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Présentée pour l'obtention du grade de

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**Ecole Doctorale Lettres et Humanités ED730-LH**

**West African Science Service Centre on Climate Change and Adapted Land Use**

**Domaine** : Sciences de l'Homme et de la Société

**Mention** : Changement Climatique et Sécurité Humaine

**Spécialité** : Changement Climatique et Gestion des Risques de Catastrophes

Par

**MILLOGO Alphonse Maré David**

## VULNERABILITY OF THE COMPLEX PROTECTED-AREAS-AND-NEIGHBORING COMMUNITIES UNDER CLIMATIC AND HUMAN FOOTPRINT DRIVERS IN THE SUDANIAN CLIMATIC ZONE IN BURKINA FASO

Soutenue publiquement le 06 mars 2025 devant le jury composé de :

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# DOCTORAL THESIS

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## School of Letters and Humanities ED730-LH

**West African Science Service Centre on Climate Change and Adapted Land Use**

**Domain: Human and Social Sciences**

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**Specialty: Climate change and disaster risk management**

By

## Alphonse Maré David MILLOGO

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Publicly defended on the 6th March Before the jury composed of:

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# DEDICATION

I dedicate this research work:

- ❖ To God and my ancestors for guiding me in my daily life;
- ❖ To my dear father, Sissouro Lambert MILLOGO (Rest in Peace), who shaped me before leaving our world.
- ❖ To my cousin Sé MILLOGO (Rest in Peace), who contributed to relieving these difficult moments of doubts during field data collection but suddenly left us.
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- ❖ To my dear mother, who continues to inspire me and push me to fight for the best achievement, you are just amazing; thank you for everything;
- ❖ To my dear sisters, you never stop praying and supporting me and my lovely family during my studies; may God bless you.
- ❖ To my lovely wife, Flore Marie Carine Lonnuor MILLOGO/SOME, every word may not sound powerful enough to highlight your support during my studies and at any time. You played a father-mother role by ensuring the necessary for our children during my absence. Even during Raphael's pregnancy, you never stopped supporting me, sometimes forgetting your health condition. May God keep us together with our lovely children forever. To my adorable children, Charbel, Adora, and Raphael, I am so sorry for being physically far from you during my studies. Despite your young age, your support through our several video calls and prayers helped me continue fighting for this thesis achievement. May God continue to improve your life.

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# ABSTRACT

Protected forest areas and their neighboring communities in Burkina Faso are facing numerous challenges related to climate change, climate variability, and human impact, without a good understanding of the relationship between forests, climate, and human activities. To overcome this situation, this study's main objective seeks to understand the effect of climate and human footprint drivers on protected areas and their neighboring community resilience in the Sudanian climatic zone of Burkina Faso. Specifically, it seeks (i) to determine rainfall and temperature factors' effect on vegetation cover in the Sudanian climatic zone in Burkina Faso from 2001 to 2022, (ii) to assess the vulnerability of ecosystems within protected areas to human footprint in the Sudanian climatic zone from 1986 to 2022, (iii) to assess protected areas neighboring communities' vulnerability to climatic and human footprint drivers in the Sudanian climatic zone in Burkina Faso. Using satellite data, including climate data (TAMSAT, ERA5), MODIS-NDVI vegetation data, Landsat data, climate ground data, individual interviews, and focus groups, specific objectives have been fully addressed in consistent and reliable qualitative and quantitative methodology analysis carried out with R, Kobocollectool, QGIS version 3.18, and Excel software's. The study findings highlighted that the vegetation of the Sudanian climatic zone experienced severe and extreme drought events from 2001 to 2005 and from 2013 to 2016, supported by SPEI6 and NDVI moderate and positive Pearson correlation (r = 0.61). In addition, with a kappa coefficient and overall accuracy of more than 90%, the study revealed that both Dinderesso and Peni classified forest, Clear Forest, and Wooded Savannah/Tree Savannah classes were converted into Shrub Savannah and Agroforestry Parklands from 1986 to 2022 mainly due to human activities representing more than 90% of forest degradation and deforestation drivers. In the Dinderesso classified forest, the annual growth rate of Shrub Savannah and Agroforestry Parklands are respectively 3.86% and 3.09%. In the Peni classified forest, the annual growth rates of Shrub Savannah and Agroforestry Parklands are, respectively, more than 100% and 0.95%. Finally, this study highlighted that Dinderesso and the Peni classified forest neighboring communities were not similarly affected by climate variability effects and human activities on forest provisioning ecosystem services, with their vulnerability ranging from low to moderate. These consistent and meaningful findings are crucial pieces of information that will contribute to improving policymakers, forest managers, and the stakeholders' ability to improve forest management and preserve population livelihoods sustainably.



**Keywords:** Anthropogenic driver, Vulnerability, Land use land cover, Protected area, Burkina Faso.

RÉSUMÉ
Au Burkina Faso, les forêts classées et les communautés riveraines sont menacées par le changement climatique et les activités anthropiques avec un déficit de connaissances de la relation foret, homme et climat. Pour remédier à cette situation, l'objectif principal de cette étude est de comprendre l'effet des facteurs climatiques et de l'empreinte humaine sur les forêts classées et la résilience des communautés riveraines. De facon spécifique, l'étude vise à (i) déterminer l'effet de la pluviométrie et de la température sur le couvert végétal dans la zone Soudanienne du Burkina Faso de 2001 à 2022, (ii) évaluer la vulnérabilité des forêts classées sous l'influence des facteurs anthropiques en zone climatique Soudanienne de 1986 à 2022, (iii) évaluer la vulnérabilité des communautés riveraines des forêts classées sous l'effet du climat et des actions anthropiques dans la zone Soudanienne au Burkina Faso. En utilisant des données satellitaires, climatiques (TAMSAT, ERA5), de végétation (MODIS-NDVI), des données Landsat, des données climatiques d'observation, des enquêtes individuelles et focus groupes dans des méthodes d'analyses qualitatives et quantitatives via les logiciels R, Kobocollectool, QGIS version 3.18, et le tableur Excel, les résultats de l'étude ont révélé que la végétation de la zone climatique Soudanienne a été affectée par des sécheresses dites graves et extrêmes de 2001 à 2005 et de 2013 à 2016. Le coefficient de Pearson (r = 0.61) a révélé l'existence d'une corrélation positive modérée entre le SPEI6 et le NDVI. Avec un coefficient de Kappa et une précision globale supérieure à 90%, l'étude de la dynamique spatiotemporelle des forêts classées de Dinderesso et de Peni a révélé une conversion des forêts claires et savanes boisées/arborées en parcs agroforestiers et savanes arbustives due aux facteurs anthropiques qui représentent plus de 90% des facteurs de dégradation, de déforestation. Cette conversion est caractérisée par un taux de croissance annuel de 3.86% et 3.09% respectif des savanes arbustives et des parcs agroforestiers dans la forêt classée de Dinderesso contre un taux de croissance annuel de plus de 100% et de 0.95% respectif pour les savanes arbustives et parcs agroforestiers dans la forêt classée de Peni. Enfin, cette étude a montré que les communautés riveraines des forêts classées de Dinderesso et de Peni sont différemment affectées par la variabilité climatique et les activités anthropiques au regard de leur vulnérabilité variant de faible à modéré. Ces résultats sont une source d'informations cruciales d'aide à la prise de décision des décideurs politiques et gestionnaires des ressources forestières pour une gestion durable des forêts classées et des moyens d'existences des communautés riveraines.

