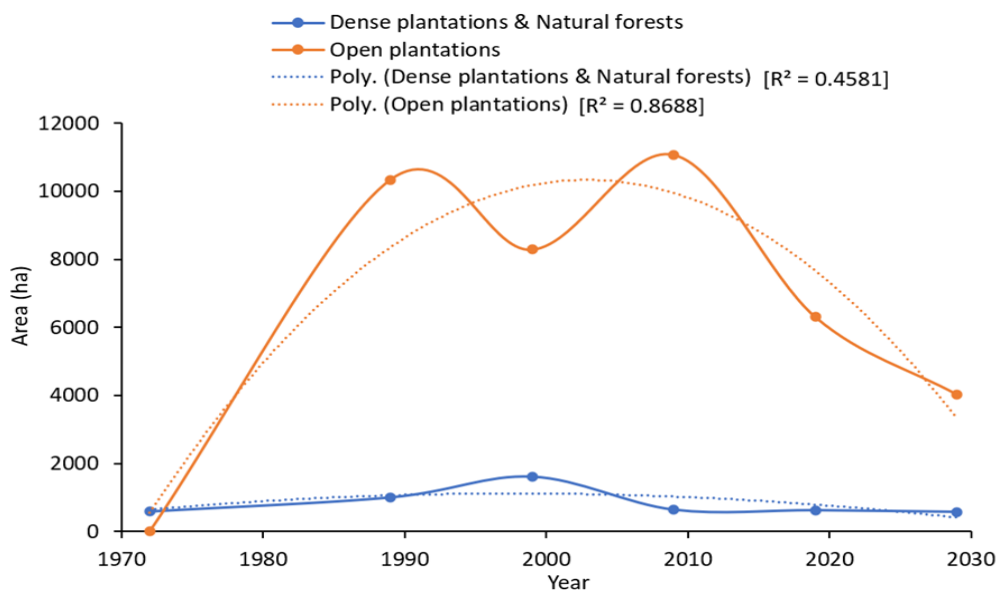


Figure 28. Temporal evolution of the areas occupied by open plantations, and dense plantations and natural forests in the Moudjbara region. The two distributions were best fitted by a quadratic polynomial function.

4.3.1.6. Anthropogenic Pressure: Population and Livestock Growth:

The evolution of land degradation processes in the study area is closely associated with increasing anthropogenic pressure, particularly driven by population growth and livestock expansion (Figure 29).

The human population of Djelfa Province has experienced rapid and sustained growth between 1996 and 2018, following an exponential trajectory. Projections based on recent growth rates indicate that the population is expected to exceed two million inhabitants by 2030, reflecting increasing pressure on land resources.

A similar trend is observed in livestock numbers, which increased markedly between 1998 and 2020. It should be noted that the livestock projection presented in Figure 29 was derived from a power function fitted directly to raw calendar years, which resulted in mathematically unrealistic parameter estimates, expressed as $y = 6 \times 10^{-187} \times x^{58.35}$. This issue arises because the model used large, non-normalized year values, such as 1996, 1998, and 2000, as the independent variable, producing an extremely small coefficient and an unrealistically large exponent. Although the observed data indicate a clear upward trend in livestock numbers, the specific numerical projection generated by this power function should be interpreted with considerable caution. Future analyses should instead use a normalized time index and compare more appropriate statistical models, such as linear, exponential, or other growth functions, to determine the model that best represents the observed livestock trajectory before generating future projections.

Projections suggest that livestock populations will continue to grow, exceeding five million heads by 2030. This expansion is particularly significant given the predominance of pastoral systems in the region.

The concurrent rise in human population and livestock density implies a progressive intensification of pressure on rangelands and afforested areas, particularly in semi-arid environments where ecological resilience is inherently limited.

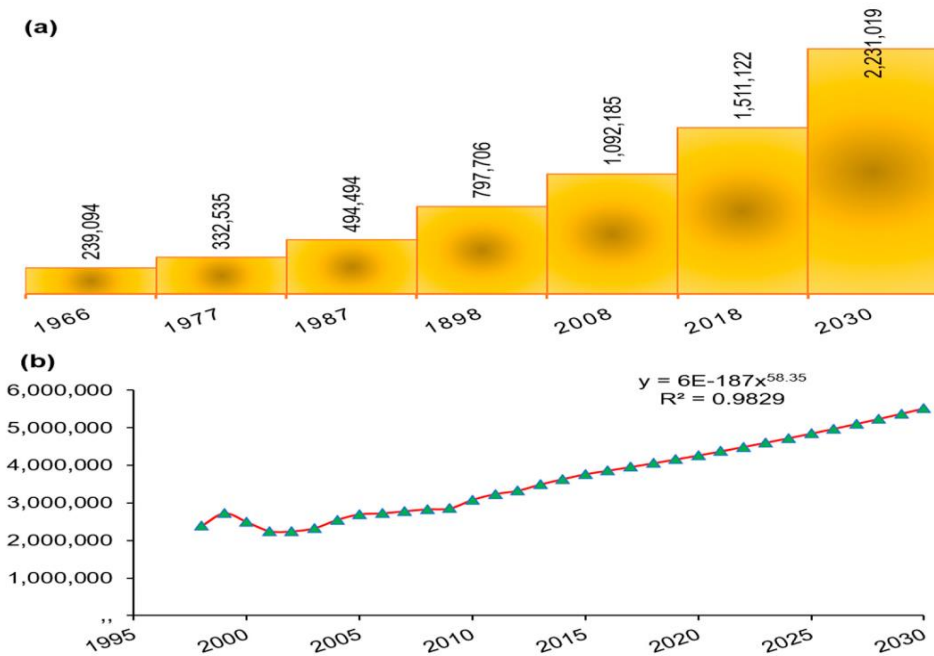


Figure 29. Evolution of the size of the human population (in millions) (a), and the number of livestock (sheep and goats) (in millions of heads) (b) in the study area over time (Year). Future prediction for the year 2030 was calculated using the mean annual growth rate (3.3%) of the period 2008–2018 in the case of population size, and the power function in the case of livestock number.

4.4. Machine Learning-Based Desertification Assessment:

The predictive performance of the Random Forest (RF) and XGBoost classifiers was evaluated using an independent hold-out validation dataset comprising 389 samples. Both models demonstrated high and consistent classification accuracy, achieving identical overall accuracies of 0.94 and macro-averaged F1-scores of 0.94 (Tables 11 and 12). These results indicate strong model capability in mapping desertification severity across heterogeneous dryland environments.

At the class level, both classifiers exhibit high precision and recall across all five desertification categories. The non-desertification class is identified with particularly high reliability (precision = 0.96; recall = 0.98), while the severe desertification class

also demonstrates strong performance, with F1-scores of 0.96 for XGBoost and 0.95 for Random Forest. In contrast, the intermediate classes (Slight, Moderate and High desertification) showed slightly lower, but still good, classification performance with F1-scores between 0.91 and 0.93. The lower accuracy for these classes is largely attributed to confusion between adjacent severity levels, particularly between Slight–Moderate and Moderate–High categories. This pattern reflects the gradual and continuous nature of desertification processes where class boundaries are inherently less clear-cut.

Table 11. Classification Performance of the XGBoost Model.

Class	Precision	Recall	F1-Score	Support
Non	0.96	0.98	0.97	91
Slight	0.92	0.92	0.92	71
Moderate	0.93	0.89	0.91	71
High	0.92	0.95	0.93	82
Severe	0.97	0.95	0.96	74
Accuracy			0.94	389
Macro Avg	0.94	0.94	0.94	389
Weighted Avg	0.94	0.94	0.94	389

Table 12. Classification Performance of the Random Forest Model

Class	Precision	Recall	F1-Score	Support
Non	0.96	0.98	0.97	91
Slight	0.92	0.93	0.92	71
Moderate	0.93	0.92	0.92	71
High	0.92	0.93	0.92	82
Severe	0.97	0.93	0.95	74
Accuracy			0.94	389
Macro Avg	0.94	0.94	0.94	389
Weighted Avg	0.94	0.94	0.94	389

Evaluated on the independent hold-out validation set (n=389).

The confusion matrices further illustrate the classification performance of both models (Figure 30). High values along the diagonal confirm strong predictive accuracy, while off-diagonal elements are primarily concentrated between adjacent classes, indicating transitional ambiguity rather than systematic misclassification.

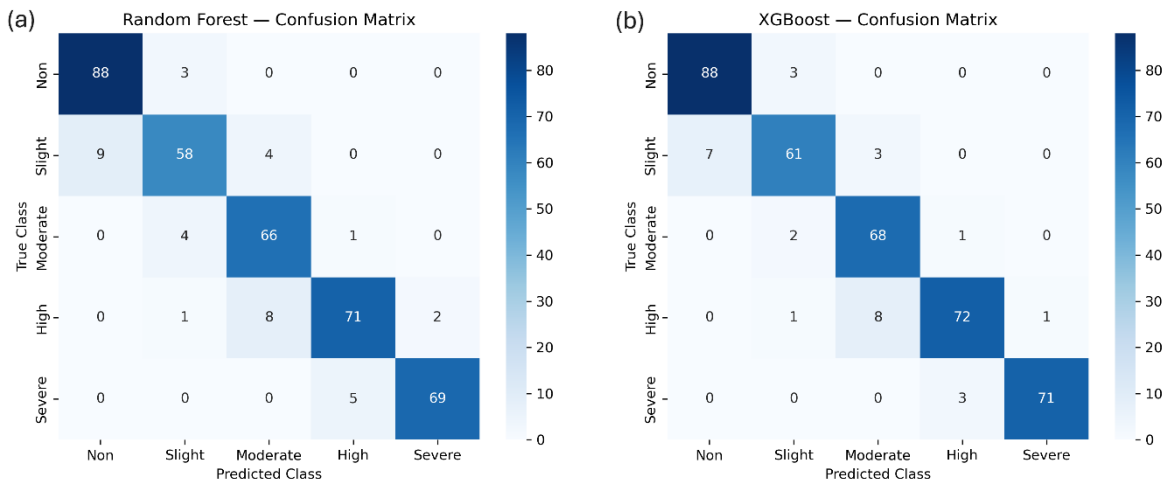


Figure 30. Confusion matrices for (a) XGBoost and (b) Random Forest models on the hold-out validation set.

4.4.1. Spatial Cross-Validation and Model Generalization:

To assess model robustness and spatial transferability, a spatial cross-validation (SCV) framework was implemented and compared with standard random cross-validation (CV) (Figure 31). The results demonstrate a high degree of consistency between the two validation strategies, indicating stable model performance across both random and spatially structured data partitions.

Although a slight reduction in performance metrics is observed under the SCV scheme, overall accuracy remains comparable to that obtained using standard CV. This marginal decrease suggests that model performance is not strongly influenced by spatial autocorrelation, indicating that the classifiers effectively capture the underlying relationships between desertification severity and environmental variables rather than relying on spatial proximity. Importantly, model performance remains stable across different spatial folds, including areas characterized by diverse ecological and climatic conditions. This consistency indicates that the learned classification rules are spatially transferable and not confined to the specific locations used for training.

The close agreement between standard and spatial cross-validation confirms that both Random Forest and XGBoost models effectively capture the biophysical drivers of desertification. This robustness is particularly important for regional-scale applications, where predictions must be extended to areas lacking ground reference data. Overall, the results demonstrate that the proposed framework delivers reliable and generalizable predictions across heterogeneous dryland environments.

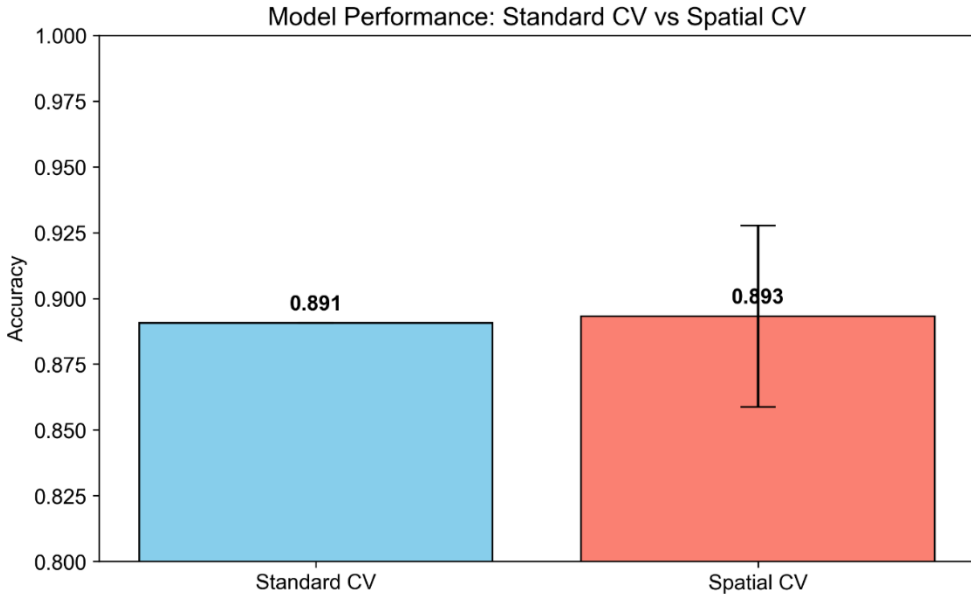


Figure 31. Comparison of Standard and Spatial Cross-Validation Performance for Desertification Severity Classification.

Bar chart showing model accuracy comparison between standard 10-fold cross-validation (0.891) and 5-fold spatial cross-validation (0.893 ± 0.035). Error bars represent standard deviation across spatial folds. The comparable performance indicates that the model generalizes well across spatially independent regions and is not overfitting to local spatial autocorrelation patterns.

4.4.2. Hyperparameter Optimization and Model Selection:

To identify optimal model configurations and ensure robust predictive performance, a stratified 10-fold cross-validation procedure was used to tune key hyperparameters for both Random Forest (RF) and XGBoost classifiers. This step is essential for balancing model complexity and generalization capacity in high-dimensional environmental classification problems such as desertification mapping.

For the XGBoost classifier, three key hyperparameters were optimized: the learning rate (η), maximum tree depth, and number of estimators. The learning rate was tested across a range of values (0.01 to 0.3), tree depths were varied from 3 to 12, and the number of estimators was evaluated between 50 and 500. The optimal configuration ($\eta = 0.1$, maximum depth = 7, and 200 estimators) achieved a mean cross-validation accuracy of 90.68%. In parallel, the Random Forest model achieved comparable performance, with a mean accuracy of 89.07%, using the square-root strategy for feature selection, unrestricted tree depth, and 200 trees.

The hyperparameter sensitivity analysis shows that both models exhibit high stability across a wide range of parameter configurations, indicating limited sensitivity to moderate changes in model complexity. This robustness is illustrated in (Figures 32

and 33), where cross-validation accuracy remains consistently high across different combinations of maximum depth, learning rate, and feature selection strategies. Although both models perform similarly overall, XGBoost shows a slight performance advantage during tuning, particularly at intermediate tree depths and higher learning rates. This suggests a stronger capacity to capture complex non-linear relationships between environmental predictors and desertification classes.

Despite this marginal improvement, the Random Forest model was selected for final mapping and spatial analysis. This decision is based on three key considerations: (i) comparable predictive accuracy to XGBoost, (ii) strong stability under spatial cross-validation, and (iii) the availability of permutation-based feature importance measures, which provide more interpretable and less biased estimates of predictor contributions compared to gain-based metrics.

Accordingly, Random Forest was adopted as the primary classifier for subsequent spatial analyses, ensuring both robust generalization and physically interpretable insights into the drivers of desertification dynamics.

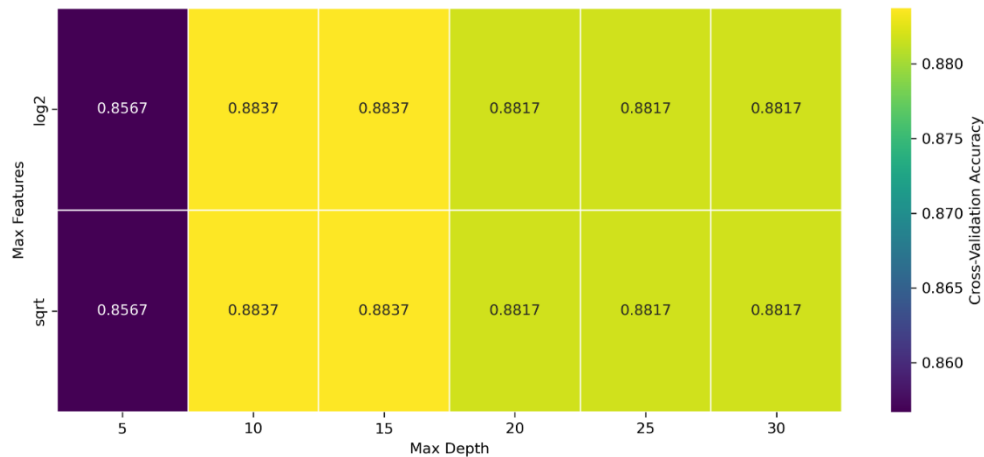


Figure 32. Hyperparameter Sensitivity Analysis for Random Forest: 10-Fold Cross-Validation Accuracy Across Maximum Depth and Maximum Features Configurations.

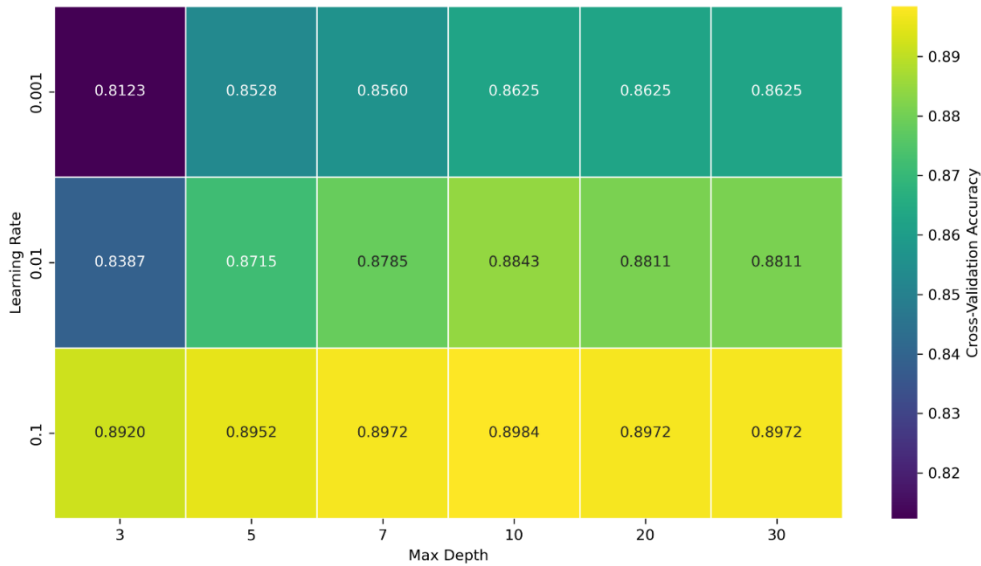


Figure 33. Hyperparameter Sensitivity Analysis for XGBoost: 10-Fold Cross-Validation Accuracy Across Maximum Depth and Learning Rate Configurations.

4.4.3. Spatial Distribution of Desertification Severity:

The spatial distribution of desertification severity derived from RF and XGBoost models reveals clear and consistent geographic patterns controlled by climatic gradients, topography, and land-use intensity (Figures 34 and 35).

Across the study period (2002–2022), the non-desertification and slight desertification classes are predominantly concentrated in the northern humid and sub-humid zones. These areas are characterized by higher precipitation levels, denser vegetation cover, and lower land surface temperatures, which collectively reduce susceptibility to land degradation processes. In contrast, the moderate and high desertification classes dominate the semi-arid steppe and High Plateaus regions, where climatic constraints and anthropogenic pressures jointly intensify land degradation processes. These zones represent transitional environments that are highly sensitive to rainfall variability and land-use pressure.

The severe desertification class is mainly concentrated along the southern margins of the study area, forming a critical ecological transition zone between steppe ecosystems and the Sahara domain. This spatial concentration highlights a persistent hotspot of land degradation vulnerability.

A strong spatial agreement is observed between RF and XGBoost outputs, particularly in the identification of desertification hotspots and extreme severity classes. Minor discrepancies occur mainly in transitional zones between the moderate and high desertification classes, reflecting inherent uncertainty in class boundaries within continuous degradation gradients.

Despite these localized differences, both models consistently reproduce the dominant north–south degradation gradient and capture fragmentation patterns within agro-pastoral landscapes. This confirms the robustness of the machine learning framework for regional-scale desertification mapping.

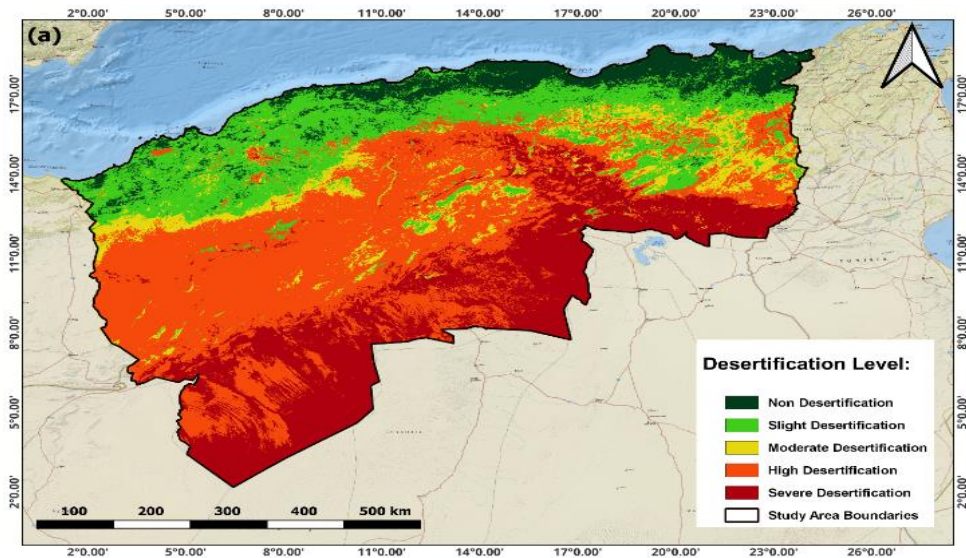


Figure 34. Spatial distribution of desertification severity in Northern Algeria 2002.

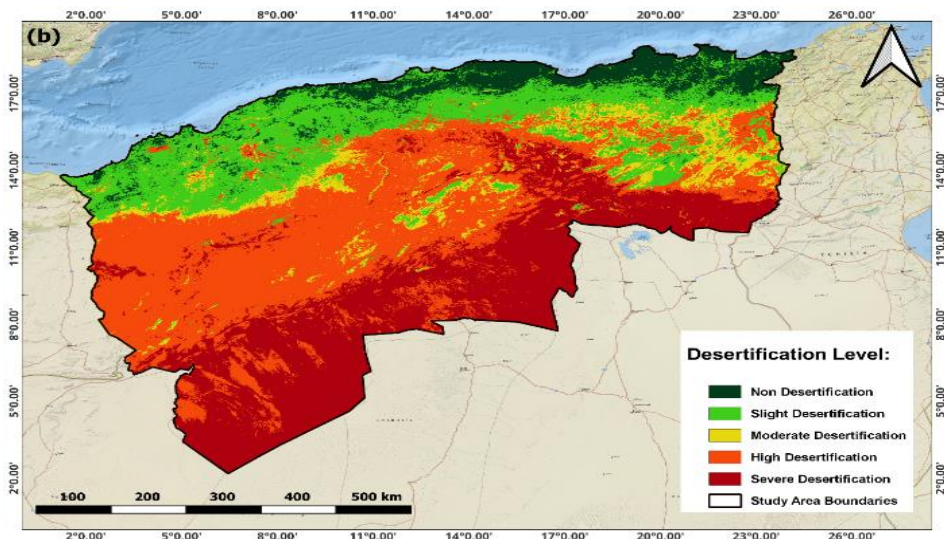


Figure 35. Spatial distribution of desertification severity in Northern Algeria 2022.

4.4.4. Environmental Drivers of Desertification and Predictor Contributions:

To identify the dominant drivers of desertification, variable importance was assessed using gain-based metrics for the XGBoost model and the Gini-based mean decrease in impurity for the Random Forest (RF) model. The resulting importance rankings

show a high degree of consistency between the two classifiers, indicating robust identification of the key environmental controls (Figures 36 and 37).

Across both models, vegetation condition, surface moisture, and radiative properties emerged as the primary determinants of desertification severity. This convergence highlights the central role of vegetation–water–energy interactions in controlling land degradation processes in semi-arid environments. In the XGBoost model, Normalized Difference Water Index (NDWI), blue reflectance, albedo, and Normalized Difference Vegetation Index (NDVI) were identified as the most influential predictors (Figure 36). These variables collectively capture surface moisture availability, vegetation greenness, and soil–vegetation spectral contrasts. In addition, vegetation structural indices such as Fractional Vegetation Cover (FVC), Modified Soil-Adjusted Vegetation Index (MSAVI), and Enhanced Vegetation Index (EVI) contributed substantially to model performance, emphasizing the sensitivity of desertification patterns to both biomass density and canopy structure.