**Mots clés :** Facteurs anthropiques, Vulnérabilité, Occupation des terres, Aire protégée, Burkina Faso.

# ACRONYMS AND ABBREVIATIONS LIST

APRM: Active Participatory Research Method

FAO: Food and Agriculture Organisation

FCFA: Financial community in Africa currency

GDP: Gross Domestic Product

GIEC: Intergovernmental Panel on Climate Change

GIS: Geographic Information System

GPS: Global Positioning System

IGB: Geographical Institute of Burkina Faso

INSD: National Institute of Statistics and Demography

IPCC: Intergovernmental Panel on Climate Change

MAE: Mean Absolute Error

MECV: Ministry of the environment and living environment

MEDD: Ministry of Environment and Sustainable Development

MEEEA: Ministry of Environment, Energy, Water and Sanitation

NDBI: Normalised Difference Built-up Index

NDVI: Normalised Difference Vegetation Index

NDWI: Normalised Difference Water Index

OMM: World Meteorological Organization

OTB: Orfeo ToolBox

PNDES: National Economic and Social Development Plan

POD: Probability of Detection

REDD+: Reducing Emissions from Deforestation and forest Degradation (Institution)

RMSE: Root Mean Square Error

SCP: Semi-automatic Classification Plugin

SD: Standard Deviation

SPEI: Standardised Precipitation-Evapotranspiration Index

TAMSAT: Tropical Applications of Meteorology using SATellite and ground-based observations

UN: United Nations

USGS: United States Geological Survey

UTM: Universal Transverse Mercator

WHO: World Health Organisation

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# GENERAL INTRODUCTION

Recognised as a landlocked Sahelian country located in West Africa with a surface area of 270,764 km$^2$ and 20,487,979 citizens (INSD, 2021), Burkina Faso's forest landscape is mainly distributed in the western, central-western, and eastern regions. It represents 48.75% of the national territory (MECV, 2007b). According to the National Assembly (2009), public forests in Burkina Faso are classified or protected. Classified areas represent 3.9 million hectares, around 14% of the country's landmass. The current situation of classified areas shows a decrease in land cover surface over the country (MECV, 2007; REDD+, 2019). The average annual forest loss is approximately 247,145 hectares (MEEEA, 2022). The degradation of forest resources is closely tied to population growth, which has increased over the years, leading to rising demands.

The forestry sector makes a significant contribution to the country's economy. From 2016 to 2020, the contribution of forestry and fauna to the country's Gross Domestic Product (GDP) varied from 1.6% to 1.7%; in terms of value, 724.9 billion FCFA was produced by forestry and fauna over the five years (INSD, 2021). In 2008, forestry's contribution to GDP was 6.58%, or 243 billion FCFA (MECV, 2010). Among the main resources, we have firewood, which represents the primary source of energy consumption for the population. Firewood's contribution to the GDP is evaluated at 85% compared to other forest timber products (PIF, 2011). The percentage of people using firewood for cooking in the country is estimated at 90% (MECV, 2010). Many people living in areas adjacent to protected areas are involved in the timber trade, which is a significant source of income for them (Belem & Zoungrana, 2018). In 2011, shea butter tree products contributed to the country's GDP, representing 0.60% or 28,991 billion FCFA (MEDD, 2012). In 2010, the global trade in traditional medicines was assessed at $ 60 billion in current US dollars (Nirmal et *al*., 2013). Forest resources play an important role in population health. More than 80% of African people use traditional medicines to treat their diseases (WHO, 2013). According to Tesfahuneygn and Gebreegziabher (2019), at least 800 plant species grown in Ethiopia are used in traditional medicines. In Burkina Faso, more than 70% of people use traditional medicines for health care (Zerbo et *al*., 2011). For approximately one billion people worldwide, food is closely tied to forest products, encompassing fauna, flora, insects, mushrooms, non-timber products, and fish (Burlingame, 2000). In Burkina Faso, non-timber forest products are consumed either raw or cooked, contributing to population food security during periods of hunger and crisis by supplementing cereal production (MEDD, 2012). The forestry sector is also a significant source of employment and income, which helps many households maintain their livelihoods and ensures food security and nutrition for more than 80 million people (FAO, 2020a). Regarding their regulating function, forests stock carbon (Boukeng & Elvire, 2021; Belle et al., 2016), which improves climate and controls rainfall at local and regional levels (OFAC, 2020; Belle et al., 2016).

Despite their importance, protected areas are facing degradation and deforestation, which reduce their capacity to continue supplying the population, especially the needs of neighboring communities, with ecosystem services. Even though forest areas are decreasing worldwide, the average annual loss of forest area from 2010 to 2020 was 4.74 million (FAO, 2020a). In Africa, this average remains high, with an average of 3.94 million hectares of forest lost per year from 2010 to 2020 (FAO, 2020a). According to Masumbuko and Somda (2014), protected areas are facing many pressure factors causing their degradation and deforestation. Using satellite images to analyse the conversion of forest to other land uses (Thiombiano & Kampmann, 2010), it was noticed that at least 260,000 hectares of forest areas were lost per year from 1990 to 2000 in Burkina Faso. By analysing the evolution of Tiogo forest land cover in Burkina Faso from 1986 to 2014, Tankoano et *al*., (2016) revealed that the forest lost around 0,49% of its canopy. Savadogo (2021), working on the provision of ecosystem services by the Bontioli total and partial wildlife reserves in the southwest of Burkina Faso, showed that this protected area lost from 2000 to 2020, 16.45% of tree savannah cover and 6.80% of the shrub and grass savannah cover. Regarding carbon dioxide emissions, the most significant portion is emitted into the atmosphere from the Sudanian climatic area, which has a high concentration of forests. The carbon dioxide emitted in this area is estimated to account for 95% of all emissions (SE/CCNUCC, 2020b). The equivalent carbon dioxide related to forest deforestation is assessed at 8,72 million tons, while 2,11 million tons belong to forest degradation (SE/CCNUCC, 2020b). Per year, the country's emission of carbon dioxide due to forest loss is assessed at 19,5 million tons (Ministry of Environment, 2019).

This degradation and deforestation of the protected area are caused by anthropogenic and climatic drivers (Boussougou et *al*., 2018; Savadogo, 2021; UNCCD, 2022). This situation prevents neighboring communities from benefiting from ecosystem services related to food security, water supply, income production, employment, health, cultural and spiritual practices, and leisure (Williamson et *al*., 2007). This situation contributes to increasing diseases, mortality, poverty, conflicts, and migration within neighboring communities that are becoming more vulnerable and less strong to ensure protected forest resources properly. Over the period 1969 to 2014, droughts have affected a cumulative number of 12,400,000 million people (OCHA, 2021), representing at least 60,52% of Burkina Faso's population. Unfortunately, all the climate predictions showed that West African countries will face more extreme events such as drought, floods, and heatwaves (Thiombiano & Kampmann, 2010; Masumbuko et Somda, 2014). According to Tomalka et *al*., (2021), the air temperature in Burkina Faso is projected to rise by 1.9 to 4.2 °C by 2080 relative to greenhouse gas emission effects. Although it indicates a decrease in rainfall in Burkina Faso, particularly in the southern part of the country, the rainfall projection does not provide certainty regarding the trend direction or whether it will increase (Tomalka et *al*., 2021).

In addition to climate change and climate variability issues, Burkina Faso has been facing insecurity since 2015 in all the country's regions due to terrorist attacks, which negatively affect forest sustainable management and population livelihoods. Indeed, it has been highlighted that terrorists used forest areas to hide themselves. This situation did not allow the population, forest managers, and researchers to access forest areas for their management safely. Also, these forest areas are now the hotspots of the war, contributing to the degradation and deforestation of those areas.

To mitigate the increasing disaster risks worldwide, the Sendai framework recommended developing suitable measures to protect more vulnerable areas and communities, particularly in developing countries (UNISDR, 2015).

Until now, all the efforts made to prevent the degradation and deforestation of protected areas seem not to be working, as evidenced by the ongoing degradation and deforestation. This unfavorable dynamic raises some points about the sustainable management approach experienced in the protected areas so far. Indeed, many efforts still need to be undertaken for the successful participation of neighboring communities in protected areas' sustainable management and the preservation of their livelihoods. For many authors, the degradation and deforestation of protected areas cannot be treated without associating neighboring communities as a key factor, looking at the interactions existing between them (REDD+, 2019; FAO, 2020). As recommended by the Sendai framework for disaster risk reduction, local communities have some knowledge that has to be integrated into disaster risk reduction plans (UNISDR, 2015). In Burkina Faso, Kabore (2009) revealed the valuable management of sacred forests by local communities at Seloghin and Teonsgo, two villages located respectively in the Sudan-Sahelian and Sahelian climatic zones. In West Africa, little scientific research has been interested in neighboring communities' relationship with protected areas and their degradation and deforestation drivers (Masumbuko et Somda, 2014). In Burkina Faso, most of the research studies related to protected area achieved so far focused on protected areas resources benefits and their degradation (Bene & Fournier, 2014; Dimobe et *al*., 2015; Etongo et *al*., 2015;

Tankoano et *al*., 2016; Millogo et *al*., 2017; Belem et *al*., 2019; Savadogo, 2021; Yaovi et *al*., 2021). Few of those studies have examined the adaptation capacity measures of neighbouring communities (Savadogo, 2021; Yaovi et *al*., 2021). Based on research studies addressing protected areas issues in Burkina Faso so far, there is a gap to fill concerning communities' relationship with their protected areas and climate change in different climatic zones to better understand the challenges before addressing solutions. To provide more scientific information on this relationship between neighboring communities, protected areas and climate for a double benefit of communities' livelihoods preservation and protected areas' ecosystem services conservation, within the context of climate change, the current topic: « **Vulnerability of the complex protected-areas-and-neighboring communities, under climatic and human footprint drivers in the Sudanian climatic zone in Burkina Faso**» has been designed. This study contributes first to world sustainable development objectives 2, 3, 4, 13, 14, and 17 (UN, 2024), Secondly, to disaster risk reduction framework priorities, including disaster risk understanding at a global and local scale in Burkina Faso, disaster risk management improvement by policymakers and natural resources managers, investments for disaster risk reduction, and disaster risk preparedness improvement to better results (UNISDR, 2015), and finally to the achievement of Burkina Faso's national socio-economic development plan from 2021 to 2025 (PNDES, 2021).

The following research questions have been developed to guide the current study:

- ❖ how does vegetation cover in the Sudanian climatic zone of Burkina Faso vulnerable to rainfall and temperature?
- ❖ how did protected ecosystems' vulnerabilities to human impact evolve, and what are the primary contributing factors?
- ❖ how vulnerable are protected areas neighboring communities in the Sudanian climatic zone to the impacts of climate variability and human activities?

The main objective of this study is to understand the effect of climate and human footprint drivers on protected areas and their neighboring community resilience.

Specifically, the study aims are:

- ❖ to determine rainfall and temperature factors' effect on vegetation cover in the Sudanian climatic zone in Burkina Faso from 2001 to 2022;
- ❖ to assess protected areas' ecosystems' vulnerability to human footprint drivers in the Sudanian climatic zone from 1986 to 2022;

- to assess protected areas neighboring communities’ vulnerability to climatic and human footprint drivers in the Sudanian climatic zone in Burkina Faso.

The study research hypotheses aligned with the specific objectives are:

- vegetation cover in the Sudanian climatic zone in Burkina Faso has been negatively affected by drought events from 2001 to 2022;
- protected areas ecosystems in the Sudanian climatic zone in Burkina Faso have become increasingly vulnerable to anthropogenic drivers from 1986 to 2022;
- protected areas neighboring communities in the Sudanian climatic zone in Burkina Faso experienced different levels of vulnerability to the climatic and human footprint.

To successfully address the study objectives, an appropriate and coherent methodology was first used to determine at a large scale the influence of rainfall and temperature on the vegetation cover in the Sudanian climatic zone from 2001 to 2022 using satellite data. Secondly, the study examined in depth how the ecosystems of protected areas in the Sudanian climatic zone have been influenced from 1986 to 2022 by anthropogenic drivers, using satellite data in the remote sensing process and field data collected through individual interviews with neighboring communities of protected areas. Thirdly and finally, this study identified the different levels of vulnerability of protected areas' neighboring communities to climatic and human impacts using a flexible assessment framework, with data collected from focus groups involving resource persons from protected areas' neighboring communities.

Apart from the general introduction and general conclusion, the current study is structured into chapters. The first chapter provides an overview of the study area and concepts clarification. The second chapter is related to the study of rainfall and temperature relationships on the Sudanian climatic zone vegetation in Burkina Faso from 2001 to 2022. The third chapter is on the spatiotemporal analysis of land use and land cover dynamics of Dinderesso and Peni forests in Burkina Faso, the fourth chapter studied the perception of Dinderesso and Peni classified forest neighboring communities on degradation and deforestation drivers, and the fifth chapter is related to the study of Dinderesso and Peni classified forest neighboring communities vulnerability to climate variability and anthropogenic drivers.

# CHAPTER 1: OVERVIEW OF THE STUDY AREA AND CONCEPTS CLARIFICATION

## 1.1 Overview of the study area

### 1.1.1 Biophysical environment

#### 1.1.1.1 Study area location

Dinderesso and Peni classified forests are located in the Sudanian climatic zone, in Burkina Faso Hauts-Bassins region, precisely, within the Houet province (Figure 1). The Dinderesso classified forest, with an area of 8500 hectares, is located between longitudes 4° 18' 46" and 4° 26' 40" West and latitudes 11° 11' 05" and 11° 18' 10" North (Yaméogo et *al*., 2020). Peni classified forest is located between longitudes 4° 27' 26.5" and 4° 29'37.5" West and latitudes 10° 55' 2.5" and 10° 56'33" North, with an area of 1131.68 hectares.