The RF model exhibits a comparable importance structure (Figure 37), with albedo, slope, NDWI, NDVI, and FVC ranking among the most influential predictors. These variables reflect the combined effects of surface energy balance, topographic control on water redistribution, and vegetation dynamics. Thermal and spectral variables, including Land Surface Temperature (LST) and visible reflectance bands (blue and red), provide additional discriminatory power by capturing surface heating and soil exposure conditions. Notably, among the spectral reflectance bands, blue reflectance consistently showed higher variable importance than the NIR and red bands in both models. The prominence of blue reflectance reflects its high sensitivity to soil brightness, surface albedo, and atmospheric aerosols, which are critical indicators of land degradation in sparse-vegetation environments where NIR tends to saturate. Furthermore, variable importance scores in RF and XGBoost are strictly data-driven, quantifying how effectively each predictor reduces classification uncertainty or loss. Therefore, the dominance of blue reflectance represents its genuine discriminatory power for mapping desertification in this semi-arid environment, rather than a methodological artifact.

Soil-related and terrain variables such as the Bare Soil Index (BSI), Topsoil Grain Size Index (TGSI), elevation, and aspect, show relatively lower importance but remain relevant for refining spatial patterns of desertification. Their contribution indicates that, while not primary drivers at the regional scale, these factors modulate

local expressions of land degradation. Overall, the strong agreement between RF and XGBoost importance rankings confirms that desertification in the study area is primarily governed by vegetation condition, moisture availability, and surface energy dynamics, with secondary modulation by topographic and soil properties. This consistency reinforces the robustness of the modeling framework and provides a physically grounded basis for interpreting desertification processes.

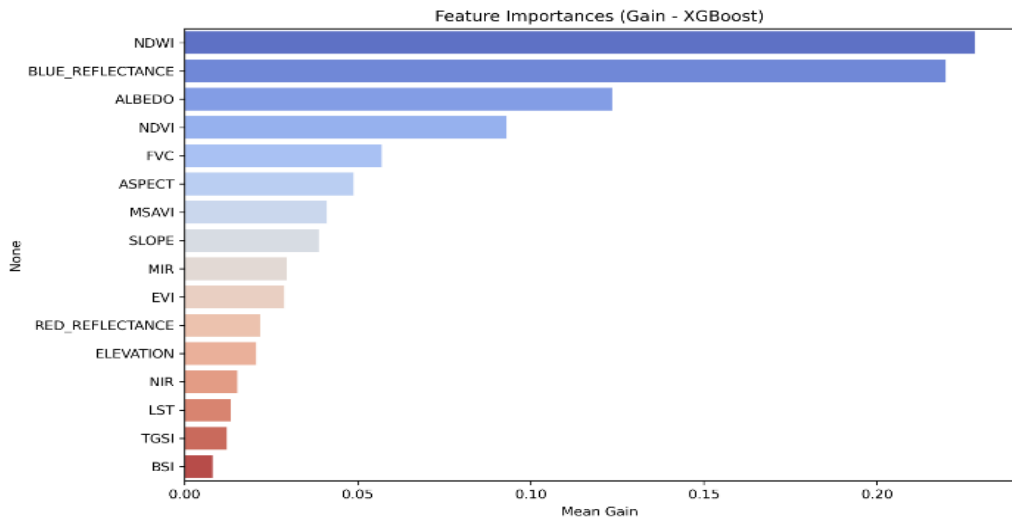


Figure 36. Relative importance of environmental predictors in the XGBoost classification model (Mean Gain).

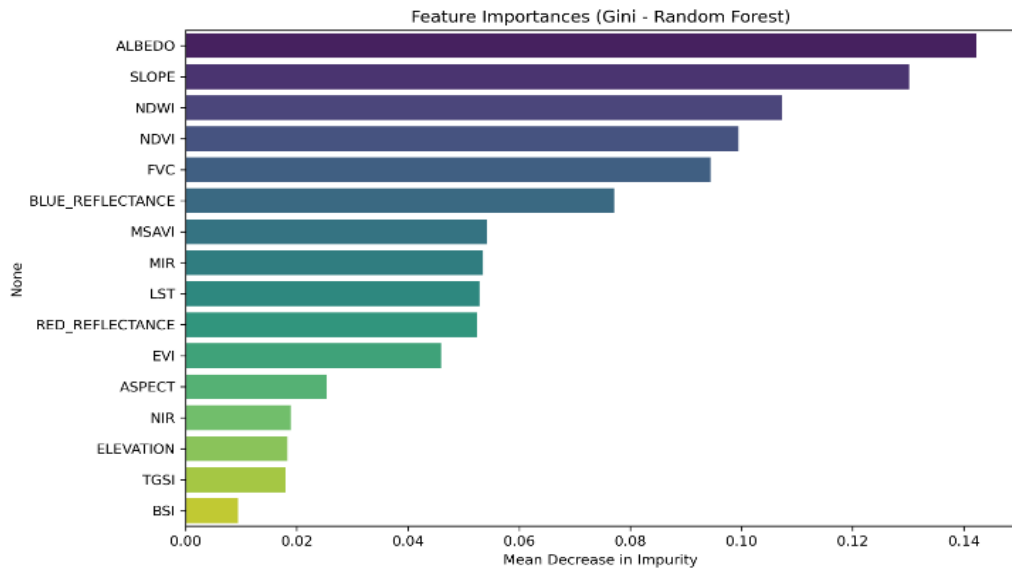


Figure 37. Relative importance of environmental predictors in the Random Forest classification model (Gini Impurity).

4.4.5. Model Agreement and Spatial Uncertainty:

The degree of agreement between the two independent classifiers (RF and XGBoost) serves as a proxy for prediction confidence. Pixel-wise comparison of the 2022 classification maps reveals strong spatial correspondence, particularly for the extreme classes (non-desertification and severe desertification). Areas of disagreement are mainly confined to transitional zones between the slight-moderate and moderate-

high classes, reflecting the inherent continuum of degradation processes rather than systematic model bias.

To further quantify predictive uncertainty, the standard deviation of class probabilities was derived from the Random Forest model (Figure 38). This probability-based metric indicates generally low uncertainty (mean standard deviation < 0.15) across the northern humid zones and the core severe desertification areas in the south. Elevated uncertainty (standard deviation > 0.25) is primarily confined to ecotonal boundaries within the High Plateaus, where spectral signatures of degraded steppe and relatively healthy rangeland overlap.

It is important to note that the uncertainty thresholds (standard deviation < 0.15 and > 0.25) are descriptive divisions based on the observed distribution of standard deviation values across the study area, rather than pre-defined statistical confidence intervals. The low uncertainty observed in the northern humid zones reflects the model's high confidence in classifying intact ecosystems, where spectral signatures are distinct and well-separated. Similarly, the low uncertainty along the southern margin, despite the high severity of degradation, suggests that the biophysical signature of severe desertification is equally distinct and consistently captured by the model. In contrast, the elevated uncertainty in the High Plateaus ecotone reflects the inherent spectral ambiguity of transitional landscapes, where degraded steppe and relatively healthy rangeland exhibit overlapping spectral signatures.

This spatial pattern is consistent with the confusion matrix results, confirming that classification ambiguity is highest in transitional zones where desertification severity shifts between intermediate classes. The low uncertainty observed along the southern margin despite the high severity of degradation suggests that the biophysical signature of severe desertification is distinct and consistently captured by the model. Overall, these results confirm that classification uncertainty is spatially structured and primarily associated with ecotonal boundaries, where spectral signatures of transitional land covers overlap, rather than with model instability or systematic misclassification.

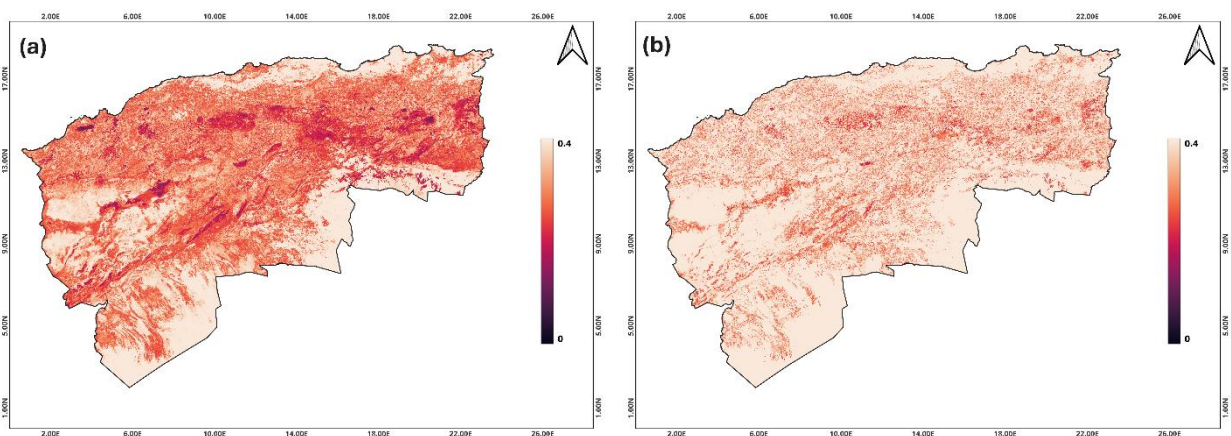


Figure 38. Spatial distribution of prediction uncertainty for (a) RF and (b) XGBoost models. The maps visualize the standard deviation of predicted class probabilities across Northern Algeria.

4.4.6. Provincial-Scale Degradation Trends (2002–2022):

Zonal statistics analysis was conducted to translate pixel-based classification results into actionable administrative insights across the 40 provinces of northern Algeria. The results reveal substantial spatial heterogeneity in both the total extent of degraded land (defined as the sum of high and severe classes) and the rate of change over the 20-year period. While the southern provinces expectedly exhibit the highest absolute extent of degraded land, the change analysis identifies the most dynamic hotspots. The provinces of Tlemcen, Sidi Bel Abbès, and Naâma show the most rapid expansion of high and severe desertification classes between 2002 and 2022 (Figure 39). This pattern indicates a northward migration of degradation pressures from the pre-Saharan steppes into traditionally more productive semi-arid zones. In contrast, coastal provinces such as Tipaza, Algiers, and Béjaïa show negligible net change, with non-desertification classes remaining dominant throughout the study period.

Figure 39 presents a choropleth map of the net change in the extent of high and severe desertification across the 40 provinces of Northern Algeria between 2002 and 2022. The spatial pattern highlights marked regional differences, with the largest increases concentrated in the western and central interior provinces. In contrast, most coastal and eastern provinces show relatively limited net changes, suggesting comparatively more stable desertification conditions over the study period.

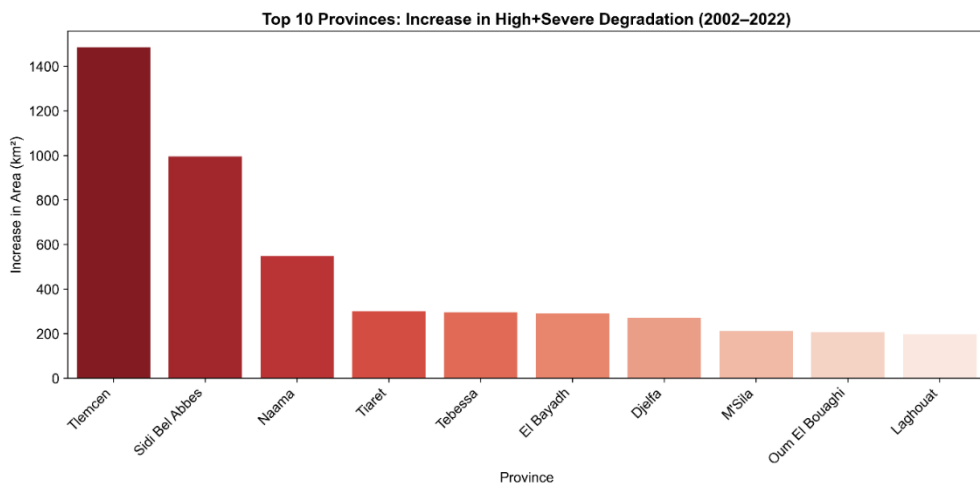


Figure 39. Provincial zonal statistics: Top 10 regions exhibiting the highest net increase in high and severe desertification area (2002–2022).

4.4.7. Future Scenario Projection to 2030:

Based on the observed linear trends in environmental predictors between 2002 and 2022, a forward projection was developed to characterize the potential state of desertification by 2030 (Figure 40). It is important to note that this projection is

illustrative, as it assumes the continuation of current climatic and land-use trajectories into the near future.

The projected map indicates a continued northward expansion of the moderate, high, and severe desertification classes. The most pronounced changes are expected within the transitional steppe zone, particularly across provinces such as Djelfa, M'Sila, and Médéa. In this region, the model predicts a substantial transition from the moderate class to high and severe categories, effectively narrowing the ecological buffer between the productive northern zones and the Saharan south.

By 2030, the model suggests that the severe desertification class may extend approximately 30–50 km further north than its 2022 extent in several sectors, particularly across the western high plains (e.g., Naâma and El Bayadh). In contrast, the northern coastal domain is projected to remain largely stable, with non-desertification classes persisting. This projected stability, however, is contingent upon the absence of major climatic shifts or intensified land-use pressures.

These forward-looking results are intended as a high-level planning tool, highlighting priority areas where proactive land management interventions may be most urgently required over the coming decade.

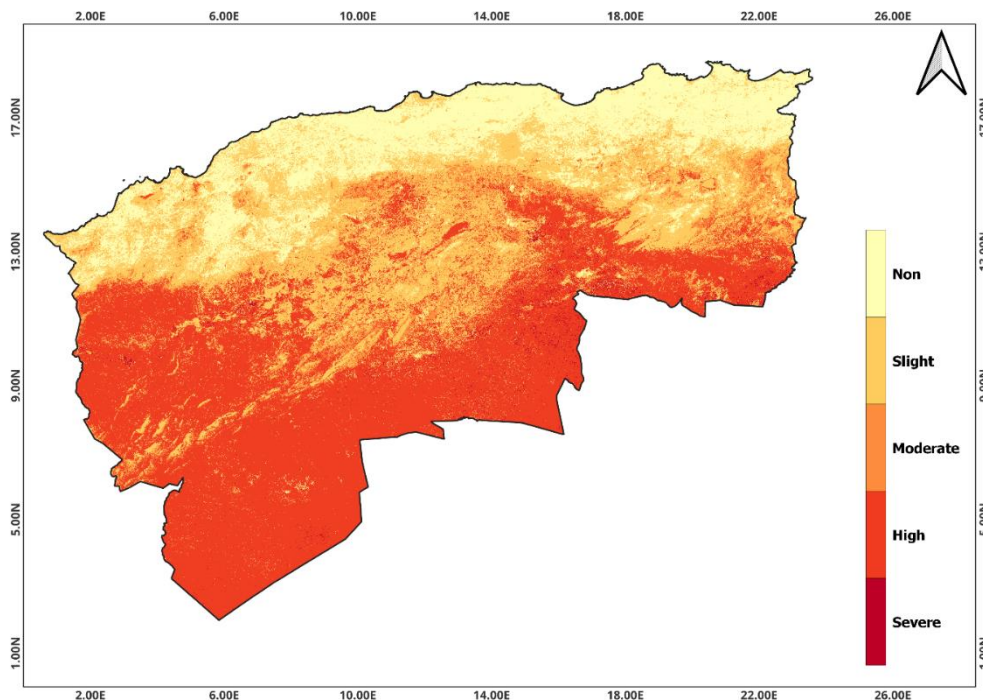


Figure 40. Spatial distribution of desertification severity classes projected to 2030 in Northern Algeria.

5. Discussion:

5.1. Hydroclimatic Intensification and Regional Aridification:

The multi-scale evidence presented in this dissertation suggests a progressive and statistically significant intensification of drought conditions across northern Algeria, with the post-2015 period marking a distinct shift in the regional hydroclimatic regime. The (SPI), computed at 3-, 6-, and 12-month timescales, indicates a spatially coherent drying trend affecting large portions of the study area, while no significant wetting trends are detected. While it is important to acknowledge that the SPI relies solely on precipitation data and does not explicitly account for temperature-driven evaporative demand, this pattern may reflect not merely short-term climatic variability, but a persistent aridification trajectory that is progressively reshaping the regional hydroclimatic balance.

These findings appear to be supported by independent studies employing diverse datasets and methodological approaches (Ceppi et al., 2025), using the ERA5-Land reanalysis across 16 hydrological basins in northern Algeria for the 1950–2022 period, reported that dry events became increasingly frequent and spatially extensive after 1980. Their analysis showed that the proportion of grid cells with SPI values below -1 exceeded 90% during several major drought episodes, particularly in 2000–2002, 2016, and 2021–2022. Their run theory analysis revealed a fundamental characteristic of drought propagation: as the SPI timescale increased from 3 to 24 months, the number of drought events declined (from 69 to 17), whereas the average duration increased substantially (from approximately 2 to 8 months), accompanied by a corresponding intensification in drought severity.

Oubadi et al., (2024) documented a significant drying trend across 81% of the Algerian steppe territory, with 9.2% of the steppe area transitioning from semi-arid to arid conditions, driven by the combined effects of declining rainfall, rising temperature, and increasing potential evapotranspiration (PET). Similarly, Achour et al., (2020) identified a major hydroclimatic shift in the late 1970s and early 1980s, after which SPI series exhibited a statistically significant trend toward drier conditions, particularly across the western plains.

Critically, Bouabdelli et al., (2020) investigated the propagation of meteorological drought into hydrological drought across three karst basins in northwestern Algeria during 1941–2011. Their findings demonstrated that drought response time is strongly controlled by basin memory effects: karst systems tend to delay the onset of hydrological drought, yet once initiated, drought conditions become more severe and persistent. Under the RCP8.5 scenario, their projections indicate a marked reduction in drought return periods, implying substantially higher drought risk across all basins. The far-future period (2058–2100) is projected to experience more frequent, prolonged, and severe hydrological droughts. These findings support the interpretation that the post-2015 shift may represent a broader hydroclimatic transition that could be translating into tangible water-resource deficits within the region's critical catchments.

The convergence of these independent lines of evidence from SPI-based meteorological drought, RDI-based aridity trends, and hydrological drought propagation suggests that northern Algeria may align with Mediterranean “climate-change hotspot” framework first highlighted by Giorgi and subsequent studies. The “hot drought” mechanism described by (K. Trenberth, 2011; K. E. Trenberth et al., 2014) provides a plausible explanation for this intensification process, whereby rising temperatures amplify precipitation deficits through enhanced evapotranspiration and accelerated soil moisture depletion. As (Mukherjee et al., 2018) et al. emphasized, drought indices that do not incorporate temperature-driven evaporative demand may substantially underestimate future drought severity. In parallel, (Quan et al., 2018) demonstrated that anthropogenic climate change tripled the frequency of flash droughts rapid-onset droughts often accompanied by heat waves across southern Africa. This mechanism appears highly relevant to Mediterranean semi-arid ecosystems, where heat extremes and soil moisture deficits are increasingly occurring simultaneously, thereby intensifying ecosystem vulnerability and accelerating land degradation processes.

Thus, the SPI-derived hydroclimatic trends are not merely statistical artefacts; they appear to be physically reflected in declining NDVI anomalies, deteriorating VCI and VHI conditions (Chapter 4), and the progressive northward expansion of moderate and high desertification classes (Chapter 4). It is important to note that the MODIS-derived indices (250 m to 1 km resolution) may smooth out finer-scale local variability; however, within these spatial limitations. This cross-index coherence, consistently observed across multiple independent studies and datasets, provides robust evidence that northern Algeria has entered a new climatic regime characterized by persistent water scarcity, increasing drought frequency and severity, and declining ecological resilience. These findings carry important profound implications for water resource management, agricultural planning, and long-term desertification mitigation strategies.

5.2. Vegetation Response to Climatic Variability:

The response of vegetation to the intensifying drying trend is neither immediate nor spatially uniform. NDVI anomaly analysis during the growing season reveals a consistent pattern in which most years exhibit positive anomalies (above-average greenness), whereas major drought years, particularly 2016 and 2020–2022 are characterized by pronounced negative excursions. Importantly, a quasi-cyclical pattern with an approximate three-year periodicity is evident, suggesting that vegetation can temporarily recover during wetter intervals. However, the amplitude of these recovery cycles has progressively diminished over time, and the post-2020 recovery phase has remained particularly weak. These observations point to a gradual decline in ecosystem resilience under increasingly recurrent drought conditions.

This episodic recovery followed by progressive deterioration is consistent with fundamental characteristic of semi-arid ecosystems: vegetation memory and lagged ecological responses. As demonstrated by (Bruzzone et al., 2023), vegetation dynamics in water-limited environments are often governed not only by current climatic conditions, but also by the cumulative legacy effects of previous drought and

recovery periods. In the rangelands of North Patagonia, Bruzzone et al. demonstrated that vegetation sensitivity to water availability, temperature, and radiation evolves dynamically rather than remaining constant through time. Their non-autonomous growth model showed that different ecosystems may experience either a gradual loss of resilience or an abrupt decoupling from climatic forcing.

In northern Algeria, the diminishing amplitude of NDVI recovery cycles after 2020 may indicate a comparable erosion of ecological buffering capacity. The system appears increasingly unable to fully recover after successive drought events, a pattern that aligns with the progressive decline in ecosystem resilience reported across multiple dryland regions by (G. Yin & Zhang, 2023).

The weak-to-moderate correlation between NDVI anomalies and rainfall (Spearman's $\rho < 0.4$) may not necessarily be interpreted as a methodological limitation, but rather as an expression of the inherent non-linearity and buffering capacity of semi-arid ecosystems. Soil moisture storage, vegetation memory effects, and species-specific drought tolerance introduce temporal lags and response attenuation, thereby weakening direct year-to-year climatic correlations. It is important to note that these correlations were computed at the growing-season (annual) scale to assess interannual variability and long-term vegetation trends, in accordance with the study objectives. While finer temporal-scale analyses (e.g., monthly or dekadal) could capture more rapid intra-annual responses, the annual approach is methodologically appropriate for evaluating multi-decadal vegetation dynamics and drought impacts. (Ren et al., 2024) demonstrated in the Mu Us Sandy Land that soil functions as a low-pass filter, generating a phase lag of approximately 1–2 months between precipitation and soil moisture response, and up to 3 months in densely vegetated grasslands. Consequently, drought indices that fail to account for these delayed responses may underestimate or misrepresent actual vegetation stress conditions. In our study, the stronger correlation observed at shorter timescales (SPI-3 vs. VHI) relative to longer timescales (SPI-12 vs. VHI) indicates that vegetation in northern Algeria is primarily sensitive to seasonal-scale precipitation variability. Supporting this interpretation, (T. Hu et al., 2020) demonstrated that temperature-based drought indices, including TRI and TCI, provided an approximately one-month lead over greenness-based indicators such as VCI in detecting emerging agricultural drought. Their findings confirm that thermal stress signals tend to appear before visible vegetation degradation becomes detectable.

Beyond moisture deficits, the growing influence of thermal stress is becoming increasingly evident. During the 2020–2023 drought period, the Temperature Condition Index (TCI) revealed that elevated land surface temperatures intensified vegetation deterioration even in areas where rainfall deficits remained only moderate. Since TCI is an inverse index where lower values indicate higher thermal stress, the observed declining trends in TCI across 0.94% of the study area confirm a progressive increase in thermal stress, consistent with the broader regional warming trend. Similarly, (Mehmood et al., 2025) identified severe temperature anomalies as the dominant driver of vegetation stress in southern Thailand, while (Lima et al., 2023)

reported that extremely low TCI values in semi-arid Brazil coincided with catastrophic crop losses.

Likewise, (Kloos et al., 2021) demonstrated that TCI and VHI exhibited stronger correlations with soil moisture deficits and crop yield anomalies than VCI alone, because thermal indicators more directly capture the immediate energy-balance response to water stress. Their results further showed that this relationship is strongest in water-limited environments characterized by a negative NDVI–LST relationship, which corresponds to the methodological framework adopted in the present study. These findings reveal a coupled land–atmosphere feedback mechanism: as vegetation cover declines, the surface energy balance is altered through competing mechanisms. While surface albedo increases (reflecting more shortwave radiation), the loss of vegetation also eliminates evaporative cooling through transpiration. In water-limited environments like Northwest Algeria, this loss of latent heat flux dominates, causing a shift toward increased sensible heat flux that intensifies land surface temperatures (as evidenced by our TCI results showing progressive thermal stress). This warming enhances evaporative demand and accelerates soil moisture depletion, creating a positive feedback loop that further exacerbates drought conditions and vegetation stress. Almouctar et al., (2024), using the Vegetation Health Index (VHI) in the Niamey region, reported that the spatial extent of extreme drought expanded from 7.4% to 13.9% between 2013 and 2019, accompanied by a weakening inverse NDVI–LST relationship.