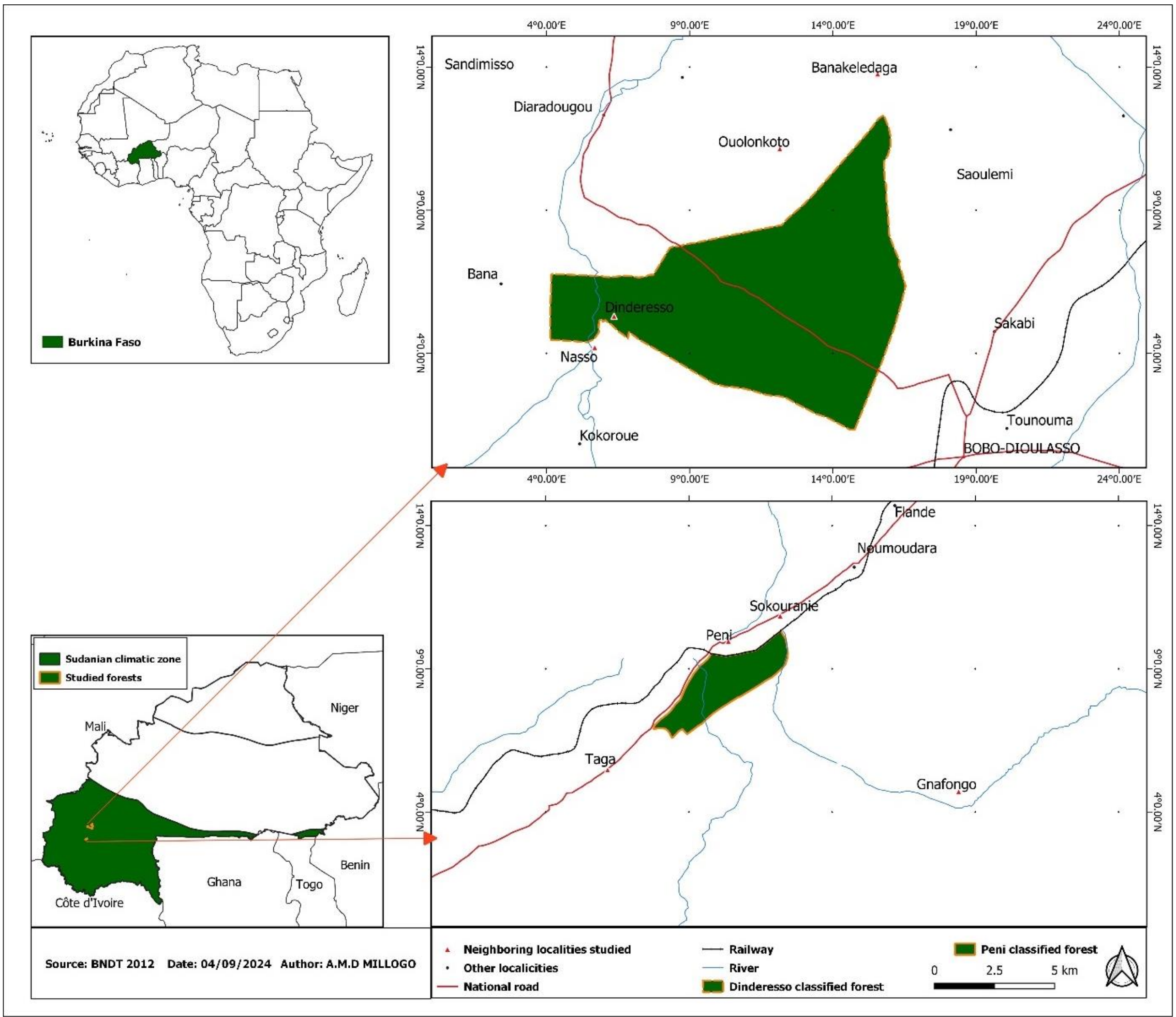


Figure 1: Dinderesso and Peni classified forest with their neighboring communities

#### 1.1.1.2 Dinderesso and Peni classified forests history

Dinderesso and Peni classified the history of forests as belonging to the decision to create a set of national forests in the former French West Africa (including actual Burkina Faso and Cote d'Ivoire) following the 4th July 1935 decree (MECV, 2007c). These forests were initially created with the objectives to mitigate harmattan dry winds, main water bodies protection, wildlife reserve for hunting purpose, lumber and utility wood, and charcoal production for train transport from Abidjan to Niger and Bobo-Dioulasso to Segou (Mali) which railway was supposed to be established.

In this context, the Dinderesso classified forest has been created for the first time, the 27th February 1936 with an area of 7000 hectares, following the decree number 422/SE. A second decree adopted on the 26th August 1941 following the number 3006/SE increased the area of Dinderesso classified forest from 7000 to 8500 hectares. The main objective of its creation was to supply charcoal to the train transport that was supposed to connect the actual Burkina Faso to the Mali Republic through the cities of Bobo-Dioulasso and Segou.

Peni classified forest was created following decree 3389 SE/F of 24th September 1942. This forest was established on the agricultural lands of the Peni and Sokouranie populations. The area of the Peni classified forest is 1131.68 hectares.

From their establishment during the colonisation and before the revolution in 1983, the management of Dinderesso and Peni classified forests was not participative with the neighboring population (Kante, 2009a). The population was progressively engaged in classified forest management in 1985, during the three fight measures, including the fight against bushfires, wood abuse, and free grazing. From the revolution time to now, many politics have been adopted, including land tenure regulation, forest politics management, improved population access to forest resources, and their contribution to forest management. Over the traditional right to collect dead wood and non-timber forest products in protected areas, some areas within the Dinderesso classified forest have been specially identified for neighboring communities' agriculture and farming.

### 1.1.1.3 Relief and soils

The study area's relief comprises peneplains, plateaus, rough terrain, and hills. It is characterised by an altitude average equal to 430 m, more significant than the country altitude average equal to 350 m (Nebie, 2014). The study area is represented by a variety of soil types, with the most prevalent being sesquioxide, poorly developed fersiallitic soils, and hydromorphic soils (Figure 2). According to INSD (2022a), the sesquioxide soils are rich in iron or manganese oxide and result from the decomposition of tropical ferruginous soils with little or no leaching.