Accordingly, the greater sensitivity of VHI relative to VCI in the present study confirms that vegetation health in northern Algeria is governed by the combined effects of precipitation deficits and rising temperatures, rather than by rainfall variability alone. Importantly, the relative contributions of moisture and thermal stress vary according to land cover characteristics and aridity conditions. (Bento et al., 2018) demonstrated that in semi-arid Mediterranean environments, the Vegetation Condition Index (VCI) should receive a higher weighting ($\alpha > 0.6$) within the VHI formulation because water availability represents the dominant limiting factor. This interpretation is consistent with the original VHI formulation proposed (Kogan, 1995a), who assigned a weight of 0.7 to VCI and 0.3 to TCI. Similarly, (Bento et al., 2018) found that more than 80% of global dryland pixels exhibit an optimal weighting coefficient greater than 0.5, with a median value of 0.68. In the Algerian steppe context, these findings imply that vegetation health remains primarily controlled by moisture deficits, while increasing temperatures progressively intensify and amplify drought impacts.

The temporal dimension of this vegetation–climate coupling is equally important. (Zhao et al., 2021) showed that VCI responds primarily to precipitation variability in grasslands, whereas TCI and VHI exhibit strong sensitivity to temperature across multiple land-cover types. Their findings highlight the importance of multi-index approaches in heterogeneous landscapes such as northern Algeria.

Similarly, (Alito et al., 2025) reported strong positive correlations between VHI and soil moisture, alongside strong negative correlations between NDVI and LST in the

Ethiopian highlands. Their study further demonstrated that replacing NDVI with NDWI and incorporating day–night LST differentials can enhance drought monitoring performance in environmentally complex regions. Vegetation response also varies substantially according to plant functional type. (G. Yin & Zhang, 2023) found that forests possess stronger buffering capacity against drought stress, whereas crops and grasslands respond more directly and rapidly to drought conditions. This type-specific sensitivity implies that NDVI signals derived from heterogeneous landscapes integrate multiple ecological response functions, thereby weakening aggregate NDVI–rainfall correlations.

Supporting this interpretation, (Ghobadi & Badehian, 2025) observed in the semi-arid region of Lorestan, Iran, that VHI provided the most spatially coherent and temporally consistent indicator of progressive ecosystem degradation.

Finally, (Fayech & Tarhouni, 2021) demonstrated in southern Tunisia that the expansion of irrigation can weaken or even eliminate NDVI–rainfall relationships, as vegetation becomes progressively less dependent on direct precipitation inputs. As irrigated agriculture expands across parts of the High Plateaus, a similar decoupling may emerge, further complicating the interpretation of satellite-derived drought indices. These findings underscore the importance of integrating remote sensing analyses with land-use and agricultural management information when assessing drought dynamics in semi-arid regions.

Overall, the vegetation response to climatic variability in northern Algeria is characterized by pronounced non-linearity, temporal lags, ecological buffering, and dynamically shifting sensitivities. The increasing influence of thermal stress, the dominant role of moisture limitations in semi-arid land covers, and the progressive erosion of ecological memory collectively suggest a system experiencing a gradual decline in resilience under recurrent drought exposure. It is important to note that the MODIS-derived NDVI and LST data (250 m to 1 km resolution) may smooth out fine-scale local heterogeneity and mixed-pixel effects; however, within these spatial constraints, integrated indicators such as the Vegetation Health Index (VHI) provide a more physically meaningful and operationally reliable representation of vegetation condition than single-factor indices based solely on greenness or precipitation variability.

5.3. Interaction Between Drought and Land Degradation Processes:

The drought-induced decline in vegetation does not occur in isolation; rather, it appears to interact directly with land degradation processes to generate a self-reinforcing degradation spiral. As perennial vegetation cover diminishes, bare soil becomes increasingly exposed to wind and water erosion, soil organic matter declines, and the capacity of soils to retain moisture is progressively reduced. Consequently, each successive drought exerts a greater ecological impact because the system's natural buffering capacity has already been weakened. This feedback mechanism is consistent with the dryland degradation framework described by (Ravi et al., 2010). The positive relationship between drought intensity and soil erosion rates, documented in comparable drylands of Tunisia by (Terwayet Bayouli et al.,

2023) and in India by (Masroor et al., 2022), suggests that these processes are strongly interconnected. Drought-induced vegetation loss accelerates both water and wind erosion, which subsequently reduces soil moisture storage capacity and intensifies the impacts of future dry periods.

This degradation feedback is further amplified by the preferential removal of fine and nutrient-rich particles through wind erosion, leading to rapid declines in soil organic carbon stocks and progressive deterioration of soil fertility, as demonstrated by (Chappell et al., 2019). At the landscape scale, this vegetation–degradation coupling is mediated by both hydrological and aeolian connectivity. As bare soil patches expand and become increasingly connected, runoff generation and sediment transport intensify, resulting in greater losses of water, nutrients, and fine particles from the ecosystem, as reported by (Mayor et al., 2013; Saco, 2018).

This connectivity-driven feedback can accelerate degradation once a critical vegetation threshold is crossed. Empirical evidence from long-term monitoring in China by (Y. Gao et al., 2011). demonstrated that when vegetation cover declines below approximately 20%, soil erosion becomes self-sustaining, thereby severely limiting the potential for natural ecosystem recovery. Similarly, modelling studies on the Loess Plateau have identified lower (10%) and upper (40%) vegetation cover thresholds for effective wind erosion control, below and above which the protective function of vegetation is either negligible or saturated, as shown by (C. Jiang et al., 2019).

The observed failure of VHI to recover during the 2020–2023 period across extensive areas, together with the clear dominance of degradation over improvement trends, strongly suggests that comparable hydroclimatic and ecological thresholds may have been exceeded in northern Algeria’s steppe ecosystems. However, it is important to note that this interpretation is based on regional-scale remote sensing data; definitive confirmation of such ecological thresholds would require targeted field surveys and local ground-truthing to validate these satellite-derived observations. This implies a potential shift toward a persistent degraded state, in which recovery capacity is substantially constrained and system resilience is markedly reduced.

The spatial pattern of this degradation concentrated in the interior steppe provinces of Saïda, Tiaret, and Mascara coincides with areas that also experienced substantial losses of pine plantations associated with the Green Dam initiative. This spatial convergence highlights the overlap between drought impacts and human-induced land cover change. Moreover, in semi-arid Mediterranean environments, grasslands and steppe vegetation may exhibit greater drought resilience than forests due to their lower evapotranspiration demands and more flexible phenological responses to water availability (Mahcer et al., 2024; G. Yin & Zhang, 2023). However, soil erosion itself significantly constrains potential vegetation biomass recovery, as demonstrated by (Luo et al., 2023).

Taken together, these findings suggest that the replacement of native steppe vegetation with poorly adapted pine plantations likely intensified erosion–drought

feedbacks in these provinces, thereby amplifying long-term land degradation dynamics.

5.4. Anthropogenic Drivers of Land Degradation: A Coupled Human–Environment System:

Climate variability alone cannot explain the observed degradation trends. Our findings on LULC dynamics in the Moudjbara region of Djelfa Province, suggest that anthropogenic pressures, particularly livestock overgrazing, cropland expansion, urban growth, and plantation harvesting have been at least as influential as climatic stressors in driving land use/land cover (LULC) change.

This pattern is consistent with coupled human–environment system framework (B. L. Turner et al., 2003) described by Turner et al., in which social and ecological processes are tightly interconnected, and where anthropogenic drivers frequently dominate degradation trajectories, as further emphasized by (D. Xu et al., 2024).

Although the study spans approximately five decades, the 1972 baseline, derived from Landsat MSS imagery at 60 m spatial resolution, was used primarily to characterize the initial landscape condition before the implementation of the Green Dam programme. The subsequent assessments for 1989–2019 were based on Landsat TM/ETM+/OLI imagery at 30 m spatial resolution, providing greater consistency for analysing changes across the later observation periods. The results indicate a dynamic land-cover trajectory rather than a simple linear progression. The conversion of degraded steppe to open plantations reflects the implementation and expansion of the Green Dam programme, whereas the subsequent conversion of open plantations back to degraded steppe indicates substantial vegetation degradation and loss of plantation cover under the combined influence of climatic and anthropogenic pressures. Although the latter transition results in a land-cover class similar to the original 1972 condition, it does not represent a return to the same ecological state. Instead, it reflects a substantial loss of vegetation biomass and associated ecosystem services and therefore represents a meaningful long-term land-cover change rather than seasonal or temporary variability.

The non-linear trajectory of the Green Dam characterized by rapid expansion during 1972–1989, subsequent decline in 1989–1999, partial recovery in 1999–2009, and pronounced collapse in 2009–2019 cannot be attributed to climatic variability alone. Rather, it reflects the combined influence of policy decisions, land-use conflicts, and broader socio-economic pressures.

Local pastoral communities, whose livelihoods are heavily dependent on livestock grazing, frequently opposed plantation expansion because it reduced the extent of available rangelands. Consequently, many pine plantations were either deliberately harvested or progressively transformed into sylvo-pastoral systems subjected to intense grazing pressure. In addition, the widespread establishment of monospecific stands of *Pinus halepensis* increased ecological vulnerability to the pine processionary caterpillar, which contributed to the degradation and destruction of extensive reforested areas. Similar experiences with large-scale afforestation initiatives in the Sahel have shown that, in the absence of meaningful community

participation, such projects frequently lead to elite capture and the marginalization of the most vulnerable resource users, ultimately undermining both ecological sustainability and social objectives (B. L. Turner et al., 2003).

This socio-ecological vulnerability is further intensified by demographic pressures. The population of Djelfa Province has grown exponentially, while livestock numbers are projected to exceed 5 million heads by 2030, greatly surpassing the ecological carrying capacity of the steppe environment. Consequently, the failure of the Green Dam cannot be interpreted solely as a technical or ecological shortcoming; rather it could reflect broader challenges in adaptive governance that did not adequately incorporate the social and economic realities of steppe communities.

This interpretation is particularly important because it suggests that land degradation should perhaps be viewed not just as purely biophysical phenomenon, but also as complex socio-environmental issue that requires integrated ecological, economic, and governance-based solutions.

5.5. Ecological Vulnerability of the Green Dam: Why Natural Steppes Are More Resilient:

The trajectory of the Green Dam offers valuable lessons for dryland restoration, demonstrating that the large-scale replacement of natural steppe vegetation with dense, even-aged tree plantations may have represented a significant ecological mismatch. Indigenous steppe species such as *Artemisia herba-alba*, *Lygeum spartum*, and *Stipa tenacissima* possess long-term evolutionary adaptations to semi-arid climatic variability, providing substantially greater resilience to drought and environmental stress than monospecific stands of *Pinus halepensis*. First, natural steppe vegetation appears to exhibit significantly lower evapotranspiration demands and more flexible phenological responses to sporadic rainfall, potentially enabling more efficient utilization of limited precipitation events without substantially depleting soil moisture reserves (T. Feng et al., 2025; Y. Yang et al., 2022). In contrast, plantations of *Pinus halepensis* frequently exceed local hydrological carrying capacities. Empirical evidence from comparable semi-arid restoration environments demonstrates that artificial afforestation within steppe ecotones can increase the biomass-to-soil water overload ratio to values as high as 5.35, thereby inducing severe soil desiccation and undermining long-term ecosystem stability (R. Jiang et al., 2021; Y. Yang et al., 2022). Second, the structural simplicity of monospecific pine stands may amplify vulnerability to both biotic and abiotic disturbances. Monoculture plantations lack the functional diversity required to buffer against climatic extremes and pest outbreaks, whereas mixed-species and native-dominated ecosystems can more effectively disrupt pest population dynamics and enhance resistance at the community level (Hezil et al., 2024; Hisano et al., 2024; D. Liu et al., 2022). Field assessments in the Djelfa Province further suggest that rehabilitated mixed-species stands exhibit significantly lower defoliator infestation rates than *Pinus halepensis* monocultures. In parallel, native steppe vegetation appears to demonstrate strong spontaneous recovery capacity and maintains high floristic richness, including a substantial proportion of therophytes (57.8%) adapted to arid climatic cycles, despite persistent anthropogenic and climatic pressures

(Ilhame et al., 2025). Furthermore, dryland ecosystems depend on self-organized spatial vegetation patterns to preserve soil multifunctionality under increasing aridity. Artificially imposed uniform canopy structures can disrupt these adaptive ecohydrological feedbacks, thereby potentially pushing the system toward critical ecological thresholds beyond which natural recovery becomes increasingly constrained and potentially self-limiting (Kéfi et al., 2024). Consequently, the Land Change Modeler projection for 2029, which indicates continued decline of open plantations and their progressive conversion into degraded and erosion-prone bare surfaces, may reflect the inherent challenges and potential unsustainability of rigid afforestation approaches within water-limited steppe ecotones. In contrast, well-established natural vegetation exhibits comparatively stable hydrological and biogeochemical functioning, highlighting that resilience in dryland ecosystems is fundamentally linked to functional diversity, species complementarity, and close adaptation to site-specific hydroclimatic thresholds (Chazdon et al., 2024; T. Feng et al., 2025). These findings provide encouraging support for a potential paradigm shift away from conventional afforestation strategies toward ecological restoration approaches that prioritize assisted natural regeneration, structural heterogeneity, and respect for local water-carrying capacities. By working with rather than against, the adaptive capacities of native steppe ecosystems, restoration initiatives are more likely to achieve long-term sustainability while reducing the risks of hydrological degradation and progressive desertification.

5.6. Reliability of Machine Learning for Desertification Assessment:

The machine learning component of this dissertation, based on the Random Forest (RF) and XGBoost classifiers, demonstrates that data-driven approaches can help overcome many of the limitations associated with traditional index-based methods. The high classification accuracy (overall accuracy > 90%), strong spatial generalization capacity evidenced by the close agreement between spatial and random cross-validation results and stable performance across heterogeneous eco-climatic zones collectively indicate that the models successfully captured fundamental biophysical relationships rather than overfitting to local spatial autocorrelation patterns (K. Feng et al., 2022; S. Feng et al., 2022; C. Kumar et al., 2025).

What is conceptually important is understanding why machine learning approaches succeed where conventional linear models often struggle. Desertification is inherently a non-linear, threshold-driven, and multi-causal process, governed by complex interactions among climatic variability, vegetation dynamics, soil properties, topography, and anthropogenic pressures (Kéfi et al., 2024; Webb et al., 2025). The relationships between environmental predictors such as NDVI, albedo, and LST and desertification severity involve complex interactions, feedback mechanisms, and context-dependent responses. Ensemble tree-based methods such as Random Forest (RF) and XGBoost can implicitly capture these non-linear relationships without requiring explicit a priori assumptions regarding their functional form or interactions (Berdyayev et al., 2024; K. Feng et al., 2022; S. Feng et al., 2022). The strong agreement between the RF and XGBoost feature importance rankings, which identify NDWI, NDVI, and albedo as the primary predictors (with

LST and topographic variables providing additional, secondary discriminatory power), provides important ecological plausibility to the modelling framework. In semi-arid environments, desertification fundamentally represents a process of vegetation decline and increasing soil exposure, which subsequently modifies surface albedo and alters the surface energy balance (K. Feng et al., 2022; S. Feng et al., 2022). The high importance of NDWI further underscores the critical role of moisture availability in controlling desertification dynamics, as similarly reported by (N. Wang et al., 2024; Z. Yang et al., 2022). In parallel, the contribution of slope highlights the influence of topographic regulation on runoff generation and water redistribution processes, consistent with the findings of (K. Feng et al., 2022). Moreover, the uncertainty map derived from the standard deviation of class probabilities shows that classification ambiguity is highest within the High Plateaus ecotone, where degraded steppe vegetation and relatively healthy rangelands exhibit overlapping spectral signatures. This should not be interpreted as a model limitation, but rather as an accurate representation of the inherently continuous nature of desertification processes. Because degradation transitions occur along gradual ecological gradients, class boundaries are intrinsically fuzzy, and the model appropriately assigns higher uncertainty to areas where the remote sensing signal is less distinct (C. Kumar et al., 2025; Ramezan et al., 2019). In contrast, the low uncertainty observed in both the northern humid zones and the core severe desertification areas indicates that the biophysical signatures of intact ecosystems and severely degraded lands are sufficiently distinct to be consistently and reliably identified by the model (K. Feng et al., 2022).

Thus, the machine learning framework developed in this dissertation is not only highly accurate, but also interpretable, spatially robust, and ecologically meaningful, consistent with the findings of (Hisano et al., 2024; D. Liu et al., 2022). These characteristics make the framework particularly suitable for operational desertification monitoring and early warning applications in data-scarce dryland regions.

By aligning algorithmic design with key principles of dryland ecological theory, especially the roles of ecological thresholds, self-organization, and functional diversity as resilience mechanisms, as emphasized by (Kéfi et al., 2024) and et al. this approach advances both methodological rigor and practical applicability for sustainable land management. This integration of ecological understanding with data-driven modelling is further supported by (Lü et al., 2021; Morant et al., 2025).

5.7. Convergence of Multi-Scale Evidence: Towards an Integrated

Degradation Framework:

The most significant contribution of this dissertation lies in the convergence of multiple independent lines of evidence across three spatial scales and four complementary analytical approaches, collectively suggesting a unified interpretation: northern Algeria is undergoing progressive environmental degradation driven by the synergistic interaction between intensifying hydroclimatic stress and anthropogenic land-use pressures (Boudjemline & Benlabiod, 2022). At the regional

scale, NDVI anomaly analysis reveals increasing drought frequency and severity, accompanied by weakening vegetation–precipitation relationships and strengthening negative correlations with temperature anomalies, indicating that thermal stress is progressively decoupling vegetation productivity from rainfall availability (L. Wang et al., 2025; S. Zhang et al., 2022). This thermal amplification of drought impacts is consistent with broader dryland research demonstrating that increasing evaporative demand is progressively overriding moisture availability as the dominant constraint on ecosystem functioning (Q. Wang et al., 2024).

At the sub-regional scale, SPI trajectories reveal a distinct post-2015 hydroclimatic regime shift toward persistent dryness, while the VCI, TCI, and VHI indices confirm that vegetation stress closely follows meteorological drought dynamics. The interior steppe provinces consequently emerge as persistent ecological hotspots characterized by heightened vulnerability to degradation processes (T. Feng et al., 2025; Q. Liu, Wang, et al., 2024). At the local scale, the diachronic LULC analysis of the Green Dam reveals a non-linear trajectory characterized by plantation expansion, partial recovery, and subsequent collapse. These dynamics were driven by the combined effects of overgrazing, cropland encroachment, pest outbreaks, and the inadequate integration of local pastoral livelihoods into restoration planning and land management strategies (Merdas et al., 2015; Mohamed et al., 2025). The vulnerability of monospecific plantation stands to defoliator outbreaks and soil desiccation further highlights the ecological mismatch associated with rigid afforestation strategies in water-limited steppe ecotones (Hezil et al., 2024; Kéfi et al., 2024).

Complementing these empirical observations, the RF and XGBoost classifications delineate a pronounced north–south degradation gradient, with moderate and severe desertification classes progressively expanding into areas that were previously considered relatively resilient (K. Feng et al., 2022; Y. Wang et al., 2023). Provincial zonal statistics derived from these classification maps successfully identify the most rapidly degrading areas, thereby enabling spatially explicit and targeted land management interventions (C. Kumar et al., 2025). The strong coherence observed across satellite-derived vegetation indices, meteorological drought metrics, LULC change trajectories, and machine learning classifications demonstrates that desertification in northern Algeria cannot be attributed to a single climatic or anthropogenic driver. Rather, it emerges from the non-linear interaction between hydroclimatic intensification, ecological vulnerability, and unsustainable land-use trajectories operating simultaneously across multiple spatial and temporal scales (Reisman-Berman et al., 2019; B. L. Turner et al., 2003). This integrated multi-scale framework should guide future monitoring protocols, restoration policies, and adaptive land-management strategies by prioritizing context-specific interventions that respect local hydrological thresholds and build upon the inherent resilience of native steppe ecosystems (Kéfi et al., 2024; Q. Liu, Wang, et al., 2024).

5.8. Methodological Limitations and Critical Reflection:

While this dissertation provides robust evidence across multiple analytical scales, several methodological limitations should be acknowledged in order to properly contextualize the findings and inform future research directions.

- The SPI metric reflects only precipitation deficits and does not explicitly account for temperature-driven evaporative demand. Under ongoing warming conditions, this limitation may lead to an underestimation of agricultural and ecological drought severity. Comparative studies conducted in semi-arid environments, including the work of (Worku, 2024), have demonstrated that the SPEI, which incorporates potential evapotranspiration, is capable of detecting greater drought severity and provides more ecologically meaningful thresholds than SPI alone.
Future drought assessments could benefit from integrating SPEI or PDSI to more effectively capture hydroclimatic stress under projected climate warming conditions.
- Temporal Extent of Drought Trend Analysis: Although the 21-year study period (2003–2023) captures recent drought variability and intensification and corresponds to the period for which consistent CHIRPS and MODIS observations are available, it remains relatively short for establishing robust long-term climatic trends. The identified trends should therefore be interpreted as evidence of recent hydroclimatic changes rather than as definitive representations of long-term drought behaviour. Future research could extend the analysis using longer historical precipitation records and reconstructed datasets to place recent drought patterns within a broader climatic context and improve the robustness of long-term trend assessment.
- Temporal Resolution Constraints: The desertification assessment was based on a comparison of two reference years (2002 and 2022) to evaluate long-term changes over a 20-year period. Although this approach effectively captures net structural changes and is widely adopted in regional-scale land degradation studies (Feng et al., 2022; Meng et al., 2021), it does not represent interannual variability, short-term recovery phases, or non-linear degradation dynamics occurring between the reference years. Similarly, the 2030 projection assumes a continuation of the observed linear trends and does not account for potential ecological thresholds, extreme climatic events, policy interventions, or socio-economic changes that could alter future degradation trajectories (D'Acunto et al., 2024). Consequently, the projected map should be interpreted as an illustrative planning scenario rather than a deterministic forecast. Future research should integrate continuous annual time-series analyses and scenario-based modelling frameworks that incorporate multiple climatic, ecological, and land-use pathways to better capture the temporal complexity of desertification processes and improve predictive reliability.
- Temporal Resolution of LULC Analysis: The LULC change analysis and future prediction were based on five discrete observation years (1972, 1989,

1999, 2009, and 2019), covering a 47-year period. Although this temporal sampling captured major land-cover transitions and corresponded to important stages of the Green Dam programme, the relatively long intervals between observations limit the ability to detect short-term fluctuations and rapid land-cover transitions. This limitation is particularly relevant for the periods between 1972 and 2009, when intermediate changes may have occurred without being captured by the selected observation dates. Future research could incorporate annual or biennial Landsat observations, particularly for the post-2000 period, to provide a more detailed representation of land-cover trajectories. Higher temporal resolution would improve the detection of gradual and abrupt changes and provide a stronger basis for future LULC modelling and scenario development using approaches such as the Land Change Modeler.

- MODIS datasets originally available at spatial resolutions ranging from 250 m to 1 km were resampled to 500 m to ensure methodological consistency across analyses. Although this harmonization facilitated multi-source integration, it may have smoothed finer-scale heterogeneity in land cover characteristics and localized degradation patterns. While Landsat imagery at 30 m resolution was employed for detailed LULC change detection, its temporal limitations prevented the development of continuous high-resolution desertification mapping throughout the study period. Recent advances in multi-sensor fusion techniques, together with the expanded capabilities of the Landsat Collection 2 archive, provide promising opportunities to better reconcile spatial and temporal resolution trade-offs in future studies, as discussed by (Radeloff et al., 2024).
- It is important to acknowledge that this study relied primarily on satellite-derived and gridded datasets (CHIRPS and MODIS) without extensive field-based validation. While these remote sensing products have demonstrated reliability in previous regional studies, the drought patterns and trends identified here would benefit from ground-truthing through field surveys, local ecological assessments, and in-situ measurements of soil moisture and vegetation condition. Future research incorporating such local validation would strengthen the confidence in these satellite-derived drought assessments and provide more precise quantification of drought impacts on local ecosystems and communities.
- Satellite-derived indices such as NDWI, BSI, and TGSi provide valuable proxies for vegetation water stress and surface dryness conditions; however, the incorporation of direct soil moisture observations would substantially improve model calibration and validation, particularly for differentiating between meteorological and agricultural drought phases. The development of ground-based monitoring networks, or the integration of satellite-derived soil moisture products such as those from SMAP and SMOS, could help address this limitation in data-scarce dryland environments, as suggested by (L. Liu et al., 2020).