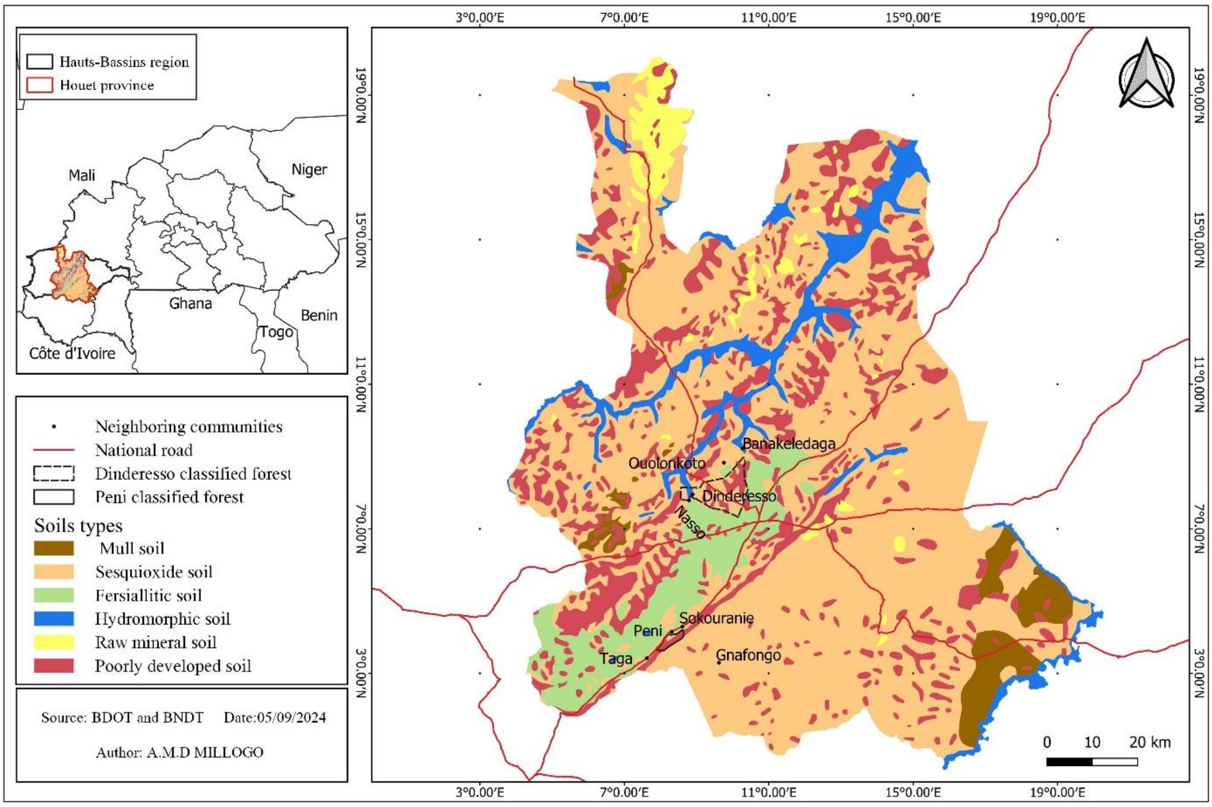


Figure 2: Dinderesso and Peni classified forest soil types

### 1.1.1.4 Climate

The study area is in the Sudanian climatic zone. The annual mean rainfall ranges from 900 mm to 1200 mm (Akoudjin et *al*., 2016). The analysis of Bobo-Dioulasso rainfall and temperature ground data collected by the National Meteorology Agency (ANAM) from 1990 to 2022 reveals that the rainy season lasts from May to October. The dry season is from November to April (Figure 3). The rainiest month is August, with an average of 273.1 mm. The hottest month is April, with an average of 31.2°C, and the coolest month is August, with an average of 25.5°C. The mean temperature is 27.9°C, with a thermal amplitude of 5.7°C.

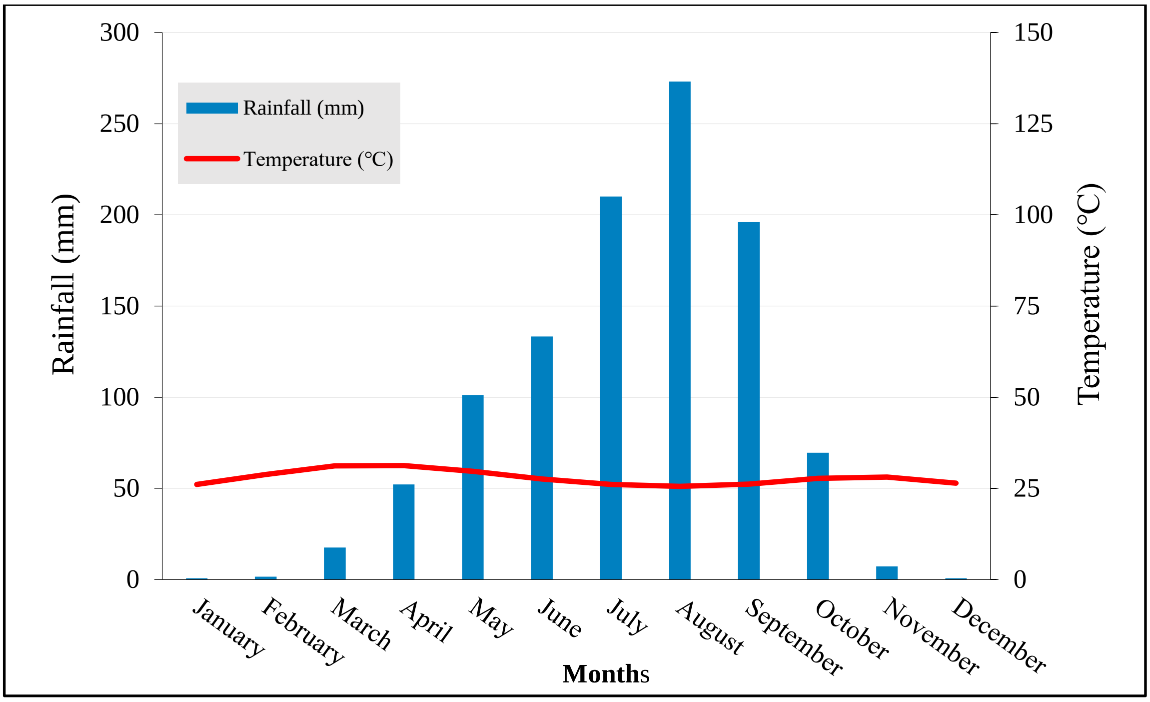


Figure 3: Bobo-dioulasso ombrothermic diagram from 1990 to 2022 (Data source: ANAM)

#### 1.1.1.5 Hydrography

An important hydrographic network involving primary and secondary rivers covers the study area. Some rivers are permanent, and others are temporary. Two rivers cross the Dinderesso classified forest: the Kou River and the Bingbele, smaller than the Kou River.

The classified forest of Peni is also crossed by primary and secondary rivers, which are permanent and temporary.

Unfortunately, the hydrographic network of Dinderesso's classified forest is threatened by silt due to deforestation and pollution from Bobo-Dioulasso factories. In the Peni classified forest, both permanent and temporary are facing many threats related to human activities and climate change.

## 1.1.2 Biological environment

### 1.1.2.1 Dinderesso and Peni classified forest vegetation

Based on species distribution and their common ecological conditions particularly related to the climate, previous studies made by Guinko (1984) and Guinko & Fontes (1995) have allowed describing Burkina Faso vegetation in two domains (Sahelian and Sudanian), with two sectors (North Sahelian Sector and South Sahelian Sector) from the Sahelian domain and other two sectors (North Sudanian Sector and South Sudanian Sector) from the Sudanian domain. The study area is located in the South Sudanian Sector, where wooded savannah and gallery forests along rivers dominate the vegetation. According to Thiombiano & Kampmann (2010), the South Sudanian Sector is characterised by many species, including *Adansonia digitata* L., *Faidherbia albida* (Del.) Chev., *Lannea microcarpa* Engl. et K. Krause, *Parkia biglobosa* (Jacq.) R. Br. Ex G. Don, *Tamarindus indica* L., *Vitellaria paradoxa* Gaertn. F. in the savannah areas, *Antiaris Africana* Engl., *Carapa procera* DC., *Dialium guineense* Willd., *Cola laurifolia* Mast., *Pterocarpus santalinoides* L'Her. Ex DC., *Elaeis guineensis* Jacq., *Khaya senegalensis* (Desr.) A. Juss., *Daniellia oliveri* (Rolfe) Hutch. et Dalz., *Anogeisus leiocarpa* (DC.) Guill. et Perr. and *Isoberlinia doka* Craib et Stapf in the gallery forests. The main herbaceous plants in this sector are *Andropogon gayanus* Kunth, *Andropogon pseudapricus* Stapf, *Loudetia togoensis* (Pilg.) C.E. Hubb., *Pennisetum pedicellatum* Trin., *Cymbopogon giganteus* Chiov., *Hyparrhenia smithiana* (Hook. F.) Stapf, and *Hyparrhenia subplumosa* Stapf.