- The NDVI anomaly assessment was conducted at the growing-season (annual) timescale, which limits the ability to detect sub-seasonal vegetation responses to short-term stress events. Monthly or dekadal analyses would provide earlier detection of drought onset and more effectively capture phenological shifts associated with climatic variability, as highlighted by (Bartold et al., 2024).
- Both the LULC (2029) and desertification (2030) projections extrapolate historical trends without explicitly quantifying confidence intervals or the sensitivity of outcomes to alternative future pathways. Incorporating explicit uncertainty visualization such as spatial agreement maps between RF and XGBoost outputs or ensemble-based probability surfaces would improve the transparency and interpretability of the projections for decision-makers and end-users (Giuliani et al., 2020; Y. Wang et al., 2023).
- The 12-year study period (2011–2022), although sufficient to characterize interannual variability in vegetation conditions, is relatively short for establishing robust long-term trends or identifying persistent cyclical patterns. Longer time series would be required to determine whether the observed fluctuations represent recurring climate–vegetation cycles or short-term variability. In addition, the relationship between precipitation and vegetation response varies among years, with some periods showing weak or non-significant correlations. This variability indicates that vegetation dynamics are controlled by multiple interacting factors, including temperature, soil moisture availability, land-cover characteristics, and anthropogenic pressures, rather than by precipitation alone.
- Finally, the correlation analysis in this study was conducted on annual aggregated means to assess interannual variability. Future research utilizing high-frequency monthly time-series data should incorporate time-lag cross-correlation analyses to explicitly capture the delayed ecological response and phenological lags in vegetation response to precipitation variability.

These limitations do not undermine the principal conclusions of this dissertation, but rather highlight important opportunities for methodological refinement and future research development. Future studies should prioritize: (1) multi-index drought assessments that explicitly incorporate temperature-driven evaporative demand; (2) scenario-based modelling approaches capable of representing non-linear degradation pathways; (3) multi-sensor data fusion techniques to better reconcile spatial and temporal resolution trade-offs; and (4) coupled socio-ecological frameworks that explicitly integrate human drivers of land-use and land-cover change.

Advances in these areas would substantially enhance the operational value of remote sensing-based monitoring systems for sustainable land management and early warning applications in data-scarce dryland environments (Kéfi et al., 2024; Q. Liu, Wang, et al., 2024).

5.9. Implications for Environmental Management, Policy, and Future Research:

The findings of this dissertation carry direct and urgent implications for drought and desertification management in northern Algeria, as well as in comparable semi-arid regions worldwide.

- **Drought early warning systems:** The relatively strong relationship observed between SPI-6 and VHI suggests that six-month accumulated precipitation anomalies can function as effective early warning indicators for agricultural drought, potentially providing a lead time of approximately 1–2 months for mitigation measures such as supplementary livestock feeding and water conservation interventions, consistent with the findings of (Luc & Van Viet, 2025).

Operational early warning frameworks should therefore integrate SPI-3 for rapid drought onset detection and SPI-6 for assessing agricultural impacts, alongside real-time vegetation condition indicators. In addition, the incorporation of SPEI would improve system performance by accounting for temperature-driven evaporative demand under ongoing warming conditions (Vicente-Serrano et al., 2010; Worku, 2024).

- **large-scale restoration:** The trajectory of the Green Dam demonstrates that monoculture-based afforestation, implemented without meaningful community participation and without adequate consideration of ecological site conditions, represents an ineffective long-term strategy for desertification control, as emphasized by (M. D. Turner et al., 2021, 2023). Future restoration initiatives should instead prioritize native steppe vegetation species adapted to low precipitation and high-temperature conditions, promote diversified multi-species plantations to reduce vulnerability to pests and climatic stress, and incorporate sylvo-pastoral systems with regulated grazing regimes rather than strict grazing exclusion. These recommendations are consistent with the ecological restoration principles highlighted by (Díaz et al., 2022). In addition, participatory planning processes involving local communities together with equitable benefit-sharing mechanisms are essential to ensure long-term adoption, social acceptance, and restoration success.
- **Targeted interventions in degradation hotspots:** Provincial zonal statistics identified Sidi Bel Abbès Province, Tlemcen Province, and Naâma Province as the most rapidly degrading provinces. These regions should therefore be prioritized for soil conservation programs, sustainable grazing management, and the restoration of perennial native vegetation through assisted natural regeneration approaches. Such strategies are consistent with recommendations proposed by (Birhanu et al., 2024; Friedl et al., 2018; Solomon et al., 2024).
- **Spatially targeted interventions and sustainable livestock management** are essential for reversing degradation within identified hotspot regions. Provincial zonal statistics consistently identify Sidi Bel Abbès Province,

Tlemcen Province, and Naâma Province as priority areas for implementing soil conservation infrastructure, rotational grazing regimes, and assisted natural regeneration initiatives. Furthermore, coupled socio-ecological monitoring frameworks can help ensure that livestock stocking rates remain within ecological carrying capacities, thereby reducing the risk of threshold-driven ecosystem collapse in overexploited steppe ecotones (Rahimi et al., 2021; Slayi et al., 2024).

- **Agricultural adaptation strategies** must transition away from high-risk dependence on rain-fed cereal production toward more climate-resilient farming systems. The weakening relationship between NDVI and precipitation, together with the increasing dominance of thermal stress, indicates that traditional cropping systems are becoming progressively more vulnerable under ongoing climatic change.

Policy frameworks should therefore incentivize the adoption of drought-tolerant cultivars, precision water-conservation practices, and decentralized water-harvesting techniques that are aligned with local hydrological constraints and ecosystem carrying capacities (Xing & Wang, 2024).

- **An integrated and low-cost environmental monitoring framework** should be institutionalized to support evidence-based governance and adaptive land management. The multi-index workflow developed in this dissertation integrating open-access satellite and reanalysis datasets such as MODIS, CHIRPS, ERA5-Land, and Landsat with cloud-based processing platforms like Google Earth Engine—provides a scalable and operational template for national agencies to monitor drought propagation and desertification dynamics in near real time, consistent with the framework proposed by (Hersbach et al., 2020; Muñoz-Sabater et al., 2021).

Operationalizing such a system would facilitate a transition from reactive crisis response toward proactive and anticipatory land management strategies.

- **Future research** should address the methodological limitations identified in this study by integrating direct soil moisture observations to improve the calibration of drought propagation models and by developing hybrid machine learning frameworks that explicitly incorporate socio-economic drivers alongside biophysical variables. In addition, rigorous field-based validation campaigns in ecotonal transition zones are required to better constrain model uncertainty in the most heterogeneous landscapes.

Furthermore, coupling these empirical modelling frameworks with climate scenario projections (RCPs/SSPs) would substantially enhance the predictive capacity of long-term land degradation risk assessments, enabling more robust evaluation of future environmental trajectories under alternative climatic and socio-economic pathways (Ipcc, 2023).

In conclusion, northern Algeria stands at a critical environmental juncture. Intensifying hydroclimatic stress and persistent anthropogenic pressures indicate that passive adaptation is no longer a viable option. Sustainable dryland management

therefore requires a strategic reorientation away from rigid, supply-side afforestation schemes and reactive, crisis-driven responses toward participatory governance approaches that are ecologically aligned and climate-resilient.

The multi-scale analytical framework and empirical evidence presented in this dissertation provide a robust scientific foundation to support and guide this necessary transition in dryland management and policy.

6. Summary

This dissertation investigated the spatiotemporal dynamics of drought, land degradation, and desertification across Northern Algeria through the integration of remote sensing data, climatic datasets, land use/land cover analyses, and machine learning modelling approaches. By combining multi-source satellite observations with statistical and predictive modelling techniques, the study aimed to provide a comprehensive assessment of environmental degradation processes operating across multiple spatial and temporal scales.

The results demonstrate that Northern Algeria has experienced increasingly pronounced environmental stress during recent decades, particularly after 2015, as reflected by the progressive deterioration of vegetation conditions, the intensification of drought episodes, and the expansion of desertification severity classes. The NDVI anomaly analysis revealed substantial interannual variability in vegetation dynamics between 2011 and 2022, with severe drought conditions particularly evident during 2016, 2021, and 2022. These periods were characterized by widespread negative NDVI anomalies, declining vegetation productivity, and extensive spatial expansion of moderate-to-severe drought classes.

The analysis further suggested that rainfall variability may be a primary driver of vegetation response across the region, whereas temperature anomalies exert a more complex and indirect influence through their interaction with evapotranspiration processes and surface moisture deficits.

The multi-index drought assessment conducted for Northwestern Algeria supported the observation of strong temporal variability of meteorological and agricultural drought conditions between 2003 and 2023. The integration of SPI, VCI, TCI, and VHI offered a more detailed representation of drought dynamics than single-indicator approaches alone. The results identified persistent drying trends across several provinces, particularly after 2015, while the correlation analysis demonstrated that vegetation response is most strongly coupled with precipitation anomalies occurring at seasonal to semi-annual timescales. Among the evaluated timescales, SPI-6 exhibited the strongest relationship with VHI, indicating that vegetation health in semi-arid environments responds more effectively to cumulative seasonal moisture conditions than to short-term precipitation variability.

The Mann–Kendall analysis identified significant drying trends across all SPI timescales, with SPI-3 showing the most extensive change: 56% of the study area exhibited significant negative trends, with a mean Sen's slope of -0.10 yr^{-1} . The TCI results require interpretation as an inverse temperature-based index, in which

declining values indicate increasing thermal stress. Accordingly, 0.94% of the study area showed significant warming, expressed as declining TCI values, whereas only 0.09% showed significant cooling. Although these significant trends affected a relatively small proportion of the study area, their spatial distribution indicates an overall increase in thermal stress. The vegetation-based indices broadly reflected this pattern, with VHI indicating a substantially larger area experiencing significant degradation than improvement (4.89% and 0.51% of the study area, respectively).

The LULC analysis of the Green Dam region in Djelfa Province highlighted the substantial nature of the anthropogenic and ecological transformations that have occurred over the last five decades. The historical analysis revealed substantial fluctuations in pine plantation extent, characterized by periods of expansion followed by progressive decline and fragmentation.

The future scenario modelling further suggests that, under continued anthropogenic pressure and increasing climatic stress, open plantations are likely to continue declining by 2029, accompanied by the further expansion of degraded steppe landscapes. These findings highlight the potential vulnerability of large-scale afforestation programs when long-term ecological constraints and human pressures are not adequately incorporated into management and restoration strategies.

The temporal evolution of demographic and livestock indicators further confirmed the significant role of anthropogenic pressure in accelerating land degradation processes. Rapid population growth, increasing livestock densities, overgrazing, and agricultural expansion have contributed substantially to vegetation degradation and landscape instability, particularly within fragile steppe ecosystems. As demonstrated in the local-scale analysis (Section 4.3), rapid population growth, increasing livestock densities, overgrazing, and agricultural expansion have contributed substantially to vegetation degradation and landscape instability, particularly within fragile steppe ecosystems. Furthermore, the interaction between intensifying climatic stress and unsustainable land-use practices therefore emerges as a major driver of desertification across Northern Algeria.

The feature importance analysis suggested that albedo, NDWI, NDVI, FVC, and topographic variables among the most influential predictors governing desertification patterns. While the regional model does not include socio-economic variables directly, the local-scale analysis provides the complementary evidence needed to address the anthropogenic dimension of the research objectives. Collectively, these variables reflect the critical roles of vegetation cover, soil moisture availability, thermal properties, and surface energy balance in shaping land degradation processes.

The agreement analysis between the Random Forest and XGBoost models further supported the consistency and potential reliability of the classification outputs, while simultaneously identifying transitional landscapes and ecologically sensitive zones where classification uncertainty remains comparatively higher.

Overall, the findings of this dissertation demonstrate that desertification in Northern Algeria is not driven by climatic variability alone, but rather by the combined

interaction of recurrent drought events, vegetation degradation, land-use transformation, and increasing anthropogenic pressure. The integration of drought monitoring, land use/land cover dynamics, and machine learning modelling within a unified analytical framework offered a more detailed understanding of land degradation processes than isolated or single-method approaches. From a methodological perspective, this dissertation suggests the importance of integrating multi-source remote sensing datasets, climatic indicators, and advanced modelling techniques for large-scale environmental monitoring. The use of cloud-based platforms such as GEE significantly enhanced the efficiency of satellite data processing and enabled long-term spatiotemporal analyses over extensive geographic areas.

Furthermore, the integration of machine learning techniques offers substantial potential for improving future desertification monitoring and early warning systems, particularly in data-scarce dryland regions.

The findings generated through this research provide valuable scientific evidence to support sustainable land management strategies and environmental decision-making in Algeria. The identification of drought hotspots, rapidly degrading landscapes, and vulnerable ecosystems can assist policymakers and land managers in prioritizing restoration programs, strengthening drought preparedness, and reducing human-induced pressure on fragile dryland systems. Despite the significant contributions of this study, several limitations should be acknowledged. The analysis primarily relied on medium-resolution satellite datasets, which may not fully capture fine-scale ecological variability and localized degradation patterns. In addition, future research could enhance predictive performance through the integration of higher spatial resolution imagery, socio-economic drivers, and advanced deep learning approaches such as convolutional neural networks.

Expanding field-based validation campaigns would further strengthen the ecological interpretation of machine learning classifications and improve model transferability across diverse dryland environments.

In conclusion, this dissertation demonstrates that the integration of remote sensing, climatic analysis, land use dynamics, and machine learning provides a powerful framework for understanding and monitoring land degradation processes in Northern Algeria. The study aims to contribute both methodological insights and practical observations into the mechanisms driving land degradation, while offering a foundational basis for future environmental monitoring, sustainable land management, and climate adaptation strategies in arid and semi-arid regions.

References:

1. Abdelkebir, B., Mokhtari, E., & Engel, B. (2024). Assessment of land use and land cover changes on hydrological responses in the Wadi Soummam

- watershed, Algeria using the HEC–HMS model. *Water Practice & Technology*, 19(9), 3555–3577. <https://doi.org/10.2166/wpt.2024.224>
2. AbdelRahman, M. A. E. (2023). An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. *Rendiconti Lincei*, 34(3), 767–808. <https://doi.org/10.1007/s12210-023-01155-3>
 3. Abdi Nidal & Allaoua Boulehouache. (2024). MAPPING AND DETECTING LAND USE LAND COVER (LULC) CHANGES DYNAMICS OF PER-URBAN SPACES IN CONSTANTINE CONTEMPORARY STATES (NORTHEAST OF ALGERIA) A GEO-SPATIAL METHODS BY USING GIS, REMOTE SENSING, LCM AND GEE PLATFORM FROM 1984 TO 2020. *International Journal of Innovative Technologies in Social Science*, (2(42)). https://doi.org/10.31435/rsglobal_ijitss/30062024/8198
 4. Abdullah, M. H., & Mustafa, Y. T. (2025). Machine Learning and SHAP-Based Analysis of Deforestation and Forest Degradation Dynamics Along the Iraq–Turkey Border. *Earth*, 6(2). <https://doi.org/10.3390/earth6020049>
 5. Abdullahi, M., Elnaggar, A., Omar, M., Murtala, A., Lawal, M., & Mosa, A. (2023). LAND DEGRADATION, CAUSES, IMPLICATIONS AND SUSTAINABLE MANAGEMENT IN ARID AND SEMI ARID REGIONS: A CASE STUDY OF EGYPT. *Egyptian Journal of Soil Science*, 63(4), 0–0. <https://doi.org/10.21608/ejss.2023.230986.1647>
 6. Achite, M., De Marco, A., Caloiero, T., & Ceppi, A. (2025). Multi-scale analysis of drought events in Northern Algeria based on ERA5-Land SPI data. *Euro-Mediterranean Journal for Environmental Integration* 2025 10:5, 10(5), 4179–4193. <https://doi.org/10.1007/S41207-025-00848-5>
 7. Achite, M., Krakauer, N. Y., Wałęga, A., & Caloiero, T. (2021). Spatial and temporal analysis of dry and wet spells in the wadi cheliff basin, algeria. *Atmosphere*, 12(6). <https://doi.org/10.3390/atmos12060798>
 8. Achour, K., Meddi, M., Zeroual, A., Bouabdelli, S., Maccioni, P., & Moramarco, T. (2020). Spatio-temporal analysis and forecasting of drought in the plains of northwestern Algeria using the standardized precipitation index. *J. Earth Syst. Sci*, 129. <https://doi.org/10.1007/s12040-019-1306-3>
 9. Ackerman, S. A., Strabala, K. I., Menzel, W. P., Frey, R. A., Moeller, C. C., & Gumley, L. E. (1998). Discriminating clear sky from clouds with MODIS. *Journal of Geophysical Research: Atmospheres*, 103(D24), 32141–32157. <https://doi.org/10.1029/1998JD200032>
 10. Adair, P. (1983). Rétrospective de la réforme agraire en Algérie (1972-1982). <https://doi.org/10.3406/tiers.1983.4265>
 11. Agarwal, V., Vishvendra Raj Singh, B., Marsh, S., Qin, Z., Sen, A., & Kulhari, K. (2025). Integrated Remote Sensing for Enhanced Drought Assessment: A

- Multi-Index Approach in Rajasthan, India. *Earth and Space Science*, 12(2).
<https://doi.org/10.1029/2024EA003639>
12. AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., & Hain, C. R. (2015). Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysics*, 53(2), 452–480.
<https://doi.org/10.1002/2014RG000456>
 13. AghaKouchak, A., Mirchi, A., Madani, K., Di Baldassarre, G., Nazemi, A., Alborzi, A., Anjileli, H., Azarderakhsh, M., Chiang, F., Hassanzadeh, E., Huning, L. S., Mallakpour, I., Martinez, A., Mazdiyasni, O., Moftakhari, H., Norouzi, H., Sadegh, M., Sadeqi, D., Van Loon, A. F., & Wanders, N. (2021). Anthropogenic Drought: Definition, Challenges, and Opportunities. *Reviews of Geophysics*, 59(2), e2019RG000683. <https://doi.org/10.1029/2019RG000683>
 14. Ahmed, Z., Gui, D., Abd-Elmabod, S. K., Murtaza, G., & Ali, S. (2024). An overview of global desertification control efforts: Key challenges and overarching solutions. *Soil Use and Management*, 40(4), e13154.
<https://doi.org/10.1111/sum.13154>
 15. Akbari, M., & Alizadeh Noughani, M. (2024). Early warning systems for desertification hazard: A review of integrated system models and risk management. *Modeling Earth Systems and Environment*, 10(4), 4611–4626.
<https://doi.org/10.1007/s40808-024-02059-3>
 16. Akbari, M., Shalamzari, M. J., Memarian, H., & Gholami, A. (2020). Monitoring desertification processes using ecological indicators and providing management programs in arid regions of Iran. *Ecological Indicators*, 111, 106011. <https://doi.org/10.1016/j.ecolind.2019.106011>
 17. Akhtar-Schuster, M., Stringer, L. C., Erlewein, A., Metternicht, G., Minelli, S., Safriel, U., & Sommer, S. (2017). Unpacking the concept of land degradation neutrality and addressing its operation through the Rio Conventions. *Journal of Environmental Management, Optimizing the Impact of Science: Translational Research and Stakeholder Engagement to Identify Sustainable Land Management Based Adaptation for Challenges Posed by Environmental Change*, 195, 4–15. <https://doi.org/10.1016/j.jenvman.2016.09.044>
 18. Alahacoon, N., & Edirisinghe, M. (2022). A comprehensive assessment of remote sensing and traditional based drought monitoring indices at global and regional scale. *Geomatics, Natural Hazards and Risk*, 13(1), 762–799.
<https://doi.org/10.1080/19475705.2022.2044394>
 19. AlAmri, A., Alshehri, M., & Alharbi, O. (2026). A Computational Sustainability Framework for Vegetation Degradation and Desertification Assessment in Arid Lands in Saudi Arabia. *Sustainability*, 18(2), 641.
<https://doi.org/10.3390/su18020641>

20. Ali, G. (2009). Desertification in Algeria: Policies and Measures for the Protection of Natural Resources. In H. G. Brauch, Ú. O. Spring, J. Grin, C. Mesjasz, P. Kameri-Mbote, N. C. Behera, B. Chourou, & H. Krummenacher (Eds.), *Facing Global Environmental Change: Environmental, Human, Energy, Food, Health and Water Security Concepts* (pp. 159–173). Springer.
https://doi.org/10.1007/978-3-540-68488-6_10
21. Alipbeki, O., Alipbekova, C., Sterenharz, A., Toleubekova, Z., Aliyev, M., Mineyev, N., & Amangaliyev, K. (2020). A Spatiotemporal Assessment of Land Use and Land Cover Changes in Peri-Urban Areas: A Case Study of Arshaly District, Kazakhstan. *Sustainability*, 12(4).
<https://doi.org/10.3390/su12041556>
22. Alito, K. T., Kerebih, M. S., & Hailu, D. A. (2025). Characterization of Drought Detection With Remote Sensing Based Multiple Indices and SPEI in Northeastern Ethiopian Highland. *Air, Soil and Water Research*, 18.
<https://doi.org/10.1177/11786221251328833>
23. Alliouche, A., & Kouba, Y. (2023). Modelling the spatiotemporal dynamics of land susceptibility to desertification in Algeria. *CATENA*, 232, 107437.
<https://doi.org/10.1016/j.catena.2023.107437>
24. Almouctar, M. A. S., Wu, Y., Zhao, F., & Qin, C. (2024). Drought analysis using normalized difference vegetation index and land surface temperature over Niamey region, the southwestern of the Niger between 2013 and 2019. *Journal of Hydrology: Regional Studies*, 52. <https://doi.org/10.1016/j.ejrh.2024.101689>
25. Alonso Vicario, S., Hornberger, G. M., Mazzoleni, M., & Garcia, M. (2025). Drivers and trends of streamflow droughts in natural and human-impacted basins across the contiguous United States. *Journal of Hydrology*, 655, 132908.
<https://doi.org/10.1016/j.jhydrol.2025.132908>
26. Al-Tameemi, N., Xuexia, Z., Shahzad, F., Mehmood, K., & Zhou, J. (2025). Enhancing desertification risk mapping with entropy-based weighting and machine learning: Insights from Iraq. *Journal of Environmental Management*, 396, 127976. <https://doi.org/10.1016/j.jenvman.2025.127976>
27. Ambalam, K. (2014). United Nations Convention to Combat Desertification: Issues and Challenges.
28. Amiraslani, F., & Caiserman, A. (2018). Multi-Stakeholder and Multi-Level Interventions to Tackle Climate Change and Land Degradation: The Case of Iran. *Sustainability*, 10(6). <https://doi.org/10.3390/su10062000>
29. Anderson, G. P., Felde, G. W., Hoke, M. L., Ratkowski, A. J., Cooley, T. W., Chetwynd, J. H., Jr., Gardner, J. A., Adler-Golden, S. M., Matthew, M. W., Berk, A., Bernstein, L. S., Acharya, P. K., Miller, D. P., & Lewis, P. E. (2002). MODTRAN4-based atmospheric correction algorithm: FLAASH (fast line-of-

- sight atmospheric analysis of spectral hypercubes). 4725, 65–71.
<https://doi.org/10.1117/12.478737>
30. Appiagyei, B. D., Belhoucine-Guezouli, L., Bessah, E., & Morsli, B. (2023). Simulating land use and land cover change in a semi-arid region from 1989 to 2039: The case of Hafir-Zariffet forest, Tlemcen, Algeria. *GeoJournal*, 88(4), 4159–4173. <https://doi.org/10.1007/s10708-023-10853-2>
 31. Arguez, A., & Vose, R. S. (2011). The Definition of the Standard WMO Climate Normal: The Key to Deriving Alternative Climate Normals. <https://doi.org/10.1175/2010BAMS2955.1>
 32. Athmania, D., & Achour, H. (2014). External Validation of the ASTER GDEM2, GMTED2010 and CGIAR-CSI- SRTM v4.1 Free Access Digital Elevation Models (DEMs) in Tunisia and Algeria. *Remote Sensing*, 6(5), 4600–4620. <https://doi.org/10.3390/rs6054600>
 33. Azare, I. M., Abdullahi, M. S., Adebayo, A. A., Dantata, I. J., & Duala, T. (2020). Deforestation, desert encroachment, climate change and agricultural production in the Sudano-Sahelian Region of Nigeria. *Journal of Applied Sciences and Environmental Management*, 24(1), 127. <https://doi.org/10.4314/jasem.v24i1.18>
 34. Azzouzi, S. A., Vidal-Pantaleoni, A., & Bentounes, H. A. (2017). Desertification Monitoring in Biskra, Algeria, With Landsat Imagery by Means of Supervised Classification and Change Detection Methods. *IEEE Access*, 5, 9065–9072. <https://doi.org/10.1109/ACCESS.2017.2700405>
 35. Baartman, J. E. M., Godert, W. J. van L., Mark S., M. S., Ritsema, C. J., & Hessel, R. (2007). Desertification and land degradation: Origins, processes and solutions. A literature review (SRIC Report number 4 Series). <https://desire-his.wur.nl/index.php/en/study-site-contexts/wp11-information-review-thematicmenu-165/515-desertification-and-land-degradation-executive-summary.html>
 36. Bailly, J. S., Arnaud, M., & Puech, C. (2007). Boosting: A classification method for remote sensing: *International Journal of Remote Sensing*: Vol 28 , No 7—Get Access. 28(7). <https://doi.org/https://doi.org/10.1080/01431160500469985>
 37. Bajocco, S., De Angelis, A., Perini, L., Ferrara, A., & Salvati, L. (2012). The Impact of Land Use/Land Cover Changes on Land Degradation Dynamics: A Mediterranean Case Study. *Environmental Management*, 49(5), 980–989. <https://doi.org/10.1007/s00267-012-9831-8>
 38. Bartold, M., Wróblewski, K., Kluczek, M., Dąbrowska-Zielińska, K., & Goliński, P. (2024). Examining the Sensitivity of Satellite-Derived Vegetation Indices to Plant Drought Stress in Grasslands in Poland. *Plants*, 13(16), 2319. <https://doi.org/10.3390/plants13162319>

39. Bashiri, M., Rahdari, M. R., Serrano-Bernardo, F., Rodrigo-Comino, J., & Rodríguez-Seijo, A. (2025). Defining a Method for Mapping Aeolian Sand Transport Susceptibility Using Bivariate Statistical and Machine Learning Methods—A Case Study of the Seqale Watershed, Eastern Iran. *Sustainability*, 17(18), 8234. <https://doi.org/10.3390/su17188234>
40. Bazza, M., Kay, M., & Knutson, C. (with FAO). (2018). Drought characteristics and management in North Africa and the Near East. Food and Agriculture Organization of the United Nations.
41. Belabbes, I., & Si Tayeb, T. (2025). Digital detection of steppe vegetation change over time in Naâma (Algeria), using the soil-adjusted vegetation index. *Biodiversity: Research and Conservation*, 78, 11–20. <https://doi.org/10.14746/biorc.2025.78.4>
42. Bendechou, H., Akakba, A., Kalla, M. I., & Hachi, A. B. S. (2024). Monitoring and Predicting Land Use/Land Cover Dynamics in Djelfa City, Algeria, using Google Earth Engine and a Multi Layer Perceptron Markov Chain Model. *Geographica Pannonica*, 28(1), 1–20. <https://doi.org/10.5937/gp28-47299>
43. Bensaid, A. (2006). SIG ET TÉLÉDÉTECTION POUR L'ÉTUDE DE L'ENSABLEMENT
DANS UNE ZONE ARIDE: LE CAS DE LA WILAYA DE NAÂMA (ALGÉRIE). [Phdthesis, Université Joseph-Fourier - Grenoble I]. <https://theses.hal.science/tel-00169433>
44. Bento, V. A., Gouveia, C. M., DaCamara, C. C., Libonati, R., & Trigo, I. F. (2020). The roles of NDVI and Land Surface Temperature when using the Vegetation Health Index over dry regions. *Global and Planetary Change*, 190, 103198. <https://doi.org/10.1016/j.gloplacha.2020.103198>
45. Bento, V. A., Gouveia, C. M., DaCamara, C. C., & Trigo, I. F. (2018). A climatological assessment of drought impact on vegetation health index. *Agricultural and Forest Meteorology*, 259, 286–295. <https://doi.org/10.1016/j.agrformet.2018.05.014>
46. Berdugo, M., Delgado-Baquerizo, M., Soliveres, S., Hernández-Clemente, R., Zhao, Y., Gaitán, J. J., Gross, N., Saiz, H., Maire, V., Lehmann, A., Rillig, M. C., Solé, R. V., & Maestre, F. T. (2020). Global ecosystem thresholds driven by aridity. *Science*, 367(6479), 787–790. <https://doi.org/10.1126/science.aay5958>
47. Berdyyev, A., Al-Masnay, Y. A., Juliev, M., & Abuduwaili, J. (2024). Desertification Monitoring Using Machine Learning Techniques with Multiple Indicators Derived from Sentinel-2 in Turkmenistan. *Remote Sensing 2024*, Vol. 16, Page 4525, 16(23), 4525–4525. <https://doi.org/10.3390/RS16234525>
48. Bernstein, L. & IPCC (Eds.). (2008). Climate Change 2007: Synthesis report: a report of the Intergovernmental Panel on Climate Change. IPCC.
49. Bichi, A. A., Mukhtar, M. K., & Sabo, A. A. (2024). EVALUATING REMOTE SENSING-BASED DROUGHT INDICES: STRENGTHS, LIMITATIONS,

- AND APPLICABILITY ACROSS SUB-SAHARAN AFRICA'S AGRO-ECOLOGICAL ZONES: A REVIEW. *FUDMA JOURNAL OF SCIENCES*, 8(4), 199–209. <https://doi.org/10.33003/fjs-2024-0804-2681>
50. Birhanu, B. Z., Desta, G., Cofie, O., Tilahun, S. A., & Mabhaudhi, T. (2024). Restoring degraded landscapes and sustaining livelihoods: Sustainability assessment (cum-review) of integrated landscape management in sub-Saharan Africa. *Frontiers in Climate*, 6. <https://doi.org/10.3389/fclim.2024.1338259>
 51. Boali, A., Asgari, H. R., Mohammadian Behbahani, A., Salmanmahiny, A., & Naimi, B. (2024). Remotely sensed desertification modeling using ensemble of machine learning algorithms. *Remote Sensing Applications: Society and Environment*, 34, 101149–101149. <https://doi.org/10.1016/J.RSASE.2024.101149>
 52. Bogale, G. A., & Erena, Z. B. (2022). Drought vulnerability and impacts of climate change on livestock production and productivity in different agro-Ecological zones of Ethiopia. *Journal of Applied Animal Research*, 50(1), 471–489. <https://doi.org/10.1080/09712119.2022.2103563>
 53. Bouabdelli, S., Meddi, M., Zeroual, A., & Alkama, R. (2020). Hydrological drought risk recurrence under climate change in the karst area of Northwestern Algeria. *Journal of Water and Climate Change*, 11(S1), 164–188. <https://doi.org/10.2166/wcc.2020.207>
 54. Boudjemline, F., & Benlabiod, D. (2022). The use of Standardized Precipitation Index values (SPI) and MODIS vegetation indices to assess drought of steppe regions, Algeria. *Technium Social Sciences Journal*, 36, 641–659. <https://doi.org/10.47577/tssj.v36i1.7405>
 55. Bougara, H., Hamed, K. B., Borgemeister, C., Tischbein, B., & Kumar, N. (2021). A comparative assessment of meteorological drought in the Tafna basin, Northwestern Algeria. *Journal of Water and Land Development*, 51, 78–93. <https://doi.org/10.24425/jwld.2021.139018>
 56. Bourbouze, A. (2006). Systèmes d'élevage et production animale dans les steppes du nord de l'Afrique: Une relecture de la société pastorale du Maghreb. 17(1–2).
 57. Bouzekri, A., Alexandridis, T. K., Toufik, A., Rebouh, N. Y., Chenchouni, H., Kucher, D., Dokukin, P., & Said Mohamed, E. (2023). Assessment of the spatial dynamics of sandy desertification using remote sensing in Nemamcha region (Algeria). *The Egyptian Journal of Remote Sensing and Space Sciences*, 26(3), 642–653. <https://doi.org/10.1016/J.EJRS.2023.07.006>
 58. Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
 59. Briassoulis, H. (2019). Combating Land Degradation and Desertification: The Land-Use Planning Quandary. *Land*, 8(2). <https://doi.org/10.3390/land8020027>

60. Bruzzone, O. A., Perri, D. V., & Easdale, M. H. (2023). Vegetation responses to variations in climate: A combined ordinary differential equation and sequential Monte Carlo estimation approach. *Ecological Informatics*, 73, 101913. <https://doi.org/10.1016/j.ecoinf.2022.101913>
61. Burrell, A. L., Evans, J. P., & De Kauwe, M. G. (2020). Anthropogenic climate change has driven over 5 million km² of drylands towards desertification. *Nature Communications*, 11(1), 3853. <https://doi.org/10.1038/s41467-020-17710-7>
62. Cai, D., Ge, Q., Wang, X., Liu, B., Goudie, A. S., & Hu, S. (2020). Contributions of ecological programs to vegetation restoration in arid and semiarid China. *Environmental Research Letters*, 15(11), 114046. <https://doi.org/10.1088/1748-9326/abbde9>
63. Cavus, Y., & Aksoy, H. (2020). Critical drought severity/intensity-duration-frequency curves based on precipitation deficit. *Journal of Hydrology*, 584, 124312. <https://doi.org/10.1016/j.jhydrol.2019.124312>
64. Ceppi, A., Achite, M., Toubal, A. K., & Caloiero, T. (2025). Mapping drought characteristics in northern Algerian Basins using the ERA5-Land dataset. *Scientific Reports*, 15(1). <https://doi.org/10.1038/s41598-025-95418-8>
65. Chalise, D., Kumar, L., & Kristiansen, P. (2019). Land Degradation by Soil Erosion in Nepal: A Review. *Soil Systems*, 3(1), 12. <https://doi.org/10.3390/soilsystems3010012>
66. Chappell, A., Webb, N. P., Leys, J. F., Waters, C. M., Orgill, S., & Eyres, M. J. (2019). Minimising soil organic carbon erosion by wind is critical for land degradation neutrality. *Environmental Science & Policy*, 93, 43–52. <https://doi.org/10.1016/j.envsci.2018.12.020>
67. Chasek, P., Akhtar-Schuster, M., Orr, B. J., Luise, A., Rakoto Ratsimba, H., & Safriel, U. (2019). Land degradation neutrality: The science-policy interface from the UNCCD to national implementation. *Environmental Science & Policy*, 92, 182–190. <https://doi.org/10.1016/j.envsci.2018.11.017>
68. Chazdon, R. L., Falk, D. A., Banin, L. F., Wagner, M., J. Wilson, S., Grabowski, R. C., & Suding, K. N. (2024). The intervention continuum in restoration ecology: Rethinking the active–passive dichotomy. *Restoration Ecology*, 32(8), e13535. <https://doi.org/10.1111/rec.13535>
69. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16*, 785–794. <https://doi.org/10.1145/2939672.2939785>
70. Chiang, F., Mazdiyasni, O., & AghaKouchak, A. (2018). Amplified warming of droughts in southern United States in observations and model simulations. *Science Advances*, 4(8), eaat2380. <https://doi.org/10.1126/sciadv.aat2380>

71. Chouikhi, F., Abbes, A. B., & Farah, I. R. (2025). An end-to-end pipeline based on a Two-Dimensional Convolutional Neural Network for monitoring desertification in Africa using remote sensing images. *Environmental Modelling & Software*, 193, 106622. <https://doi.org/10.1016/j.envsoft.2025.106622>
72. Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37(1), 35–46. [https://doi.org/10.1016/0034-4257\(91\)90048-B](https://doi.org/10.1016/0034-4257(91)90048-B)
73. Cook, B. I., Mankin, J. S., & Anchukaitis, K. J. (2018). Climate Change and Drought: From Past to Future. *Current Climate Change Reports*, 4(2), 164–179. <https://doi.org/10.1007/s40641-018-0093-2>
74. Cosmas, P., Philip, M. T., Ronald, M., & Handsen, T. (2025). Climate Change and Land Degradation in Semi-Arid Agricultural Landscapes: A Case Study of Zimbabwean Communal Areas. *Trends in Environmental Sciences*, 1(2), 158–166. <https://doi.org/10.21124/tes.2025.158.166>
75. Cowie, A. L., Orr, B. J., Castillo Sanchez, V. M., Chasek, P., Crossman, N. D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G. I., Minelli, S., Tengberg, A. E., Walter, S., & Welton, S. (2018). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental Science & Policy*, 79, 25–35. <https://doi.org/10.1016/j.envsci.2017.10.011>
76. D’Acunto, F., Marinello, F., & Pezzuolo, A. (2024). Rural Land Degradation Assessment through Remote Sensing: Current Technologies, Models, and Applications. *Remote Sensing*, 16(16), 3059. <https://doi.org/10.3390/rs16163059>
77. Dai, A. (2011). Drought under global warming: A review. *WIREs Climate Change*, 2(1), 45–65. <https://doi.org/10.1002/wcc.81>
78. Davis, D. K. (2004). Desert ‘wastes’ of the Maghreb: Desertification narratives in French colonial environmental history of North Africa. *Cultural Geographies*, 11(4), 359–387. <https://doi.org/10.1191/1474474004eu3130a>
79. De Boeck, H. J., & Verbeeck, H. (2011). Drought-associated changes in climate and their relevance for ecosystem experiments and models. *Biogeosciences*, 8(5), 1121–1130. <https://doi.org/10.5194/bg-8-1121-2011>
80. Decuyper, M., Chávez, R. O., Lohbeck, M., Lastra, J. A., Tsendbazar, N., Hackländer, J., Herold, M., & Vågen, T.-G. (2022). Continuous monitoring of forest change dynamics with satellite time series. *Remote Sensing of Environment*, 269, 112829. <https://doi.org/10.1016/j.rse.2021.112829>
81. Deng, A., Hao, X., & Qu, J. J. (2024). A Preliminary Assessment of Land Restoration Progress in the Great Green Wall Initiative Region Using Satellite

- Remote Sensing Measurements. *Remote Sensing*, 16(23).
<https://doi.org/10.3390/rs16234461>
82. Derdous, O., Bouamrane, A., & Mrad, D. (2021). Spatiotemporal analysis of meteorological drought in a Mediterranean dry land: Case of the Cheliff basin–Algeria. *Modeling Earth Systems and Environment*, 7(1), 135–143.
<https://doi.org/10.1007/S40808-020-00951-2/FIGURES/6>
 83. Dhillon, M. S., Kübert-Flock, C., Dahms, T., Rummler, T., Arnault, J., Steffan-Dewenter, I., & Ullmann, T. (2023). Evaluation of MODIS, Landsat 8 and Sentinel-2 Data for Accurate Crop Yield Predictions: A Case Study Using STARFM NDVI in Bavaria, Germany. *Remote Sensing*, 15(7), 1830.
<https://doi.org/10.3390/rs15071830>
 84. Díaz, S., Kattge, J., Cornelissen, J. H. C., Wright, I. J., Lavorel, S., Dray, S., Reu, B., Kleyer, M., Wirth, C., Prentice, I. C., Garnier, E., Bönisch, G., Westoby, M., Poorter, H., Reich, P. B., Moles, A. T., Dickie, J., Zanne, A. E., Chave, J., ... Zotz, G. (2022). The global spectrum of plant form and function: Enhanced species-level trait dataset. *Scientific Data*, 9(1), 755.
<https://doi.org/10.1038/s41597-022-01774-9>
 85. Djeddaoui, F., Chadli, M., & Gloaguen, R. (2017). Desertification Susceptibility Mapping Using Logistic Regression Analysis in the Djelfa Area, Algeria. *Remote Sensing*, 9(10). <https://doi.org/10.3390/rs9101031>
 86. D’Odorico, P., Bhattachan, A., Davis, K. F., Ravi, S., & Runyan, C. W. (2013). Global desertification: Drivers and feedbacks. *Advances in Water Resources*, 51, 326–344. <https://doi.org/10.1016/j.advwatres.2012.01.013>
 87. D’Odorico, P., Rosa, L., Bhattachan, A., & Okin, G. S. (2019). Desertification and Land Degradation. In P. D’Odorico, A. Porporato, & C. Wilkinson Runyan (Eds.), *Dryland Ecohydrology* (pp. 573–602). Springer International Publishing.
https://doi.org/10.1007/978-3-030-23269-6_21
 88. Dregne, H. E. (1986). Desertification of Arid Lands. In F. El-Baz & M. H. A. Hassan (Eds.), *Physics of desertification* (pp. 4–34). Springer Netherlands.
https://doi.org/10.1007/978-94-009-4388-9_2
 89. Ebrahimi, A., Zolfaghari, F., Ghodsi, M., & Narmashiri, F. (2024). Assessing the accuracy of spectral indices obtained from Sentinel images using field research to estimate land degradation. *PLOS ONE*, 19(7), e0305758.
<https://doi.org/10.1371/journal.pone.0305758>
 90. Eklundh, L., & Olsson, L. (2003). Vegetation index trends for the African Sahel 1982–1999. *Geophysical Research Letters*, 30(8).
<https://doi.org/10.1029/2002GL016772>
 91. El Zerey, W., Gael, M., & El Zerey-Belaskri, A. (2017). MONITORING LAND USE CHANGE AND VEGETATION DYNAMICS BY REMOTE

- SENSING IN THE STEPPE REGION OF SIDI BEL ABBES (NORTHWEST, ALGERIA). *INTERNATIONAL JOURNAL OF ENVIRONMENT*, 6(3), 1–11.
92. El-Baz, F., & Hassan, M. H. A. (Eds.). (1986). *Physics of desertification*. Springer Netherlands. <https://doi.org/10.1007/978-94-009-4388-9>
 93. El-Beltagy, A., & Madkour, M. (2012). Impact of climate change on arid lands agriculture. *Agriculture & Food Security*, 1(1), 3. <https://doi.org/10.1186/2048-7010-1-3>
 94. Elouissi, A., Benzater, B., Dabanli, I., Habi, M., Harizia, A., & Hamimed, A. (2021). Drought investigation and trend assessment in Macta watershed (Algeria) by SPI and ITA methodology. *Undefined*, 14(14). <https://doi.org/10.1007/S12517-021-07670-7>
 95. Emadodin, I., Reinsch, T., & Taube, F. (2019). Drought and Desertification in Iran. *Hydrology*, 6(3). <https://doi.org/10.3390/hydrology6030066>
 96. Erdogan, S. (2009). A comparison of interpolation methods for producing digital elevation models at the field scale. *Earth Surface Processes and Landforms*, 34(3), 366–376. <https://doi.org/10.1002/esp.1731>
 97. Eskandari Dameneh, H., Gholami, H., Telfer, M. W., Comino, J. R., Collins, A. L., & Jansen, J. D. (2021). Desertification of Iran in the early twenty-first century: Assessment using climate and vegetation indices. *Scientific Reports*, 11(1), 20548. <https://doi.org/10.1038/s41598-021-99636-8>
 98. Exavier, R., & Zeilhofer, P. (2021). OpenLand: Software for Quantitative Analysis and Visualization of Land Use and Cover Change. *The R Journal*, 12(2), 373–388. <https://doi.org/10.32614/RJ-2021-021>
 99. Fadl, M. E., AbdelRahman, M. A. E., El-Desoky, A. I., & Sayed, Y. A. (2024). Assessing soil productivity potential in arid region using remote sensing vegetation indices. *Journal of Arid Environments*, 222, 105166. <https://doi.org/10.1016/j.jaridenv.2024.105166>
 100. Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., & Alsdorf, D. (2007). The Shuttle Radar Topography Mission. *Reviews of Geophysics*, 45(2). <https://doi.org/10.1029/2005RG000183>
 101. Fayeche, D., & Tarhouni, J. (2021). Climate variability and its effect on normalized difference vegetation index (NDVI) using remote sensing in semi-arid area. *Modeling Earth Systems and Environment*, 7(3), 1667–1682. <https://doi.org/10.1007/s40808-020-00896-6>
 102. Fellag, M., Achite, M., & Walega, A. (2021). Spatial-temporal characterization of meteorological drought using the Standardized precipitation index. Case study in Algeria. *Acta Scientiarum Polonorum. Formatio Circumiectus*, 20(1), 19–31. <https://doi.org/10.15576/ASP.FC/2021.20.1.19>

103. Feng, K., Wang, T., Liu, S., Kang, W., Chen, X., Guo, Z., & Zhi, Y. (2022). Monitoring Desertification Using Machine-Learning Techniques with Multiple Indicators Derived from MODIS Images in Mu Us Sandy Land, China. *Remote Sensing* 2022, Vol. 14, Page 2663, 14(11), 2663–2663.
<https://doi.org/10.3390/RS14112663>
104. Feng, Q., Ma, H., Jiang, X., Wang, X., & Cao, S. (2015). What Has Caused Desertification in China? *Scientific Reports*, 5(1), 15998.
<https://doi.org/10.1038/srep15998>
105. Feng, S., Zhao, W., Yan, J., Xia, F., & Pereira, P. (2024). Land degradation neutrality assessment and factors influencing it in China's arid and semiarid regions. *Science of The Total Environment*, 925, 171735.
<https://doi.org/10.1016/j.scitotenv.2024.171735>
106. Feng, S., Zhao, W., Zhan, T., Yan, Y., & Pereira, P. (2022). Land degradation neutrality: A review of progress and perspectives. *Ecological Indicators*, 144. <https://doi.org/10.1016/j.ecolind.2022.109530>
107. Feng, T., Zheng, H., Wei, W., Wang, P., Bi, H., Zhang, J., Wei, T., Wang, R., & Wang, L. (2025). Natural Forests Accelerate Soil Hydrological Processes and Enhance Water-Holding Capacities Compared to Planted Forests After Long-Term Restoration. *Water Resources Research*, 61(9), e2025WR040857.
<https://doi.org/10.1029/2025WR040857>
108. Fernández, F. J., Vásquez-Lavín, F., Ponce, R. D., Garreaud, R., Hernández, F., Link, O., Zambrano, F., & Hanemann, M. (2023). The economics impacts of long-run droughts: Challenges, gaps, and way forward. *Journal of Environmental Management*, 344, 118726.
<https://doi.org/10.1016/j.jenvman.2023.118726>
109. Ferreira, C. S. S., Seifollahi-Aghmiuni, S., Destouni, G., Ghajarnia, N., & Kalantari, Z. (2022). Soil degradation in the European Mediterranean region: Processes, status and consequences. *Science of The Total Environment*, 805, 150106. <https://doi.org/10.1016/j.scitotenv.2021.150106>
110. Fettam, D., Gherissi, R., & Belarbi, H. (2025). Comparison of meteorological indices for drought assessment and monitoring: A case study from the Tafna watershed, Northwestern Algeria. *Atmosfera*, 39, 419–436.
<https://doi.org/10.20937/ATM.53453>
111. Flasse, S. (2005). Remote Sensing and GIS Accuracy Assessment. *The Photogrammetric Record*, 20(111), 306–307. https://doi.org/10.1111/j.1477-9730.2005.00333_3.x
112. Fleming-Muñoz, D. A., Whitten, S., & Bonnett, G. D. (2023). The economics of drought: A review of impacts and costs. *Australian Journal of Agricultural and Resource Economics*, 67(4), 501–523.
<https://doi.org/10.1111/1467-8489.12527>

113. Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, 29(11), 3137–3158.
<https://doi.org/10.1080/01431160701442120>
114. Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment*, 239, 111630.
<https://doi.org/10.1016/j.rse.2019.111630>
115. Friedl, P., Seehaus, T. C., Wendt, A., Braun, M. H., & Höppner, K. (2018). Recent dynamic changes on Fleming Glacier after the disintegration of Wordie Ice Shelf, Antarctic Peninsula. *The Cryosphere*, 12(4), 1347–1365.
<https://doi.org/10.5194/tc-12-1347-2018>
116. Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Scientific Data*, 2(1), 150066.
<https://doi.org/10.1038/sdata.2015.66>
117. Gao, B. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, 58(3), 257–266. [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3)
118. Gao, Y., Zhong, B., Yue, H., Wu, B., & Cao, S. (2011). A degradation threshold for irreversible loss of soil productivity: A long-term case study in China. *Journal of Applied Ecology*, 48(5), 1145–1154.
<https://doi.org/10.1111/j.1365-2664.2011.02011.x>
119. Genovese, E., Maesano, C., & Barrile, V. (2025). Augmented Statistics for Hydroclimatic Extremes: Spearman, Mann–Kendall, and AI Classification for Drought Risk Mapping. *Sustainability*, 17(20), 9251.
<https://doi.org/10.3390/su17209251>
120. Ghobadi, M., & Badehian, Z. (2025). Assessment of agricultural drought severity using multi-temporal remote sensing data in Lorestan region. *Scientific Reports*, 15(1), 18528. <https://doi.org/10.1038/s41598-025-03087-4>
121. Giorgi, F., & Lionello, P. (2008). Climate change projections for the Mediterranean region. *Global and Planetary Change, Mediterranean Climate: Trends, Variability and Change*, 63(2), 90–104.
<https://doi.org/10.1016/j.gloplacha.2007.09.005>
122. Giuliani, G., Chatenoux, B., Benvenuti, A., Lacroix, P., Santoro, M., & Mazzetti, P. (2020). Monitoring land degradation at national level using satellite Earth Observation time-series data to support SDG15 – exploring the potential of data cube. *Big Earth Data*, 4(1), 3–22.
<https://doi.org/10.1080/20964471.2020.1711633>