The Dinderesso classified forest is made of natural and artificial plantations. The last forest inventory conducted in 2003 in the Dinderesso classified forest revealed that the forest was composed of 1% clear forest, 1% gallery forest, around 7% wooded and tree savannah, 68% shrub savannah and herbaceous, 13% agroforestry park and fallow, and around 10% for plantations.

The Peni classified forest vegetation consists of natural vegetation and plantations. According to Tiendrébeogo et *al*., (2022), the vegetation types encountered in the Peni classified forest are forest gallery, wooded savannah, shrub savannah, and plantations. The tree species in the plantations are related to *Gmelina arborea* (Roxb.), *Tectona grandis* (Linn.f.), *Anacardium occidentale* L., and *Mangifera indica* L. Dinderesso and Peni classified forest vegetation is threatened by anthropogenic drivers and climate effects.

#### 1.1.2.2 Fauna

Based on the Dinderesso classified forest management plan report, a daytime walking inventory of wildlife in the Dinderesso classified forest conducted from 30 June to 04 July 2004 to improve forest management has highlighted the existence of several mammal species (Kaboré, 2011). These species included *Eurythrocebus patas* (Schreber), *Sylvicarpa grimmia* (Linnaeus), *Ourebia ourebi* (Zimmermann), *Lepus crawshayi* (Winton), *Thryonomys swindrianus* (Temminck), *Ictonix striatus* (Perry). Other species' droppings and footprints, such as *Lupulella adusta* (Sundevall), *Felis sylvestris* (Schreber), *Loxodonta africana* (Blumenbach), *Hystrix cristata* (Linnaeus), have also been encountered.

According to MEEA (2022), the Peni classified forest fauna is mainly composed of small preys like *Erythrocebus patas*, *Thryonomys swinderianus*, *Xerus erythropus* (Geoffroy Saint-Hilaire), *Lepus capensis* (Linnaeus), *Numida meleagris* (Linnaeus), *Ptilopachus petrosus* (Gmelin, JF), *Streptopelia decaocto* (Frivaldszky), snake and rat species. Some appearance of elephants (*Loxodonta africana*) has also been mentioned in the forest management report plan.

## 1.1.3 Population and socio-economic activities

### 1.1.3.1 Population

The study area's population is increasing, making it challenging to manage protected areas that are subject to human pressure sustainably. Located near the Dinderesso and Peni classified forests, the population of Bobo-Dioulasso grew from 633,694 to 887,778 people between 2010 and 2020, respectively (INSD, 2022c). This trend in population size evolution is also observed in Dinderesso classified neighboring communities (Dinderesso, Banakeledaga, Ouolonkoto, Nasso) and Peni classified forest neighboring communities (Peni, Taga, Gnafongo, Sokouranie). Several local spoken languages are practised in the study area, such as Dioula or Bambara (30.72%), Moore (28.83%), Bobo (9.87%), Fulfulde (4.16%), Toussian (1.84%), and San (1.72%) (INSD, 2022c).

According to INSD (2022a), the population in the study area is predominantly Muslim, accounting for 79.1% of the population in the Houet province.

### 1.1.3.2 Socio-economic activities

#### 1.1.3.2.1 Agriculture

Similar to the rural communes of the country, agriculture continues to be the primary socio-economic activity practised by the majority of the population residing in the rural communes involved in this study area. This agriculture is highly dependent on the rainy season. According to Obulbiga (2022), the Sudanian climatic zone agriculture area represents 22% of the country's landmass, where several crops, including maise, sorghum, rice, groundnuts, cotton, mangoes, cashews, yams, tomatoes, cabbage, and sugar cane, are produced. During the 2022 to 2023 agricultural season, the Houet province produced around 318,849 tons of cereals (INSD, 2023). Peni’s neighboring communities experience extensive agriculture, which employs 80% of the rural population (PCD, 2019). The crops generally produced in Peni neighboring communities are maise, sorghum, sesame, rice, groundnut, little millet, beans, and voandzou (MEEA, 2022). *Anaccardium occidentale*, and *Mangifera indica* are also cultivated by Dinderesso and Peni neighboring communities to improve their incomes. Several efforts are being made to transform the agricultural production system, which is still dominated by extensive slash-and-burn agriculture.

#### 1.1.3.2.2 Livestock farming

Livestock farming is practiced in a sedentary manner by farmers in the Sudanian climatic zone (Thiombiano & Kampmann, 2010). According to INSD (2023), the Houet province in the Sudanian climatic zone accounted for 575,301 bovines, 416,304 sheep, 318,521 goats, and 57,911 pigs in 2022. This livestock is bred using extensive and semi-intensive methods (Obulbiga, 2022). This activity involves cattle, sheep, goats, and poultry. Livestock farming is extensive and semi-intensive. The extensive livestock farming system remains the main practice used by the population in the study area. Livestock activity is considered a second economic activity in Peni’s neighboring communities, which is made extensively (MEEA, 2022). According to MEEA (2022), the livestock in neighboring communities is dominated by bovines, sheep, goats, and poultry, with a few livestock related to pigs and donkeys (MEEA, 2022). This practice system sometimes causes many conflicts among the population and contributes to the degradation and deforestation of protected forest areas.

#### 1.1.3.2.3 Other activities

Many other activities, including fishing, hunting, beekeeping, crafts, and marketing of non-timber forest products, are practised by the populations, especially those living near the classified forest areas in the study area (Kaboré, 2011; MEEA, 2022). All these activities contribute to population incomes and livelihoods but require a crucial organisation to mitigate the human pressure on forest resources, considering the demographic growth and climate change induced by human activities.

## 1.2. Concepts clarification

### 1.2.1 Climate change/climate variability

Climate change has been defined as the long-term variation in climate properties and parameters that can be measured using statistical tests (GIEC, 2007). Climate change is also appreciated based on the significant variation in weather averages over a long-term scale (World Bank, 2024). According to CCNUCC (2024), climate change is explained by changes to the world's atmospheric composition directly or indirectly caused by human activity, in addition to natural climate variability is related to a given location climatic parameters such as rainfall and temperature changes over the year in a specific period (Dinse, 2010). Climate change or climate variability has negatively impacted natural resources, sustainable management, and livelihoods, thereby affecting preservation (UNEP, 2009).

In the context of Burkina Faso, numerous studies have been conducted on climate change and climate variability (MECV, 2007a; Bonkoungou et *al*., 2010; PNA, 2015; Dipama, 2016). Even if there are some small variations in climate change and climate variability definition, there is a common understanding of climate change and climate variability from previous works, which explained climate change and climate variability in terms of rainfall and temperature variability with an increasing frequency of extreme events such as drought, flood, and heatwaves affecting many socio-economic sectors (PNA, 2015; AMMA, 2018; Zoungrana et *al*., 2023). The definition of climate change and climate variability in the context of Burkina Faso is similar to the one provided by the Intergovernmental Panel on Climate Change (IPCC). From previous studies on climate change and climate variability, there is a general agreement that temperatures are rising, and some uncertainty remains regarding rainfall patterns, with evidence suggesting that extreme events will increase in the future (PNA, 2015; AMMA, 2018). According to PNA (2015), there is a 0.2℃ increase in temperature per decade in the Sahelian climatic zone and a 0.3℃ increase in temperature in the Sudan-Sahelian and Sudanian climatic zones.