123. Gizachew, L., & Suryabhadgavan, K. V. (2014). Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia. 55(3), 349–363.
124. Glantz, M. H., & Orlovsky, N. (1983). Desertification: A review of the concept. *Desertification Control Bulletin*, 9, 15–22.
125. Grove, A. T. (1977). Desertification. *Progress in Physical Geography: Earth and Environment*, 1(2), 296–310. <https://doi.org/10.1177/030913337700100204>
126. Gu, L., Chen, J., Yin, J., Sullivan, S. C., Wang, H.-M., Guo, S., Zhang, L., & Kim, J.-S. (2020). Projected increases in magnitude and socioeconomic exposure of global droughts in 1.5 and 2°C warmer climates. *Hydrology and Earth System Sciences*, 24(1), 451–472. <https://doi.org/10.5194/hess-24-451-2020>
127. Guo, B., Zang, W., Han, B., Yang, F., Luo, W., He, T., Fan, Y., Yang, X., & Chen, S. (2020). Dynamic monitoring of desertification in Naiman Banner based on feature space models with typical surface parameters derived from LANDSAT images. *Land Degradation & Development*, 31(12), 1573–1592. <https://doi.org/10.1002/ldr.3533>
128. Gutiérrez-Hernández, O., & García, L. V. (2024). Robust Trend Analysis in Environmental Remote Sensing: A Case Study of Cork Oak Forest Decline. *Remote Sensing*, 16(20), 3886. <https://doi.org/10.3390/rs16203886>
129. Gutman, G., & Ignatov, A. (1998). The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models. *International Journal of Remote Sensing*, 19(8), 1533–1543. <https://doi.org/10.1080/014311698215333>
130. Haied, N., Fofou, A., Khadri, S., Boussaid, A., Azlaoui, M., & Bougherira, N. (2023). Spatial and Temporal Assessment of Drought Hazard, Vulnerability and Risk in Three Different Climatic Zones in Algeria Using Two Commonly Used Meteorological Indices. *Sustainability (Switzerland)*, 15(10). <https://doi.org/10.3390/su15107803>
131. Haile, G. G., Tang, Q., Li, W., Liu, X., & Zhang, X. (2020). Drought: Progress in broadening its understanding. *WIREs Water*, 7(2), e1407. <https://doi.org/10.1002/wat2.1407>
132. Halima, K. (2003). Diversité biologique et phytogéographique des formations à *Stipa tenacissima* L. de l'Algérie. *La Revue Sécheresse*, 14(3), 169–179.
133. Hamitouche, Y., Zeroual, A., Meddi, M., Assani, A. A., Alkama, R., Şen, Z., & Zhang, X. (2024). Projected Changes in Extreme Precipitation Patterns across Algerian Sub-Regions. *Water (Switzerland)*, 16(10), 1353–1353. <https://doi.org/10.3390/W16101353/S1>

134. Hammouda, R. F., Huguenin, J., Julien, L., & Nedjraoui, D. (2019). Impact of agrarian practices and some pastoral uses on vegetation in Algerian steppe rangelands. *The Rangeland Journal*, 41(2), 97–107.
<https://doi.org/10.1071/RJ18081>
135. Hashemi, Z., Sodaeizadeh, H., Mokhtari, M. H., Ardakani, M. A. H., & Aliabadi, K. K. (2024). Monitoring and forecasting desertification and land degradation using remote sensing and machine learning techniques in Sistan plain, Iran. *Journal of African Earth Sciences*, 218, 105375.
<https://doi.org/10.1016/j.jafrearsci.2024.105375>
136. Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. <https://doi.org/10.1175/2010BAMS3103.1>
137. He, Z., Gu, X., Wang, M., & Xu, M. (2025). The coupled effect of climate change and LUCC on meteorological drought in a karst drainage basin, Southwest China. *Scientific Reports*, 15(1), 9134.
<https://doi.org/10.1038/s41598-025-93035-z>
138. Helldén, U. (1991). Desertification: Time for an Assessment? *Ambio*, 20(8), 372–383.
139. Helldén, U. (2003). Desertification and Theories of Desertification Control: A discussion of Chinese and European concepts. *Proceedings of the China-EU Workshop on Integrated Approach to Combat Desertification*, 94–104.
<https://lucris.lub.lu.se/ws/files/5861293/623506.pdf>
140. Hermans, K., & McLeman, R. (2021). Climate change, drought, land degradation and migration: Exploring the linkages. *Current Opinion in Environmental Sustainability*, 50, 236–244.
<https://doi.org/10.1016/j.cosust.2021.04.013>
141. Herrmann, S. M., & Hutchinson, C. F. (2005). The changing contexts of the desertification debate. *Journal of Arid Environments*, Special Issue on The “Greening” of the Sahel, 63(3), 538–555.
<https://doi.org/10.1016/j.jaridenv.2005.03.003>
142. Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., ... Thépaut, J. N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049.
<https://doi.org/10.1002/qj.3803>
143. Hezil, S., Aouadj, S. A., Degaichia, H., Ouinten, Y., Lafri, I., Bounab, S., & Chakali, G. (2024). The role of rehabilitating and restoration the green dam in managing the impact of invasive forest pests in Algeria. *Brazilian Journal of*

- Animal and Environmental Research, 7(4), e75010–e75010.
<https://doi.org/10.34188/bjaerv7n4-081>
144. Higginbottom, T. P., & Symeonakis, E. (2014). Assessing Land Degradation and Desertification Using Vegetation Index Data: Current Frameworks and Future Directions. *Remote Sensing*, 6(10), 9552–9575.
<https://doi.org/10.3390/rs6109552>
 145. Hirche, A., Salamani, M., Abdellaoui, A., Benhouhou, S., & Valderrama, J. M. (2011). Landscape changes of desertification in arid areas: The case of south-west Algeria. *Environmental Monitoring and Assessment*, 179(1), 403–420. <https://doi.org/10.1007/s10661-010-1744-5>
 146. Hisano, M., Ghazoul, J., Chen, X., & Chen, H. Y. H. (2024). Functional diversity enhances dryland forest productivity under long-term climate change. *Science Advances*, 10(17), eadn4152. <https://doi.org/10.1126/sciadv.adn4152>
 147. Hoffmann, S., & Beierkuhnlein, C. (2020). Climate change exposure and vulnerability of the global protected area estate from an international perspective. 26(11), 1496–1509. <https://doi.org/10.1111/ddi.13136>
 148. Hu, P., Sharifi, A., Tahir, M. N., Tariq, A., Zhang, L., Mumtaz, F., & Shah, S. H. I. A. (2021). Evaluation of Vegetation Indices and Phenological Metrics Using Time-Series MODIS Data for Monitoring Vegetation Change in Punjab, Pakistan. *Water*, 13(18). <https://doi.org/10.3390/w13182550>
 149. Hu, T., Van Dijk, A. I. J. M., Renzullo, L. J., Xu, Z., He, J., Tian, S., Zhou, J., & Li, H. (2020). On agricultural drought monitoring in Australia using Himawari-8 geostationary thermal infrared observations. *International Journal of Applied Earth Observation and Geoinformation*, 91, 102153.
<https://doi.org/10.1016/j.jag.2020.102153>
 150. Huang, J., Li, Y., Fu, C., Chen, F., Fu, Q., Dai, A., Shinoda, M., Ma, Z., Guo, W., Li, Z., Zhang, L., Liu, Y., Yu, H., He, Y., Xie, Y., Guan, X., Ji, M., Lin, L., Wang, S., ... Wang, G. (2017). Dryland climate change: Recent progress and challenges. *Reviews of Geophysics*, 55(3), 719–778.
<https://doi.org/10.1002/2016RG000550>
 151. Huang, J., Yu, H., Guan, X., Wang, G., & Guo, R. (2016). Accelerated dryland expansion under climate change. *Nature Climate Change*, 6(2), 166–171. <https://doi.org/10.1038/nclimate2837>
 152. Huang, J., Zhang, G., Zhang, Y., Guan, X., Wei, Y., & Guo, R. (2020). Global desertification vulnerability to climate change and human activities. *Land Degradation and Development*, 31(11), 1380–1391.
<https://doi.org/10.1002/LDR.3556>
 153. Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment, The Moderate*

- Resolution Imaging Spectroradiometer (MODIS): A New Generation of Land Surface Monitoring, 83(1), 195–213. [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2)
154. IDMC. (2023). Global Report on Internal Displacement 2023: Internal displacement and food security (GRID 2023). IDMC / Norwegian Refugee Council (NRC). <https://www.internal-displacement.org/global-report/grid2023/>
 155. Ilhame, R., Benchohra, M., Mohamed, G., Belgacem, N., Ahmed, A. S., & Walid, B. (2025). Phytodiversity of the green dam: Case of Djelfa region (Algeria). *Brazilian Journal of Animal and Environmental Research*, 8(1), e76695. <https://doi.org/10.34188/bjaerv8n1-024>
 156. Intergovernmental Panel On Climate Change (Ipcc). (2023). Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (1st ed.). Cambridge University Press. <https://doi.org/10.1017/9781009157896>
 157. IPBES. (2018). Summary for policymakers of the assessment report on land degradation and restoration of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. <https://www.ipbes.net>
 158. Islam, W., Zeng, F., Siddiqui, J. A., Zhihao, Z., Du, Y., Zhang, Y., Alshaharni, M. O., & Khan, K. A. (2025). Combating desertification: Comprehensive strategies, challenges, and future directions for sustainable solutions. *Biological Reviews*, 100(4), 1594–1614. <https://doi.org/10.1111/brv.70015>
 159. Ismail, G., Tarik, G., Abdeldjalil, B., Abdelaziz, K., Bilal, B., Djilali, M., & Miloud Sallay. (2022). LAND MASTERY, MAJOR ISSUE FOR WETLANDS CONSERVATION IN RURAL AREAS Case of Macta in northwestern Algerian. *African Journal on Land Policy and Geospatial Sciences*, 5(5), 2657–2664. <https://doi.org/10.48346/IMIST.PRSM/ajlp-gs.v5i5.33317>
 160. Jagdish, C. K., & Vlek, P. L. G. (2000). Desertification: Concept, causes and amelioration (No. 33; ZEF Discussion Papers on Development Policy, p. 65). Center for Development Research (ZEF), University of Bonn. <https://hdl.handle.net/10419/84771>
 161. Jain, S., Srivastava, A., Khadke, L., Chatterjee, U., & Elbeltagi, A. (2024). Global-scale water security and desertification management amidst climate change. *Environmental Science and Pollution Research*, 31(49), 58720–58744. <https://doi.org/10.1007/s11356-024-34916-0>
 162. Jalayer, S., Sharifi, A., Abbasi-Moghadam, D., Tariq, A., & Qin, S. (2023). Assessment of Spatiotemporal Characteristic of Droughts Using In Situ and Remote Sensing-Based Drought Indices. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 16, 1483–1502. <https://doi.org/10.1109/JSTARS.2023.3237380>

163. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning* (Vol. 103). Springer. <https://doi.org/10.1007/978-1-4614-7138-7>
164. Janse, R. J., Hoekstra, T., Jager, K. J., Zoccali, C., Tripepi, G., Dekker, F. W., & Van Diepen, M. (2021). Conducting correlation analysis: Important limitations and pitfalls. *Clinical Kidney Journal*, 14(11), 2332–2337. <https://doi.org/10.1093/ckj/sfab085>
165. Jiang, C., Zhang, H., Zhang, Z., & Wang, D. (2019). Model-based assessment soil loss by wind and water erosion in China's Loess Plateau: Dynamic change, conservation effectiveness, and strategies for sustainable restoration. *Global and Planetary Change*, 172, 396–413. <https://doi.org/10.1016/j.gloplacha.2018.11.002>
166. Jiang, H., Wu, R., Zhang, Y., Li, M., Lian, H., Fan, Y., Yang, W., & Zhou, P. (2024). Classification Model of Grassland Desertification Based on Deep Learning. *Sustainability*, 16(19), 8307. <https://doi.org/10.3390/su16198307>
167. Jiang, J., & Zhou, T. (2023). Agricultural drought over water-scarce Central Asia aggravated by internal climate variability. *Nature Geoscience*, 16(2), 154–161. <https://doi.org/10.1038/s41561-022-01111-0>
168. Jiang, R., Liang, J., Zhao, Y., Wang, H., Xie, J., Lu, X., & Li, F. (2021). Assessment of vegetation growth and drought conditions using satellite-based vegetation health indices in Jing-Jin-Ji region of China. *Scientific Reports*, 11(1), 13775. <https://doi.org/10.1038/s41598-021-93328-z>
169. Jiao, W., Wang, L., & McCabe, M. F. (2021). Multi-sensor remote sensing for drought characterization: Current status, opportunities and a roadmap for the future. *Remote Sensing of Environment*, 256. <https://doi.org/10.1016/j.rse.2021.112313>
170. Kar, A. (2018). *Desertification: Causes and Effects*. In *Exploring Natural Hazards*. Chapman and Hall/CRC.
171. Katyal, J. C., & Vlek, P. L. G. (2000). *Desertification: Concept, causes and amelioration* (ZEF Discussion Papers on Development Policy 33, p. 65). Center for Development Research (ZEF), University of Bonn. <https://doi.org/10.22004/ag.econ.281247>
172. Kchouk, S., Melsen, L. A., Walker, D. W., & van Oel, P. R. (2022). A geography of drought indices: Mismatch between indicators of drought and its impacts on water and food securities. *Natural Hazards and Earth System Sciences*, 22(2), 323–344. <https://doi.org/10.5194/nhess-22-323-2022>
173. Kéfi, S., Génin, A., Garcia-Mayor, A., Guirado, E., Cabral, J. S., Berdugo, M., Guerber, J., Solé, R., & Maestre, F. T. (2024). Self-organization as a mechanism of resilience in dryland ecosystems. *Proceedings of the National*

- Academy of Sciences, 121(6), e2305153121.
<https://doi.org/10.1073/pnas.2305153121>
174. Keyantash, J. (2021). Indices for Meteorological and Hydrological Drought. In A. Pandey, S. Kumar, & A. Kumar (Eds.), *Hydrological Aspects of Climate Change* (pp. 215–235). Springer. https://doi.org/10.1007/978-981-16-0394-5_11
 175. Keyantash, J., & Dracup, J. A. (2002). The Quantification of Drought: An Evaluation of Drought Indices. <https://doi.org/10.1175/1520-0477-83.8.1167>
 176. Khan, R., & Gilani, H. (2023). Global drought monitoring with big geospatial datasets using Google Earth Engine. <https://doi.org/10.1007/s11356-020-12023-0/Published>
 177. Kim, W., Park, E., Jo, H.-W., Roh, M., Kim, J., Song, C., & Lee, W.-K. (2023). A meta-analytic review on the spatial and climatic distribution of meteorological drought indices. *Environmental Reviews*, 31(1), 95–110. <https://doi.org/10.1139/er-2021-0098>
 178. Kiouss, C., Maatoug, M., Bouacha, M. I., & Maatoug, Z. Z. (2024). Monitoring vegetation cover trends in the steppe region of western Algeria using MODIS imagery. *Sains Tanah*, 21(1), 15–21. <https://doi.org/10.20961/stjssa.v21i1.80849>
 179. Kloos, S., Yuan, Y., Castelli, M., & Menzel, A. (2021). Agricultural Drought Detection with MODIS Based Vegetation Health Indices in Southeast Germany. *Remote Sensing*, 13(19), 3907. <https://doi.org/10.3390/rs13193907>
 180. Knapp, A. K., Condon, K. V., Folks, C. C., Sturchio, M. A., Griffin-Nolan, R. J., Kannenberg, S. A., Gill, A. S., Hajek, O. L., Siggers, J. A., & Smith, M. D. (2024). Field experiments have enhanced our understanding of drought impacts on terrestrial ecosystems—But where do we go from here? *Functional Ecology*, 38(1), 76–97. <https://doi.org/10.1111/1365-2435.14460>
 181. Kogan, F. N. (1995a). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research, Natural Hazards: Monitoring and Assessment Using Remote Sensing Technique*, 15(11), 91–100. [https://doi.org/10.1016/0273-1177\(95\)00079-T](https://doi.org/10.1016/0273-1177(95)00079-T)
 182. Kogan, F. N. (1995b). Droughts of the Late 1980s in the United States as Derived from NOAA Polar-Orbiting Satellite Data. https://journals.ametsoc.org/view/journals/bams/76/5/1520-0477_1995_076_0655_dotlit_2_0_co_2.xml
 183. Kogan, F. N. (2001). Operational Space Technology for Global Vegetation Assessment. https://journals.ametsoc.org/view/journals/bams/82/9/1520-0477_2001_082_1949_ostfgv_2_3_co_2.xml
 184. Koppa, A., Keune, J., Schumacher, D. L., Michaelides, K., Singer, M., Seneviratne, S. I., & Miralles, D. G. (2024). Dryland self-expansion enabled by

- land–atmosphere feedbacks. *Science*, 385(6712), 967–972.
<https://doi.org/10.1126/science.adn6833>
185. Kosaki, T., & Gabriels, D. (2015). Preface to Special Section “Desertification and Land Degradation (DesertLand I).” *Soil Science and Plant Nutrition*, 61(3), 371–371. <https://doi.org/10.1080/00380768.2015.1061391>
 186. Kumar, B. P., Babu, K. R., Anusha, B. N., & Rajasekhar, M. (2022). Geo-environmental monitoring and assessment of land degradation and desertification in the semi-arid regions using Landsat 8 OLI / TIRS, LST, and NDVI approach. *Environmental Challenges*, 8, 100578.
<https://doi.org/10.1016/j.envc.2022.100578>
 187. Kumar, B. P., Babu, K. R., Rajasekhar, M., & Ramachandra, M. (2022). Assessment of the Visual Disaster of Land Degradation and Desertification Using TGSI, SAVI, and NDVI Techniques. In *Geospatial Modeling for Environmental Management*. CRC Press.
 188. Kumar, C., Walton, G., Santi, P., & Luza, C. (2025). Random Cross-Validation Produces Biased Assessment of Machine Learning Performance in Regional Landslide Susceptibility Prediction. *Remote Sensing*, 17(2), 213.
<https://doi.org/10.3390/rs17020213>
 189. Kumar, S., Shwetank, & Jain, K. (2020). A Multi-Temporal Landsat Data Analysis for Land-use/Land-cover Change in Haridwar Region using Remote Sensing Techniques. *Procedia Computer Science*, Third International Conference on Computing and Network Communications (CoCoNet’19), 171, 1184–1193. <https://doi.org/10.1016/j.procs.2020.04.127>
 190. Kumar, V., Sharma, K. V., Pham, Q. B., Srivastava, A. K., Bogireddy, C., & Yadav, S. M. (2024). Advancements in drought using remote sensing: Assessing progress, overcoming challenges, and exploring future opportunities. *Theoretical and Applied Climatology*, 155(6), 4251–4288.
<https://doi.org/10.1007/s00704-024-04914-w>
 191. Lal, R. (2015). Restoring Soil Quality to Mitigate Soil Degradation. *Sustainability*, 7(5), 5875–5895. <https://doi.org/10.3390/su7055875>
 192. Lamchin, M., Lee, W.-K., Jeon, S. W., Lee, J.-Y., Song, C., Piao, D., Lim, C. H., Khaulenbek, A., & Navaandorj, I. (2017). Correlation between Desertification and Environmental Variables Using Remote Sensing Techniques in Hognu Khaan, Mongolia. *Sustainability*, 9(4).
<https://doi.org/10.3390/su9040581>
 193. Le Houérou, H. N. (1996). Climate change, drought and desertification. *Journal of Arid Environments*, 34(2), 133–185.
<https://doi.org/10.1006/jare.1996.0099>
 194. LE HOUEROU, H. N., CLAUDIN, J., & POUGET, M. (1977). ETUDE BIOCLIMATIQUE DES STEPPES ALGERIENNES * (Avec une carte

- bioclimatique à 1j1.000.000ème). *Le Bulletin de La Société d'histoire Naturelle d'Afrique Du Nord*, 68(3–4).
195. Lei, J., Du, M., Zhou, N., Wang, Y., & You, Y. (2025). Greening the Edge of the Sahara: China's Approach to the African Great Green Wall. *Bulletin of the Chinese Academy of Sciences*, 39, 2025002. <https://doi.org/10.1051/bcas/2025002>
 196. Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, 13(7). <https://doi.org/10.3390/su13073740>
 197. Lewin, A., Murali, G., Roll, U., Sternberg, T., & Rachmilevitch, S. (2026). Rethinking desert definitions: Bridging the gap between science, policy, and conservation. *Ambio*, 55(4), 743–754. <https://doi.org/10.1007/s13280-025-02276-9>
 198. Li, C., Fu, B., Wang, S., Stringer, L. C., Wang, Y., Li, Z., Liu, Y., & Zhou, W. (2021). Drivers and impacts of changes in China's drylands. *Nature Reviews Earth & Environment*, 2(12), 858–873. <https://doi.org/10.1038/s43017-021-00226-z>
 199. Li, P., Chen, P., Shen, J., Deng, W., Kang, X., Wang, G., & Zhou, S. (2022). Dynamic Monitoring of Desertification in Ningdong Based on Landsat Images and Machine Learning. *Sustainability*, 14(12), 7470. <https://doi.org/10.3390/su14127470>
 200. Lian, X., Piao, S., Chen, A., Huntingford, C., Fu, B., Li, L. Z. X., Huang, J., Sheffield, J., Berg, A. M., Keenan, T. F., McVicar, T. R., Wada, Y., Wang, X., Wang, T., Yang, Y., & Roderick, M. L. (2021). Multifaceted characteristics of dryland aridity changes in a warming world. *Nature Reviews Earth & Environment*, 2(4), 232–250. <https://doi.org/10.1038/s43017-021-00144-0>
 201. Liang, S. (2001). Narrowband to broadband conversions of land surface albedo I: Algorithms. *Remote Sensing of Environment*, 76(2), 213–238. [https://doi.org/10.1016/S0034-4257\(00\)00205-4](https://doi.org/10.1016/S0034-4257(00)00205-4)
 202. Lima, S. C. D., Moraes Neto, J. M. D., Lima, J. P., Lima, F. C. D., & Saboya, L. M. F. (2023). Response of semi-arid vegetation to agricultural drought determined by indices derived from MODIS satellite. *Revista Brasileira de Engenharia Agrícola e Ambiental*, 27(8), 632–642. <https://doi.org/10.1590/1807-1929/agriambi.v27n8p632-642>
 203. Liu, D., Wang, T., Peñuelas, J., & Piao, S. (2022). Drought resistance enhanced by tree species diversity in global forests. *Nature Geoscience*, 15(10), 800–804. <https://doi.org/10.1038/s41561-022-01026-w>
 204. Liu, H., Wang, X., Liang, C., Xue, P., Wang, Z., Chen, Y., & Zhang, M. (2024). Divergent nonlinear trends of global drought and its multivariate

- characteristics. *Journal of Hydrology*, 630, 130759.
<https://doi.org/10.1016/j.jhydrol.2024.130759>
205. Liu, H., Xu, C., Allen, C. D., Hartmann, H., Wei, X., Yakir, D., Wu, X., & Yu, P. (2022). Nature-based framework for sustainable afforestation in global drylands under changing climate. *Global Change Biology*, 28(7), 2202–2220.
<https://doi.org/10.1111/gcb.16059>
 206. Liu, L., Gudmundsson, L., Hauser, M., Qin, D., Li, S., & Seneviratne, S. I. (2020). Soil moisture dominates dryness stress on ecosystem production globally. *Nature Communications*, 11(1), 4892. <https://doi.org/10.1038/s41467-020-18631-1>
 207. Liu, Q., Liu, G., & Huang, C. (2018). Monitoring desertification processes in Mongolian Plateau using MODIS tasseled cap transformation and TGSi time series. *Journal of Arid Land*, 10(1), 12–26. <https://doi.org/10.1007/s40333-017-0109-0>
 208. Liu, Q., Wang, G., Gui, D., Liu, Y., Kotb Abd-Elmabod, S., & Wei, G. (2024). Precise ecological restoration under water diversions-groundwater-ecosystem interactions in drylands. *Journal of Hydrology*, 628, 130601.
<https://doi.org/10.1016/j.jhydrol.2023.130601>
 209. Liu, Q., Yang, S., Li, S., Zhang, H., Zhang, J., & Fan, H. (2024). The optimal applications of scPDSI and SPEI in characterizing meteorological drought, agricultural drought and terrestrial water availability on a global scale. *Science of The Total Environment*, 952, 175933–175933.
<https://doi.org/10.1016/J.SCITOTENV.2024.175933>
 210. Liu, X. B., Zhang, X. Y., Wang, Y. X., Sui, Y. Y., Zhang, S. L., Herbert, S. J., & Ding, G. (2010). Soil degradation: A problem threatening the sustainable development of agriculture in Northeast China. *Plant, Soil and Environment*, 56(2), 87–97. <https://doi.org/10.17221/155/2009-PSE>
 211. Liu, X.-H., Skidmore, A. K., & Van Oosten, H. (2002). Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, 56(4), 257–268.
[https://doi.org/10.1016/S0924-2716\(02\)00061-8](https://doi.org/10.1016/S0924-2716(02)00061-8)
 212. Liu, Y., Shan, F., Yue, H., Wang, X., & Fan, Y. (2023). Global analysis of the correlation and propagation among meteorological, agricultural, surface water, and groundwater droughts. *Journal of Environmental Management*, 333, 117460. <https://doi.org/10.1016/j.jenvman.2023.117460>
 213. Lloyd-Hughes, B. (2014). The impracticality of a universal drought definition. *Theoretical and Applied Climatology*, 117(3), 607–611.
<https://doi.org/10.1007/s00704-013-1025-7>

214. Lombe, P., Carvalho, E., & Rosa-Santos, P. (2024). Drought Dynamics in Sub-Saharan Africa: Impacts and Adaptation Strategies. *Sustainability*, 16(22). <https://doi.org/10.3390/su16229902>
215. Lu, L., Kuenzer, C., Wang, C., Guo, H., & Li, Q. (2015). Evaluation of Three MODIS-Derived Vegetation Index Time Series for Dryland Vegetation Dynamics Monitoring. *Remote Sensing*, 7(6), 7597–7614. <https://doi.org/10.3390/rs70607597>
216. Lü, Y., Lü, D., Feng, X., & Fu, B. (2021). Multi-scale analyses on the ecosystem services in the Chinese Loess Plateau and implications for dryland sustainability. *Current Opinion in Environmental Sustainability*, 48, 1–9. <https://doi.org/10.1016/j.cosust.2020.08.001>
217. Luc, H. C., & Van Viet, L. (2025). Early forecasting of vegetation health index in the Srepok basin based on meteorological and hydrological drought indices. *Environmental Research Communications*, 7(5), 055027. <https://doi.org/10.1088/2515-7620/add861>
218. Luo, Z., Zhang, H., Pang, J., Yang, J., & Li, M. (2023). Coupling of SWAT and EPIC Models to Investigate the Mutual Feedback Relationship between Vegetation and Soil Erosion, a Case Study in the Huangfuchuan Watershed, China. *Forests*, 14(4), 844. <https://doi.org/10.3390/f14040844>
219. Lyapustin, A., Wang, Y., Korkin, S., & Huang, D. (2018). MODIS Collection 6 MAIAC algorithm. *Atmospheric Measurement Techniques*, 11(10), 5741–5765. <https://doi.org/10.5194/amt-11-5741-2018>
220. Lydia, Dr. B. (2023). The Phenomenon of Desertification: Causes, Consequences and Control Solutions: The Case of the El-Outaya Area in Biskra (Algeria). *International Journal of Innovative Studies in Sociology and Humanities*, 8(1), 326–337. <https://doi.org/10.20431/2456-4931.080134>
221. Macheroum, A., Kadik, L., Neffar, S., & Chenchouni, H. (2021). Environmental drivers of taxonomic and phylogenetic diversity patterns of plant communities in semi-arid steppe rangelands of North Africa. *Ecological Indicators*, 132. <https://doi.org/10.1016/j.ecolind.2021.108279>
222. Mahcer, I., Baahmed, D., Oudin, L., & Chemirik, C. H. K. (2024). Multidimensional analysis of NDVI dynamics in response to climate and land use/land cover change in Northwest Algeria. *Journal of Hydrology and Hydromechanics*, 72(4), 399–412. <https://doi.org/10.2478/JOHH-2024-0020>
223. Malika, A., Abderrahman, H., Aicha, L., Laounia, N., & Habib, M. (2018). USE OF HIGH SPATIAL RESOLUTION SATELLITE DATA FOR MONITORING AND CHARACTERIZATION OF DROUGHT CONDITIONS IN THE NORTHWESTERN ALGERIA. *Mining Science*, 25, 1–29. <https://doi.org/10.5277/msc182507>

224. Markham, B. L., & Helder, D. L. (2012). Forty-year calibrated record of earth-reflected radiance from Landsat: A review. *Remote Sensing of Environment, Landsat Legacy Special Issue*, 122, 30–40.
<https://doi.org/10.1016/j.rse.2011.06.026>
225. Martin, T. G., & Watson, J. E. M. (2016). Intact ecosystems provide best defence against climate change. *Nature Climate Change*, 6(2), 122–124.
<https://doi.org/10.1038/nclimate2918>
226. Mas, J.-F., Kolb, M., Paegelow, M., Camacho Olmedo, M. T., & Houet, T. (2014). Inductive pattern-based land use/cover change models: A comparison of four software packages. *Environmental Modelling & Software*, 51, 94–111.
<https://doi.org/10.1016/j.envsoft.2013.09.010>
227. Masroor, M., Sajjad, H., Rehman, S., Singh, R., Hibjur Rahaman, M., Sahana, M., Ahmed, R., & Avtar, R. (2022). Analysing the relationship between drought and soil erosion using vegetation health index and RUSLE models in Godavari middle sub-basin, India. *Geoscience Frontiers*, 13(2), 101312.
<https://doi.org/10.1016/j.gsf.2021.101312>
228. Mathbout, S., Lopez-Bustins, J. A., Royé, D., & Martin-Vide, J. (2021). Mediterranean-scale drought: Regional datasets for exceptional meteorological drought events during 1975-2019. *Atmosphere*, 12(8).
<https://doi.org/10.3390/atmos12080941>
229. Mayor, Á. G., Kéfi, S., Bautista, S., Rodríguez, F., Cartení, F., & Rietkerk, M. (2013). Feedbacks between vegetation pattern and resource loss dramatically decrease ecosystem resilience and restoration potential in a simple dryland model. *Landscape Ecology*, 28(5), 931–942.
<https://doi.org/10.1007/s10980-013-9870-4>
230. Mazen, H., & Mohammed, T. A. (2023). Tools for Drought Identification and Assessment: A Review. *Journal of Engineering*, 29(10), 90–105.
<https://doi.org/10.31026/j.eng.2023.10.06>
231. McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January). THE RELATIONSHIP OF DROUGHT FREQUENCY AND DURATION TO TIME SCALES. Eighth Conference on Applied Climatology.
232. MEA, Adeel, Z., & World Resources Institute (Eds.). (2005). *Ecosystems and human well-being: Desertification synthesis ; a report of the Millennium Ecosystem Assessment*. World Resources Inst.
233. Meddi, M., & Toumi, S. (2013). STUDY OF THE INTERANNUAL RAINFALL VARIABILITY IN NORTHERN ALGERIA ETUDE DE LA VARIABILITE INTER-ANNUELLE DES PLUIES DE L'ALGERIE SEPTENTRIONALE. *Le Journal de l'Eau et de l'Environnement*, 12(23), 40–59.

234. Mehmood, K., Anees, S. A., Shahzad, F., Muhammad, S., Liu, Q., Khan, W. R., Shah, M., & Jamjareegulgarn, P. (2025). Exploring vegetation health in Southern Thailand under climate stress from temperature and water impacts between 2000 and 2023. *Scientific Reports*, 15(1), 30491. <https://doi.org/10.1038/s41598-025-16293-x>
235. Mehmoud, K., Shoaib Ahmad, A., Sultan, M., Khadim, H., Fahad, S., Qijing, L., Javed Ansari, M., Ali Alharbi, S., & Razzaq Khan, W. (2024). Analyzing vegetation health dynamics across seasons and regions through NDVI and climatic variables | *Scientific Reports*. 14(11775). <https://doi.org/https://doi.org/10.1038/s41598-024-62464-7>
236. Merdas, S., Boulghobra, N., & Lakhdari, F. (2015). The Green Dam in Algeria as a tool to combat desertification. *Planet@Risk*, 3, 1–4.
237. Merniz, N., Tahar, A., & Benmehaia, A. M. (2019). Statistical assessment of rainfall variability and trends in northeastern Algeria. *Journal of Water and Land Development*, 40(1), 87–96. <https://doi.org/10.2478/jwld-2019-0009>
238. Mianabadi, A., Salari, K., & Pourmohamad, Y. (2022). Drought monitoring using the long-term CHIRPS precipitation over Southeastern Iran. *Applied Water Science*, 12(8). <https://doi.org/10.1007/s13201-022-01705-4>
239. Milton, S. J., Dean, W. R. J., & Ellis, R. P. (1998). Rangeland health assessment: A practical guide for ranchers in arid Karoo shrublands. *Journal of Arid Environments*, 39(2), 253–265. <https://doi.org/10.1006/jare.1998.0395>
240. Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, 391(1), 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
241. Mohamed, O. S. (2025). The Green Dam in Algeria: From an Ambitious Project in 1971 to an Environmental Rehabilitation Strategy in 2023, Djelfa Province as a Model. *Journal of Information Systems Engineering and Management*, 10(4), 1812–1827. <https://doi.org/10.52783/jisem.v10i4.11444>
242. Mohamed, O. S., M'hammed, S., Mohamed, A., & Saad, C. (2025). The Green Dam in Algeria: From an Ambitious Project in 1971 to an Environmental Rehabilitation Strategy in 2023, Djelfa Province as a Model.
243. Mohammed, G., Boutkhil, M., & Ayoub, B. (2024). Assessing the impact of anthropogenic activities on land use and land cover changes in the semi-arid and arid regions of Algeria. *Environmental Monitoring and Assessment*, 196(4), 383. <https://doi.org/10.1007/s10661-024-12524-2>
244. Morant, J., Sánchez-Zapata, J. A., Monfort-Calatayud, M., & Soliveres, S. (2025). Sequential Thresholds Shape Drylands' Multitrophic Response to Aridification. *Ecology Letters*, 28(11), e70242. <https://doi.org/10.1111/ele.70242>

245. Moss, W. E., Crausbay, S. D., Rangwala, I., Wason, J. W., Trauernicht, C., Stevens-Rumann, C. S., Sala, A., Rottler, C. M., Pederson, G. T., Miller, B. W., Magness, D. R., Littell, J. S., Frelich, L. E., Frazier, A. G., Davis, K. T., Coop, J. D., Cartwright, J. M., & Booth, R. K. (2024). Drought as an emergent driver of ecological transformation in the twenty-first century. *BioScience*, 74(8), 524–538. <https://doi.org/10.1093/biosci/biae050>
246. Moumane, A., Azougarh, Y., Enajar, A. A., Alkhurairi, W. S., Bahdou, I., Al Karkouri, J., Nahas, F., Rebouh, N. Y., & Youssef, Y. M. (2026). Desertification monitoring in arid oasis environment using Google Earth Engine, machine learning, and field-based hydrogeological assessment. *Scientific Reports*, 16(1), 9212. <https://doi.org/10.1038/s41598-026-41216-9>
247. Moussa Kourouma, J., Eze, E., Negash, E., Phiri, D., Vinya, R., Girma, A., & Zenebe, A. (2021). Assessing the spatio-temporal variability of NDVI and VCI as indices of crops productivity in Ethiopia: A remote sensing approach. <http://www.tandfonline.com/action/journalInformation?show=aimsScope&journalCode=tgnh20#.VsXodSCLRhE>, 12(1), 2880–2903. <https://doi.org/10.1080/19475705.2021.1976849>
248. Mukherjee, S., Mishra, A., & Trenberth, K. E. (2018). Climate Change and Drought: A Perspective on Drought Indices. *Current Climate Change Reports*, 4(2), 145–163. <https://doi.org/10.1007/s40641-018-0098-x>
249. Müller, L. M., & Bahn, M. (2022). Drought legacies and ecosystem responses to subsequent drought. *Global Change Biology*, 28(17), 5086–5103. <https://doi.org/10.1111/gcb.16270>
250. Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J. N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9), 4349–4383. <https://doi.org/10.5194/essd-13-4349-2021>
251. Nandgude, N., Singh, T. P., Nandgude, S., & Tiwari, M. (2023). Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies. *Sustainability*, 15(15). <https://doi.org/10.3390/su151511684>
252. Nanzad, L., Zhang, J., Tuvdendorj, B., Nabil, M., Zhang, S., & Bai, Y. (2019). NDVI anomaly for drought monitoring and its correlation with climate factors over Mongolia from 2000 to 2016. *Journal of Arid Environments*, 164, 69–77. <https://doi.org/10.1016/j.jaridenv.2019.01.019>
253. Nkonya, E., Nicolas, G., Philipp, B., von Braun, J., De Pinto, A., Graw, V., Kato, E., Kloos, J., & Walter, T. (2011). The Economics of Desertification,

- Land Degradation, and Drought (No. 150; ZEF- Discussion Papers on Development Policy, p. 184). Center for Development Research,.
254. Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., Hermans, K., Jobbagy, E., Kurz, W., Li, D., Sonwa, D. J., Stringer, L., Crews, T., Dallimer, M., Eekhout, J., Erb, K., Haughey, E., Houghton, R., Iqbal, M. M., ... Stringer, L. (2022). Land degradation. In *Climate Change and Land* (pp. 345–436). Cambridge University Press. <https://doi.org/10.1017/9781009157988.006>
 255. Omar, A. A., Hassan, S. M., & Mohamed, M. J. (2022). Drought Effects in Somalia and Solution Proposals (SSRN Scholarly Paper No. 4217209). Social Science Research Network. <https://papers.ssrn.com/abstract=4217209>
 256. Ontel, I., Cheval, S., Irimescu, A., Boldeanu, G., Amihaesei, V.-A., Mihailescu, D., Nertan, A., Angearu, C.-V., & Craciunescu, V. (2023). Assessing the Recent Trends of Land Degradation and Desertification in Romania Using Remote Sensing Indicators. *Remote Sensing*, 15(19), 4842. <https://doi.org/10.3390/rs15194842>
 257. Oubadi, M., Faci, M., & Pham, Q. B. (2024). Drought and aridity trends on the Algerian steppe. *Theoretical and Applied Climatology*, 155(3), 1541–1551. <https://doi.org/10.1007/S00704-024-04865-2>
 258. Oukaddour, K., Page, M. L., & Fakir, Y. (2023). Toward a Redefinition of Agricultural Drought Periods—A Case Study in a Mediterranean Semi-Arid Region. *Remote Sensing*, 16(1). <https://doi.org/10.3390/rs16010083>
 259. Pacheco, F. A. L., Sanches Fernandes, L. F., Valle Junior, R. F., Valera, C. A., & Pissarra, T. C. T. (2018). Land degradation: Multiple environmental consequences and routes to neutrality. *Current Opinion in Environmental Science & Health, Sustainable Soil Management and Land Restoration*, 5, 79–86. <https://doi.org/10.1016/j.coesh.2018.07.002>
 260. Pandit, R., Parrotta, J. A., Chaudhary, A. K., Karlen, D. L., Vieira, D. L. M., Anker, Y., Chen, R., Morris, J., Harris, J., & Ntshotsho, P. (2020). A framework to evaluate land degradation and restoration responses for improved planning and decision-making. *Ecosystems and People*, 16(1), 1–18. <https://doi.org/10.1080/26395916.2019.1697756>
 261. Peters, A. J., Rundquist, D. C., & Wilhite, D. A. (1991). Satellite detection of the geographic core of the 1988 Nebraska drought. *Agricultural and Forest Meteorology*, 57(1), 35–47. [https://doi.org/10.1016/0168-1923\(91\)90077-4](https://doi.org/10.1016/0168-1923(91)90077-4)
 262. Pontius Jr, R. G., & Millones, M. (2011). Death to Kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing*, 32(15), 4407–4429. <https://doi.org/10.1080/01431161.2011.552923>

263. Prabhakar, S. V. R. K. (2021). A succinct review and analysis of drivers and impacts of agricultural land transformations in Asia. *Land Use Policy*, 102, 105238–105238. <https://doi.org/10.1016/j.landusepol.2020.105238>
264. Prăvălie, R. (2021). Exploring the multiple land degradation pathways across the planet. *Earth-Science Reviews*, 220, 103689. <https://doi.org/10.1016/j.earscirev.2021.103689>
265. Prăvălie, R., Patriche, C., Borrelli, P., Panagos, P., Roșca, B., Dumitrașcu, M., Nita, I.-A., Săvulescu, I., Birsan, M.-V., & Bandoc, G. (2021). Arable lands under the pressure of multiple land degradation processes. A global perspective. *Environmental Research*, 194, 110697. <https://doi.org/10.1016/j.envres.2020.110697>
266. Pricope, N. G., Daldegan, G. A., Zvoleff, A., Mwenda, K. M., Noon, M., & Lopez-Carr, D. (2023). Operationalizing an integrative socio-ecological framework in support of global monitoring of land degradation. *Land Degradation & Development*, 34(1), 109–124. <https://doi.org/10.1002/ldr.4447>
267. Prieto-Amparan, J. A., Villarreal-Guerrero, F., Martinez-Salvador, M., Manjarrez-Domínguez, C., Santellano-Estrada, E., & Pinedo-Alvarez, A. (2018). Atmospheric and Radiometric Correction Algorithms for the Multitemporal Assessment of Grasslands Productivity. *Remote Sensing*, 10(2). <https://doi.org/10.3390/rs10020219>
268. Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A modified soil adjusted vegetation index. *Remote Sensing of Environment*, 48(2), 119–126. [https://doi.org/10.1016/0034-4257\(94\)90134-1](https://doi.org/10.1016/0034-4257(94)90134-1)
269. Quan, X.-W., Hoerling, M., Smith, L., Perlwitz, J., Zhang, T., Hoell, A., Wolter, K., & Eischeid, J. (2018). Extreme California Rains During Winter 2015/16: A Change in El Niño Teleconnection? *Bulletin of the American Meteorological Society*, 99(1), S49–S53. <https://doi.org/10.1175/BAMS-D-17-0118.1>
270. Radeloff, V. C., Roy, D. P., Wulder, M. A., Anderson, M., Cook, B., Crawford, C. J., Friedl, M., Gao, F., Gorelick, N., Hansen, M., Healey, S., Hostert, P., Hulley, G., Huntington, J. L., Johnson, D. M., Neigh, C., Lyapustin, A., Lymburner, L., Pahlevan, N., ... Zhu, Z. (2024). Need and vision for global medium-resolution Landsat and Sentinel-2 data products. *Remote Sensing of Environment*, 300, 113918. <https://doi.org/10.1016/j.rse.2023.113918>
271. Rahimi, J., Haas, E., Grote, R., Kraus, D., Smerald, A., Laux, P., Goopy, J., & Butterbach-Bahl, K. (2021). Beyond livestock carrying capacity in the Sahelian and Sudanian zones of West Africa. *Scientific Reports*, 11(1), 22094. <https://doi.org/10.1038/s41598-021-01706-4>
272. Ramezan, C., A. Warner, T., & E. Maxwell, A. (2019). Evaluation of Sampling and Cross-Validation Tuning Strategies for Regional-Scale Machine

- Learning Classification. *Remote Sensing*, 11(2), 185.
<https://doi.org/10.3390/rs11020185>
273. Rampone, S., & Valente, A. (2019). Assessment of desertification vulnerability using soft computing methods. *Journal of Ambient Intelligence and Humanized Computing*, 10(2), 701–707. <https://doi.org/10.1007/s12652-018-0720-8>
 274. Rastgoo, M., & Hasanfard, A. (2022). Desertification in Agricultural Lands: Approaches to Mitigation. In Y. Zhu, Q. Luo, & Y. Liu (Eds.), *Deserts and Desertification*. IntechOpen. <https://doi.org/10.5772/intechopen.98795>
 275. Rath, A., Kumar, P., Nangla, S., Sharma, S., & Sharma, S. (2024). Soil Restoration Strategies for Sustaining Soil Productivity: A Review. *Asian Research Journal of Agriculture*, 17(1), 33–48.
<https://doi.org/10.9734/arja/2024/v17i1408>
 276. Ravi, S., Breshears, D. D., Huxman, T. E., & D'Odorico, P. (2010). Land degradation in drylands: Interactions among hydrologic–aeolian erosion and vegetation dynamics. *Geomorphology*, 116(3–4), 236–245.
<https://doi.org/10.1016/j.geomorph.2009.11.023>
 277. Rayne, L., Brandolini, F., Makovics, J. L., Hayes-Rich, E., Levy, J., Irvine, H., Assi, L., & Bokbot, Y. (2023). Detecting desertification in the ancient oases of southern Morocco. *Scientific Reports*, 13(1), 19424.
<https://doi.org/10.1038/s41598-023-46319-1>
 278. Reis, S. (2008). Analyzing Land Use/Land Cover Changes Using Remote Sensing and GIS in Rize, North-East Turkey. *Sensors* (Basel, Switzerland), 8(10), 6188–6202. <https://doi.org/10.3390/s8106188>
 279. Reisman-Berman, O., Keasar, T., & Tel-Zur, N. (2019). Native and non-native species for dryland afforestation: Bridging ecosystem integrity and livelihood support. *Annals of Forest Science*, 76(4), 114.
<https://doi.org/10.1007/s13595-019-0903-2>
 280. Ren, J., Zheng, H., Wang, J., Tong, C., Tian, D., Lu, H., & Liang, D. (2024). Assessment of Soil Moisture in Vegetation Regions of Mu Us Sandy Land Using Several Aridity Indicators. *Atmosphere*, 15(11), 1329.
<https://doi.org/10.3390/atmos15111329>
 281. Reynolds, J. F. (2021). Desertification is a prisoner of history: An essay on why young scientists should care. *Ecosistemas*, 30(3), 2302–2302.
<https://doi.org/10.7818/ECOS.2302>
 282. Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B. L., Mortimore, M., Batterbury, S. P. J., Downing, T. E., Dowlatabadi, H., Fernández, R. J., Herrick, J. E., Huber-Sannwald, E., Jiang, H., Leemans, R., Lynam, T., Maestre, F. T., Ayarza, M., & Walker, B. (2007). Global desertification:

- Building a science for dryland development. *Science*, 316(5826), 847–851.
<https://doi.org/10.1126/science.1131634>
283. Richards, J. A., & Jia, X. (Eds.). (2006). Supervised Classification Techniques. In *Remote Sensing Digital Image Analysis: An Introduction* (pp. 193–247). Springer. https://doi.org/10.1007/3-540-29711-1_8
 284. Rikimaru, A., Roy, P. S., & Miyatake, S. (2002). Tropical forest cover density mapping. 43(1).
 285. Rivera-Marin, D., Dash, J., & Ogutu, B. (2022). The use of remote sensing for desertification studies: A review. *Journal of Arid Environments*, 206.
<https://doi.org/10.1016/j.jaridenv.2022.104829>
 286. Rodriguez, E., Morris, C. S., & Belz, J. E. (2006). A Global Assessment of the SRTM Performance. *Photogrammetric Engineering & Remote Sensing*, 72(3), 249–260. <https://doi.org/10.14358/PERS.72.3.249>
 287. Rouse, J. W., Haas, R. H., Deering, D. W., Schell, J. A., & Harlan, J. C. (1973). Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. [Great Plains Corridor].
<https://api.semanticscholar.org/CorpusID:129198382>
 288. Rousta, I., Olafsson, H., Moniruzzaman, M., Zhang, H., Liou, Y.-A., Mushore, T. D., & Gupta, A. (2020). Impacts of Drought on Vegetation Assessed by Vegetation Indices and Meteorological Factors in Afghanistan. *Remote Sensing*, 12(15). <https://doi.org/10.3390/rs12152433>
 289. Roy, D. P., Kovalsky, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S., & Egorov, A. (2016). Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment, Landsat 8 Science Results*, 185, 57–70.
<https://doi.org/10.1016/j.rse.2015.12.024>
 290. Sabljčić, L., Lukić, T., Bajić, D., Marković, S. B., & Delić, D. (2024). Application of remote sensing in monitoring land degradation: A case study of Stanari municipality (Bosnia and Herzegovina).
<https://doi.org/https://doi.org/10.1515/geo-2022-0671>
 291. Saco, P. M. (2018). Vegetation and soil degradation in drylands: Non linear feedbacks and early warning signals.
 292. Safriel, U. N. (2007). The Assessment of Global Trends in Land Degradation. In M. V. K. Sivakumar & N. Ndiang'ui (Eds.), *Climate and Land Degradation* (pp. 1–38). Springer. https://doi.org/10.1007/978-3-540-72438-4_1
 293. Salhi, C., Touaibia, B., Zeroual, A., Benblida, N., & Assani, A. (2022). Evaluation of soil erosion in Northern Algeria watershed using SWAT and RUSLE models. *Geocarto International*, 37(26), 11559–11589.
<https://doi.org/10.1080/10106049.2022.2060314>