### 1.2.2 Drought

Drought is a natural phenomenon that occurs in any climate and worldwide (OMM, 2016). According to the GIEC (2007), drought is defined as an abnormal disruption of precipitation that lasts for an extended period. It is recognised as one of the main hazards that affect developed and undeveloped countries (UNCCD, 2022a) in various critical life domains. Based on the different domains affected by drought, many types have been defined by IPCC (2023) as follows:

- meteorological drought: it is characterised by a lack or scarcity of rainfall;
- agricultural drought: it is related to soil with a low threshold of soil moisture that prevents crops' water supply and leads to crop mortality and loss of yield;
- ecological drought: it is characterised by critical stress of water observed on plants that leaves become yellow, highlighting the water stress which can lead to plant mortality;
- hydrological drought: it refers to water deficit in lakes, lagoons, groundwater, and streams.

Drought events negatively affect various sectors worldwide, including the economy, forests, soil, human society and agriculture(UNCCD, 2023).

In the context of Burkina Faso, drought is considered the primary climate extreme event, affecting 12.4 million people from 1969 to 2014 (OCHA, 2024). According to Sawadogo (2022), 15 million people have been affected by drought from 1969 to 2020. According to studies on drought, it is defined as a maximum number of consecutive dry days during the rainy season with daily precipitation less than 1 mm (PNA, 2015; Zoungrana et *al*., 2023). Many studies also defined drought in terms of rainfall deficiency and unequal rainfall spatial distribution (MECV, 2007a; Dipama, 2016) or terms of the late onset of the rainy season, early cessation of the rainy season and dry spells during the rainy season (Bonkoungou et *al*., 2010; Zoungrana et *al*., 2023).

### 1.2.3 Vulnerability, Exposure, Sensitivity, Adaptation capacity

According to UNDRR (2024), vulnerability is a function of several factors, including physical, environmental, social and economic, which contribute to shaping conditions for a given system or an individual's susceptibility to hazard impacts. People are considered vulnerable when they fail to access resources necessary for their stable livelihood at the individual or household level (Proag, 2014). Vulnerability is also recognised as a characteristic of a social group, community, or individual expressing their capacity to face or cope with external stresses such as environmental changes and socio-economic factors (Adger & Brown, 2009). Vulnerability refers to a measure of a given system's ability to cope with or adapt to climate variability and climate change, considering this system's exposure, sensitivity, and adaptive capacity (GIEC, 2007). According to GIEC (2007):

- the exposure is related to a given system submitted to the magnitude, the duration and the severity of climate factors variability;
- the sensitivity measures the threshold to which a given system is positively or negatively impacted by climate change or climate variability;
- the adaptation capacity corresponds to all the means and initiatives an individual or a group has to face or cope with the effects of climate change.

The system sensitivity can also be influenced by human society or the environment (GIZ, 2017).

### 1.2.4 Remote sensing and Geographic Information System (GIS)

Remote sensing is a process which aims to identify and monitor a given area's physical characteristics based on the radiation reflected and emitted from a satellite or an aircraft (USGS, 2024). According to Denis (2020), remote sensing implies using devices involving drones, planes, satellites, boats, or any spatial material able to acquire data from the environment. Figure 4 shows the process of remote sensing.

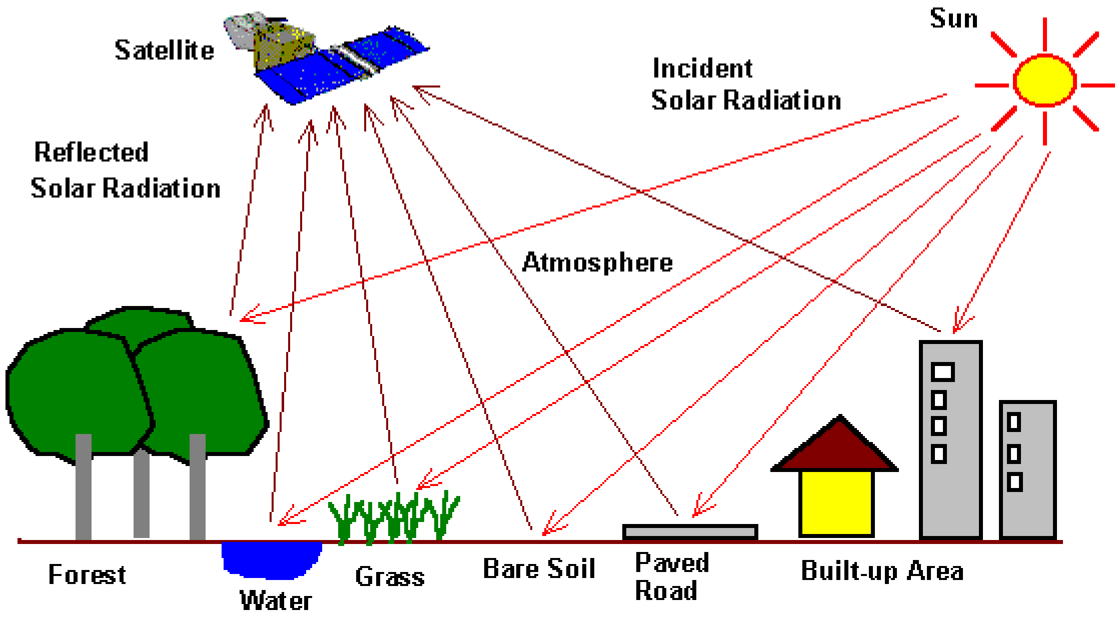


Figure 4: Remote sensing process (Source: CRISP, 2024)

The Geographical Information System (GIS) is a technology used to spatially represent and analyse data for decision improvement by policymakers and environmental managers (ESRI, 2024).

GIS technology is utilised in various domains, including mining, urban planning, hydrology, oceanography, healthcare, agriculture, and forestry.

Several studies (Dimobe et *al.*, 2015; Tankoano et *al.*, 2015; Savadogo, 2021) have been conducted in Burkina Faso using remote sensing and GIS to monitor landscapes and protected areas for their sustainable management purpose.

### 1.2.5 classified forest

A classified forest suggests that the forest, through a decree, belongs to the state territorial or to local municipalities (MECV, 2007c). The classified title confers a special statute on a forest, aiming to protect it through the regulation of its use and exploitation. The country has several classified forests, most of which are in the Sudanian climatic zone. The classified forests represent 14% of the country's area. Forest resource management in Burkina Faso has a long history, dating back to before colonisation and continuing to the present day. According to Kante (2009b), this forest resources management includes, firstly, the time before the colonisation, during which forest resources were managed by customary authorities (village chief, land chief and bush chief); secondly, the colonisation time characterised by the forests classification through the decree of 04$^{th}$ July 1935. During this colonisation period, the forests were classified to mitigate the influence of the Harmattan dry wind, protect the main waterways, produce charcoal for train mobility, establish a fauna resource for hunting, and produce wood for local administrative development (MECV, 2007d). Thirdly, following the colonial period with non-participatory forest resource management, came the independence period with a forest resource management approach similar to the colonial period (Kante, 2009b). Finally, after the period of independence and the revolution, the current time will mark the beginning of forest resource management with the introduction of the participatory approach.