294. Sampson, C. C., Smith, A. M., Bates, P. D., Neal, J. C., & Trigg, M. A. (2016). Perspectives on Open Access High Resolution Digital Elevation Models to Produce Global Flood Hazard Layers. *Frontiers in Earth Science*, 3. <https://doi.org/10.3389/feart.2015.00085>
295. Satoh, Y., Shiogama, H., Hanasaki, N., Pokhrel, Y., Boulange, J. E. S., Burek, P., Gosling, S. N., Grillakis, M., Koutroulis, A., Müller Schmied, H., Thiery, W., & Yokohata, T. (2021). A quantitative evaluation of the issue of drought definition: A source of disagreement in future drought assessments. *Environmental Research Letters*, 16(10), 104001. <https://doi.org/10.1088/1748-9326/ac2348>
296. Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analgesia*, 126(5), 1763. <https://doi.org/10.1213/ANE.0000000000002864>
297. Scholes, R. J. (2020). The Future of Semi-Arid Regions: A Weak Fabric Unravels. *Climate*, 8(3), 43. <https://doi.org/10.3390/cli8030043>
298. Schwilch, G., Liniger, H. P., & Hurni, H. (2014). Sustainable Land Management (SLM) Practices in Drylands: How Do They Address Desertification Threats? *Environmental Management*, 54(5), 983–1004. <https://doi.org/10.1007/s00267-013-0071-3>
299. Seely, M., & Wöhl, H. (2004). Connecting Research to Combating Desertification. *Environmental Monitoring and Assessment*, 99(1), 23–32. <https://doi.org/10.1007/s10661-004-3997-3>
300. Selmy, S. A. H., Kucher, D. E., Mozgeris, G., Moursy, A. R. A., Jimenez-Ballesta, R., Kucher, O. D., Fadl, M. E., & Mustafa, A. A. (2023). Detecting, Analyzing, and Predicting Land Use/Land Cover (LULC) Changes in Arid Regions Using Landsat Images, CA-Markov Hybrid Model, and GIS Techniques. *Remote Sensing*, 15(23), 5522. <https://doi.org/10.3390/rs15235522>
301. Shao, W., Zhang, Z., Guan, Q., Yan, Y., & Zhang, J. (2024). Comprehensive assessment of land degradation in the arid and semiarid area based on the optimal land degradation index model. *CATENA*, 234, 107563–107563. <https://doi.org/10.1016/J.CATENA.2023.107563>
302. Sheffield, J., & Wood, E. F. (2008). Global Trends and Variability in Soil Moisture and Drought Characteristics, 1950–2000, from Observation-Driven Simulations of the Terrestrial Hydrologic Cycle. <https://doi.org/10.1175/2007JCLI1822.1>
303. Sheffield, J., & Wood, E. F. (2012). Drought: Past Problems and Future Scenarios. Routledge. <https://doi.org/10.4324/9781849775250>
304. Sivakumar, M. V. K. (2007). Interactions between climate and desertification. *Agricultural and Forest Meteorology*, The Contribution of

- Agriculture to the State of Climate, 142(2), 143–155.
<https://doi.org/10.1016/j.agrformet.2006.03.025>
305. Slayi, M., Zhou, L., Dzvene, A. R., & Mpanyaro, Z. (2024). Drivers and Consequences of Land Degradation on Livestock Productivity in Sub-Saharan Africa: A Systematic Literature Review. *Land*, 13(9), 1402.
<https://doi.org/10.3390/land13091402>
 306. Smail, M., Boubaker, Z., Sbabdji, M., Mouaissa, H., & Kombate, B. (2024). Detecting land use/land cover changes and forest degradation: A case study of the lower Soummam valley, northern Algeria. *Journal of Forest Science*, 70(3), 122–134. <https://doi.org/10.17221/86/2023-JFS>
 307. Smith, P., Poch, R. M., Lobb, D. A., Bhattacharyya, R., Alloush, G., Eudoxie, G. D., Anjos, L. H. C., Castellano, M., Ndzana, G. M., Chenu, C., Naidu, R., Vijayanathan, J., Muscolo, A. M., Studdert, G. A., Eugenio, N. R., Calzolari, M. C., Amuri, N., & Hallett, P. (2024). Status of the World's Soils. *Annual Review of Environment and Resources*, 49(1), 73–104.
<https://doi.org/10.1146/annurev-environ-030323-075629>
 308. Solomon, N., Birhane, E., Tilahun, M., Schauer, M., Gebremedhin, M. A., Gebremariam, F. T., Gidey, T., & Newete, S. W. (2024). Revitalizing Ethiopia's highland soil degradation: A comprehensive review on land degradation and effective management interventions. *Discover Sustainability*, 5(1), 106. <https://doi.org/10.1007/s43621-024-00282-7>
 309. Spiekermann, R., Brandt, M., & Samimi, C. (2015). Woody vegetation and land cover changes in the Sahel of Mali (1967–2011). *International Journal of Applied Earth Observation and Geoinformation*, 34, 113–121.
<https://doi.org/10.1016/j.jag.2014.08.007>
 310. Spinoni, J., Naumann, G., Carrao, H., Barbosa, P., & Vogt, J. (2014). World drought frequency, duration, and severity for 1951–2010. *International Journal of Climatology*, 34(8), 2792–2804. <https://doi.org/10.1002/joc.3875>
 311. Stagge, J. H., Tallaksen, L. M., Lukas, G., Anne F, V. L., & Stahl, K. (2015). Candidate Distributions for Climatological Drought Indices (SPI and SPEI)—Stagge. 35(13). <https://doi.org/https://doi.org/10.1002/joc.4267>
 312. Stavi, I., Priori, S., & Thevs, N. (2022). Editorial: Impacts of Climate Change and Land-Use on Soil Functions and Ecosystem Services in Drylands. *Frontiers in Environmental Science*, 10, 851751.
<https://doi.org/10.3389/fenvs.2022.851751>
 313. Stavi, I., Xu, C., & Argaman, E. (2024). Climate-smart forestry in the world's drylands: A review of challenges and opportunities. *The Anthropocene Review*, 11(1), 67–90. <https://doi.org/10.1177/20530196231182354>

314. Sterk, G., & Stoorvogel, J. J. (2020). Desertification—Scientific Versus Political Realities. *Land* 2020, Vol. 9, Page 156, 9(5), 156–156. <https://doi.org/10.3390/LAND9050156>
315. Su, Y., & Guo, Q. (2014). A practical method for SRTM DEM correction over vegetated mountain areas. *ISPRS Journal of Photogrammetry and Remote Sensing*, 87, 216–228. <https://doi.org/10.1016/j.isprsjprs.2013.11.009>
316. Tanarhte, M., De Vries, A. J., Zittis, G., & Chfadi, T. (2024). Severe droughts in North Africa: A review of drivers, impacts and management. *Earth-Science Reviews*, 250. <https://doi.org/10.1016/j.earscirev.2024.104701>
317. Tang, T., Ge, J., Shi, H., Wang, L., Cao, J., & Lee, X. (2025). Drought frequency, intensity, and exposure have increased due to historical land use and land cover changes. *Communications Earth & Environment*, 6(1), 398. <https://doi.org/10.1038/s43247-025-02392-0>
318. Tariq, A., Sardans, J., Zeng, F., Graciano, C., Hughes, A. C., Farré-Armengol, G., & Peñuelas, J. (2024). Impact of aridity rise and arid lands expansion on carbon-storing capacity, biodiversity loss, and ecosystem services. *Global Change Biology*, 30(4), e17292. <https://doi.org/10.1111/gcb.17292>
319. Tarun, Kshatriya., & Rajeswari., C. (2025). Impact of Soil Degradation on Agronomic Productivity and Strategies for Restoration. *International Journal of Environment and Climate Change*, 15(11), 28–36. <https://doi.org/10.9734/ijecc/2025/v15i115093>
320. Tayeb, S. T., & Kheloufi, B. (2019). Spatio-temporal dynamics of vegetation cover in North-West Algeria using remote sensing data. *Polish Cartographical Review*, 51(3), 117–127. <https://doi.org/10.2478/pcr-2019-0009>
321. Terwayet Bayouli, O., Zhang, W., & Terwayet Bayouli, H. (2023). Combining RUSLE model and the vegetation health index to unravel the relationship between soil erosion and droughts in southeastern Tunisia. *Journal of Arid Land*, 15(11), 1269–1289. <https://doi.org/10.1007/s40333-023-0110-8>
322. Tilahun, A., & Teferie, B. (2015). Accuracy Assessment of Land Use Land Cover Classification using Google Earth. *American Journal of Environmental Protection*, 4(4), 193–198. <https://doi.org/10.11648/j.ajep.20150404.14>
323. Trenberth, K. (2011). Changes in precipitation with climate change. *Climate Research*, 47(1), 123–138. <https://doi.org/10.3354/cr00953>
324. Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., & Sheffield, J. (2014). Global warming and changes in drought. *Nature Climate Change*, 4(1), 17–22. <https://doi.org/10.1038/nclimate2067>
325. Tripathy, K. P., Mukherjee, S., Mishra, A. K., Mann, M. E., & Williams, A. P. (2023). Climate change will accelerate the high-end risk of compound drought and heatwave events. *Proceedings of the National Academy of Sciences*, 120(28), e2219825120. <https://doi.org/10.1073/pnas.2219825120>

326. Tsyganko, E., Shtyrkhunova, N., Modina, M., & Voskanyan, A. (2024). Soil degradation in the process of agricultural activities. *BIO Web of Conferences*, 103, 00061. <https://doi.org/10.1051/bioconf/202410300061>
327. Turner, B. L., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Hovelsrud-Broda, G. K., Kasperson, J. X., Kasperson, R. E., Luers, A., Martello, M. L., Mathiesen, S., Naylor, R., Polsky, C., Pulsipher, A., Schiller, A., Selin, H., & Tyler, N. (2003). Illustrating the coupled human–environment system for vulnerability analysis: Three case studies. *Proceedings of the National Academy of Sciences*, 100(14), 8080–8085. <https://doi.org/10.1073/pnas.1231334100>
328. Turner, M. D., Carney, T., Lawler, L., Reynolds, J., Kelly, L., Teague, M. S., & Brottem, L. (2021). Environmental rehabilitation and the vulnerability of the poor: The case of the Great Green Wall. *Land Use Policy*, 111, 105750. <https://doi.org/10.1016/j.landusepol.2021.105750>
329. Turner, M. D., Davis, D. K., Yeh, E. T., Hiernaux, P., Loizeaux, E. R., Fornof, E. M., Rice, A. M., & Suiter, A. K. (2023). Great Green Walls: Hype, Myth, and Science. *Annual Review of Environment and Resources*, 48(1), 263–287. <https://doi.org/10.1146/annurev-environ-112321-111102>
330. UNEP. (1978). Desertification control bulletin.
331. Uyar, N. (2025). Index-Driven Soil Loss Mapping Across Environmental Scenarios: Insights from a Remote Sensing Approach. *Sustainability*, 17(17). <https://doi.org/10.3390/su17177913>
332. Vaani, K. N., & Porchelvan, P. (2017). Assessment of long term agricultural drought in Tamilnadu, India using NDVI anomaly. 10(10), 1–10.
333. Van Loon, A. F. (2015). Hydrological drought explained. *WIREs Water*, 2(4), 359–392. <https://doi.org/10.1002/wat2.1085>
334. Verstraete, M. M. (1986). Defining desertification: A review. *Climatic Change*, 9(1–2), 5–18. <https://doi.org/10.1007/BF00140520>
335. Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. <https://doi.org/10.1175/2009JCLI2909.1>
336. Vicente-Serrano, S. M., Lopez-Moreno, J.-I., Beguería, S., Lorenzo-Lacruz, J., Sanchez-Lorenzo, A., García-Ruiz, J. M., Azorin-Molina, C., Morán-Tejeda, E., Revuelto, J., Trigo, R., Coelho, F., & Espejo, F. (2014). Evidence of increasing drought severity caused by temperature rise in southern Europe. *Environmental Research Letters*, 9(4), 044001. <https://doi.org/10.1088/1748-9326/9/4/044001>
337. Vicente-Serrano, S. M., Peña-Angulo, D., Beguería, S., Domínguez-Castro, F., Tomás-Burguera, M., Noguera, I., Gimeno-Sotelo, L., & El Kenawy, A.

- (2022). Global drought trends and future projections. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 380(2238), 20210285. <https://doi.org/10.1098/rsta.2021.0285>
338. Vicente-Serrano, S. M., Quiring, S. M., Peña-Gallardo, M., Yuan, S., & Domínguez-Castro, F. (2020). A review of environmental droughts: Increased risk under global warming? *Earth-Science Reviews*, 201. <https://doi.org/10.1016/j.earscirev.2019.102953>
339. Vieira, R. M. D. S. P., Tomasella, J., Cunha, A. P. M. D. A., Barbosa, A. A., Pompeu, J., Ferreira, Y., Santos, F. C., Alves, L. M., & Ometto, J. (2023). Socio-Environmental Vulnerability to Drought Conditions and Land Degradation: An Assessment in Two Northeastern Brazilian River Basins. *Sustainability*, 15(10), 8029. <https://doi.org/10.3390/su15108029>
340. Von Schoenborn, M.-I., & Bick, M. (2023). Promises and Challenges Relating to Machine Learning Techniques to Predict Areas at Risk of Desertification: A State-of-the-Art Review. In Z. Sun (Ed.), *Advances in Data Mining and Database Management* (pp. 44–75). IGI Global. <https://doi.org/10.4018/978-1-6684-5959-1.ch003>
341. Wafa, C. (2019). The phenomenon of desertification and its effects on Algerian economy. 17–1, الإبتكار والتنمية الصناعية, (1)2.
342. Wan, Z. (2013). MODIS Land Surface Temperature Products. NASA Land Processes Distributed Active Archive Center (LP DAAC).
343. Wang, H., Liu, Y., Wang, Y., Yao, Y., & Wang, C. (2023). Land cover change in global drylands: A review. *Science of The Total Environment*, 863, 160943–160943. <https://doi.org/10.1016/j.scitotenv.2022.160943>
344. Wang, J., Zhen, J., Hu, W., Chen, S., Lizaga, I., Zeraatpisheh, M., & Yang, X. (2023). Remote sensing of soil degradation: Progress and perspective. *International Soil and Water Conservation Research*, 11(3), 429–454. <https://doi.org/10.1016/j.iswcr.2023.03.002>
345. Wang, L., Guo, S., Hijri, M., Farooq, M., Rehman, A., Ge, T., Feng, S., Wei, Z., Zhang, J., Zhao, C., Kang, S., Siddique, K. H. M., Jin, Z., Zhao, M., & Gan, G. Y. (2025). Enhancing carbon restoration and ecosystem resilience in global drylands via water-to-carbon biotransformation strategies. *Communications Earth & Environment*, 6(1), 916. <https://doi.org/10.1038/s43247-025-02874-1>
346. Wang, N., Naz, I., Aslam, R. W., Quddoos, A., Soufan, W., Raza, D., Ishaq, T., & Ahmed, B. (2024). Spatio-Temporal Dynamics of Rangeland Transformation using machine learning algorithms and Remote Sensing data. *Rangeland Ecology & Management*, 94, 106–118. <https://doi.org/10.1016/J.RAMA.2024.02.008>

347. Wang, Q., Liu, H., Liang, B., Shi, L., Wu, L., & Cao, J. (2024). Will large-scale forestation lead to a soil water deficit crisis in China's drylands? *Science Bulletin*, 69(10), 1506–1514. <https://doi.org/10.1016/j.scib.2024.03.005>
348. Wang, Q., Yang, X., Qu, Y., Qiu, H., Wu, Y., Qi, J., Song, H., Chen, Y., Chu, H., & Zeng, J. (2025). Global Climate Change Exacerbates Socioeconomic Drought Severity Across Vegetation Zones During 1901–2018. *International Journal of Disaster Risk Science*, 16(2), 291–306. <https://doi.org/10.1007/s13753-025-00631-8>
349. Wang, Y., Khodadadzadeh, M., & Zurita-Milla, R. (2023). Spatial+: A new cross-validation method to evaluate geospatial machine learning models. *International Journal of Applied Earth Observation and Geoinformation*, 121, 103364. <https://doi.org/10.1016/j.jag.2023.103364>
350. Wardlaw, B. D., Anderson, M. C., & Verdin, J. P. (Eds.). (2012). *Remote Sensing of Drought: Innovative Monitoring Approaches*. CRC Press. <https://doi.org/10.1201/b11863>
351. Watson, J. E. M., Venter, O., Lee, J., Jones, K. R., Robinson, J. G., Possingham, H. P., & Allan, J. R. (2018). Protect the last of the wild. 27(30). <https://doi.org/doi:%20https://doi.org/10.1038/d41586-018-07183-6>
352. Webb, N. P., Wheeler, B., Edwards, B. L., Schallner, J. W., Macanowicz, N., Van Zee, J. W., Courtright, E. M., Cooper, B., McCord, S. E., Browning, D., Dhital, S., Young, K. E., & Bestelmeyer, B. T. (2025). Magnitude Shifts in Aeolian Sediment Transport Associated With Degradation and Restoration Thresholds in Drylands. *Journal of Geophysical Research: Biogeosciences*, 130(3), e2024JG008581. <https://doi.org/10.1029/2024JG008581>
353. Weng, Q. (2002). Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling. *Journal of Environmental Management*, 64(3), 273–284. <https://doi.org/10.1006/jema.2001.0509>
354. Wilhite, D. A. (2000). Chapter 1 Drought as a Natural Hazard: Concepts and Definitions. In *Drought: A Global Assessment (Vol. I)* (pp. 3–18). Routledge.
355. Wilhite, D. A., & Glantz, M. H. (1985). Understanding: The Drought Phenomenon: The Role of Definitions. *Water International*, 10(3), 111–120. <https://doi.org/10.1080/02508068508686328>
356. WMO, W. (2006). *Drought monitoring and early warning: Concepts, progress, and future challenges*. World Meteorological Organization.
357. Worku, M. A. (2024). Spatiotemporal analysis of drought severity using SPI and SPEI: Case study of semi-arid Borana area, southern Ethiopia. *Frontiers in Environmental Science*, 12, 1337190. <https://doi.org/10.3389/fenvs.2024.1337190>

358. Wu, R., Zhang, C., Li, Y., Zhu, C., Lu, L., Cui, C., Zhang, Z., Wang, S., Chu, J., & Li, Y. (2023). Assessment of Variability and Attribution of Drought Based on GRACE in China from Three Perspectives: Water Storage Component, Climate Change, Water Balance. *Remote Sensing*, 15(18). <https://doi.org/10.3390/rs15184426>
359. Xiao, jun, Shen, y, Tateishi, R., & Bayaer, W. (2007). Development of topsoil grain size index for monitoring desertification in arid land using remote sensing: *International Journal of Remote Sensing: Vol 27 , No 12—Get Access*. 27(12). <https://www.tandfonline.com/doi/full/10.1080/01431160600554363>
360. Xiao, C., Ye, J., Esteves, R. M., & Rong, C. (2016). Using Spearman's correlation coefficients for exploratory data analysis on big dataset. *Concurrency and Computation: Practice and Experience*, 28(14), 3866–3878. <https://doi.org/10.1002/cpe.3745>
361. Xing, Y., & Wang, X. (2024). Precision Agriculture and Water Conservation Strategies for Sustainable Crop Production in Arid Regions. *Plants*, 13(22), 3184. <https://doi.org/10.3390/plants13223184>
362. Xiong, C., Ma, H., Liang, S., He, T., Zhang, Y., Zhang, G., & Xu, J. (2023). Improved global 250 m 8-day NDVI and EVI products from 2000–2021 using the LSTM model. *Scientific Data*, 10(1), 800. <https://doi.org/10.1038/s41597-023-02695-x>
363. Xu, D., Wang, Y., & Wang, J. (2024). A review of social-ecological system vulnerability in desertified regions: Assessment, simulation, and sustainable management. *Science of The Total Environment*, 931, 172604. <https://doi.org/10.1016/j.scitotenv.2024.172604>
364. Xu, Z., Liang, W., Lei, J., Wu, Y., & Wang, Z. (2025). Monitoring and assessment of desertification reversal in ecologically fragile areas: A case study of the Mu Us Sandy Land. *Journal of Environmental Management*, 373, 123695. <https://doi.org/10.1016/j.jenvman.2024.123695>
365. Yang, X., Liao, X., Di, D., & Shi, W. (2023). A Review of Drought Disturbance on Socioeconomic Development. *Water*, 15(22). <https://doi.org/10.3390/w15223912>
366. Yang, Y., Fan, Y., Basang, C. M., Lu, J., Zheng, C., & Wen, Z. (2022). Different biomass production and soil water patterns between natural and artificial vegetation along an environmental gradient on the Loess Plateau. *Science of The Total Environment*, 814, 152839. <https://doi.org/10.1016/j.scitotenv.2021.152839>
367. Yang, Z., Gao, X., Lei, J., Meng, X., & Zhou, N. (2022). Analysis of spatiotemporal changes and driving factors of desertification in the Africa Sahel. *CATENA*, 213, 106213–106213. <https://doi.org/10.1016/J.CATENA.2022.106213>

368. Yin, G., & Zhang, H. (2023). A new integrated index for drought stress monitoring based on decomposed vegetation response factors. *Journal of Hydrology*.
369. Yin, W., Hu, Q., Liu, J., He, P., Zhu, D., & Boali, A. (2024). Assessing Climate and Land-Use Change Scenarios on Future Desertification in Northeast Iran: A Data Mining and Google Earth Engine-Based Approach. *Land* 2024, Vol. 13, Page 1802, 13(11), 1802–1802.
<https://doi.org/10.3390/LAND13111802>
370. Yirdaw, E., Tigabu, M., & Monge, A. (2017). Rehabilitation of degraded dryland ecosystems – review. *Silva Fennica*, 51(1B).
<https://www.silvafennica.fi/article/1673>
371. Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, 19(NA), 333–349.
<https://doi.org/10.1139/a11-013>
372. Zeng, J., Zhou, T., Qu, Y., Bento, V. A., Qi, J., Xu, Y., Li, Y., & Wang, Q. (2023). An improved global vegetation health index dataset in detecting vegetation drought. *Scientific Data*, 10(1). <https://doi.org/10.1038/s41597-023-02255-3>
373. Zeng, N. (2003). Drought in the Sahel. *Science*, 302(5647), 999–1000.
<https://doi.org/10.1126/science.1090849>
374. Zerouali, B. (2021). A new regionalization of rainfall patterns based on wavelet transform information and hierarchical cluster analysis in northeastern Algeria. [https://doi.org/https://doi.org/10.21203/rs.3.rs-559269/v1](https://doi.org/10.21203/rs.3.rs-559269/v1)
375. Zerouali, B., Chettih, M., Abda, Z., Mesbah, M., Santos, C. A. G., Brasil Neto, R. M., & da Silva, R. M. (2021). Spatiotemporal meteorological drought assessment in a humid Mediterranean region: Case study of the Oued Sebaou basin (northern central Algeria). *Natural Hazards*, 108(1), 689–709.
<https://doi.org/10.1007/s11069-021-04701-0>
376. Zhang, S., Ye, L., Huang, C., Wang, M., Yang, Y., Wang, T., & Tan, W. (2022). Evolution of vegetation dynamics and its response to climate in ecologically fragile regions from 1982 to 2020: A case study of the Three Gorges Reservoir area. *CATENA*, 219, 106601.
<https://doi.org/10.1016/j.catena.2022.106601>
377. Zhang, X., Chen, N., Li, J., Chen, Z., & Niyogi, D. (2017). Multi-sensor integrated framework and index for agricultural drought monitoring. *Remote Sensing of Environment*, 188, 141–163.
<https://doi.org/10.1016/j.rse.2016.10.045>
378. Zhang, X., Hao, Z., Singh, V. P., Zhang, Y., Feng, S., Xu, Y., & Hao, F. (2022). Drought propagation under global warming: Characteristics,

- approaches, processes, and controlling factors. *Science of The Total Environment*, 838, 156021. <https://doi.org/10.1016/j.scitotenv.2022.156021>
379. Zhao, X., Xia, H., Pan, L., Song, H., Niu, W., Wang, R., Li, R., Bian, X., Guo, Y., & Qin, Y. (2021). Drought Monitoring over Yellow River Basin from 2003–2019 Using Reconstructed MODIS Land Surface Temperature in Google Earth Engine. *Remote Sensing*, 13(18), 3748. <https://doi.org/10.3390/rs13183748>
380. Zhou, S., Williams, A. P., Berg, A. M., Cook, B. I., Zhang, Y., Hagemann, S., Lorenz, R., Seneviratne, S. I., & Gentile, P. (2019). Land–atmosphere feedbacks exacerbate concurrent soil drought and atmospheric aridity. *Proceedings of the National Academy of Sciences*, 116(38), 18848–18853. <https://doi.org/10.1073/pnas.1904955116>
381. Zhu, X., Liu, Y., Xu, K., & Pan, Y. (2021). Effects of Drought on Vegetation Productivity of Farmland Ecosystems in the Drylands of Northern China. *Remote Sensing*, 13(6), 1179–1179. <https://doi.org/10.3390/rs13061179>
382. Zhuang, Y., Fu, R., Lisonbee, J., Sheffield, A. M., Parker, B. A., & Deheza, G. (2024). Anthropogenic warming has ushered in an era of temperature-dominated droughts in the western United States. *Science Advances*, 10(45), eadn9389. <https://doi.org/10.1126/sciadv.adn9389>
383. Ziadat, F. M., Zdruli, P., Christiansen, S., Caon, L., Monem, M. A., & Fetsi, T. (2021). An Overview of Land Degradation and Sustainable Land Management in the Near East and North Africa. *Sustainable Agriculture Research*, 11(1), 11–11. <https://doi.org/10.5539/sar.v11n1p11>
384. Zolfaghari, F., Azarnivand, H., Khosravi, H., Zehtabian, G., & Sigaroudi, S. K. (2022). Monitoring the severity of degradation and desertification by remote sensing (case study: Hamoun International Wetland). *Frontiers in Environmental Science*, 10. <https://doi.org/10.3389/fenvs.2022.902687>
385. Zongfan, B., Ling, H., Xuhai, J., Ming, L., Liangzhi, L., Huiqun, L., & Jiaxin, L. (2022). Spatiotemporal evolution of desertification based on integrated remote sensing indices in Duolun County, Inner Mongolia. *Ecological Informatics*, 70, 101750. <https://doi.org/10.1016/j.ecoinf.2022.101750>