Dinderesso forest was classified for the first time on 27 February 1936, following decree N° 422/SE, with an area of 7,000 hectares. It was classified for the second time on August 26, 1941, under decree N° 3006/SE, with an area of 8,500 hectares (Kaboré, 2011). Concerning the Peni forest, it was classified on September 24, 1942, with an area of 1,131.68 hectares, following decree N° 3389 SE/F (MEEA, 2022).

### 1.2.6 Degradation and Deforestation

Forest degradation is defined as the decrease or loss of forest production capacities, resulting in the decline or disruption of forest resources, including biodiversity and livelihoods (FAO, 2020a).

The term deforestation refers to the transformation of a forest area into another land use type, resulting from human activities or environmental factors that are not dependent on humans (FAO, 2018). The literature review in studied achieved in Burkina Faso related to forest resources has highlighted that those forest resources are facing degradation and deforestation, raising a critical need on forest resources sustainable management (Dimobe et *al*., 2015; Savadogo et *al*., 2019; Savadogo, 2021; MEEEA, 2022; Tindano et *al*., 2024). Forest degradation and deforestation are perceived at both the species and habitat levels.

### 1.2.7 Neighboring community

The neighboring community term in this study refers to indigenous and non-indigenous populations living near the classified forest and sharing some relationships related to forest resources management or exploitation (FAO, 2018). For Dinderesso classified forest studied, the neighboring communities include Dinderesso, Nasso, Wolonkoto (Ouolonkoto) and Banakeledaga, which are close to the forest and share a relationship in various domains related to agriculture, fuelwood, livestock, fishing, traditional medicine, water provisioning, hunting, harvesting and trading (Kaboré, 2011). Concerning the Peni classified forest, neighboring communities include Peni, Sokourani, Taga and Gnafongo (MEEA, 2022).

# CHAPTER 2: STUDY OF RAINFALL AND TEMPERATURE RELATIONSHIPS ON THE SUDANIAN CLIMATIC ZONE VEGETATION IN BURKINA FASO FROM 2001 TO 2022


## Abstract

In the context of climate change, protected forest areas in Burkina Faso have struggled with insufficient information regarding the spatiotemporal response of vegetation to climate change on a large scale. To address the knowledge gap, this study aims to analyse the relationship between rainfall and temperature in the vegetation of the Sudanian climatic zone in Burkina Faso from 2001 to 2022. To conduct this study, monthly rainfall and temperature data from TAMSAT and ERA5 satellite datasets have been validated against ten synoptic stations distributed across the climatic regions zones. This validation was followed by computing the Standardised Precipitation-Evapotranspiration Index (SPEI 6), which was then associated with MODIS NDVI data to conduct a linear correlation analysis between the two indices using R software. The study's results first highlighted a strong reliability in using TAMSAT and ERA5 satellite data for spatiotemporal analysis of rainfall and temperature in Burkina Faso. Secondly, the study revealed a strong positive correlation between the SPEI 6 and the NDVI from 2001 to 2022, with a correlation coefficient of $r = 0.61$ and a t-test p-value of 0.0027, indicating that the relationship between rainfall, temperature, and vegetation is statistically significant. Finally, the study highlighted that numerous severe and extreme drought events have negatively affected the Sudanian climatic zone from 2001 to 2022. These findings highlight a pressing need to develop sustainable strategies and policies to address vegetation degradation and deforestation in the country, particularly in the Sudanian climatic zone, and to prevent future issues arising from climate change, which is expected to be exacerbated by human-induced global warming, as announced to be critical in the country.



**Keywords:** Burkina Faso, ERA 5, MODIS-NDVI, SPEI 6, Sudanian climatic zone, TAMSAT

# INTRODUCTION

Drought is a common global phenomenon, yet it is also recognised as one of the most costly natural disasters, given its impacts across various domains, including agriculture, ecosystem services, education, livelihoods, and human health, among others (OMM, 2016). Various types of drought are defined based on variables used to characterise them or the impacted sectors, including meteorological, agricultural/ecological, hydrological, and socioeconomic (GIEC, 2007; Sherval & Mcguirk, 2014; Casey, 2016; IPCC, 2023). All these droughts are related to water scarcity, shortages and disruption (IPCC, 2023), negatively affecting vegetation cover. According to Boussougou et *al*., (2018), certain vegetation classes involving savannah and cropland are more sensitive to rainfall variability than mangroves and forests, which are less affected. The negative impact of rainfall spatiotemporal variability on vegetation has also been mentioned by Ayanlade et *al*., (2021). Apart from rainfall, temperature is also noted to significantly influence landscape formation vegetation. According to Hatfield & Prueger (2015), plant exposure to non optimal temperature negatively affects their productivity regarding fruits and seeds. The relevance of temperature is emphasised through a study examining the response of tomato plants to temperature variability (Ohtaka et *al*., 2020). The study findings of Fu et *al*., (2024) highlighted that every 1℃ increase in warming temperature increases at 0.5% the risk of forest ecosystem loss. The global warming induced by anthropogenic actions recognised by GIEC (2007) announced an increasing temperature and risk of water shortage in many African regions, showing the persistent influence of drought in the region in the future. The vulnerability of African regions to drought compared to other regions worldwide is highlighted by the consistent work of the UNCCD (2022a), which shows that during the last 100 years, from 1900 to 2022, African regions experienced more than 300 severe drought events.

In Burkina Faso, drought is classified as the main climate disaster (Toure et *al*., 2015). The country has experienced drought since 1970, with the most severe droughts recorded in 1972, 1973, 1974, 1983, and 1984 (Sawadogo, 2022). Consistent analyses based on historical rainfall data from 1960 to 2011 have highlighted a decreasing trend in rainfall across all climatic zones (MERH, 2015). The analysis of historical data from 1990 to 2010 showed an increase in temperature in Sudan-Sahelian and Sudanian climatic zones (SP/CONEDD, 2012). These drought events, characterised by water shortage, disruption, and temperature increase, negatively affected forest resources and population livelihoods (Couteron, 1997; Toure et *al*., 2015; MERH, 2015). Unfortunately, some studies related to future climate predicted an increase in the frequency and severity of climate extreme events, including drought due to climate change induced by human activities with a high risk of disaster for developing countries in Africa (GIEC, 2007; UNISDR, 2015; IPCC, 2023; FAO, 2020). Numerous consistent studies on the future climate in Burkina Faso have revealed a high risk to forest resources and the preservation of population livelihoods due to increases in temperature, rainfall variability, and extreme events, such as drought, which are expected to become more frequent and severe (SP/CONEDD, 2012; MERH, 2015; Toure et *al*., 2015).

Many studies conducted at the local scale have highlighted the vulnerability of protected forest areas to drought, which is essential for the sustainable management of forestry resources and the preservation of populations' livelihoods. Using rainfall, temperature, and evapotranspiration, Belem et *al*., (2019) highlighted the risk of degradation and deforestation in the Toessin classified forest due to climate variability and drought events. According to Savadogo (2021), based on historical rainfall data from 1981 to 2020, the Bontioli total and partial fauna reserves experienced droughts from 1991 to 2000 and from 2001 to 2010, which contributed to the degradation and deforestation of the protected area. Other scientific research studies (Dimobe et *al*., 2015; Tankoano et *al*., 2015; Balima et *al*., 2021; Millogo et *al*., 2024) have identified drought as an extreme climate event that hinders vegetation regeneration and contributes to the mortality of plant species due to water shortages and scarcity. Despite the relevance of previous studies in providing meaningful insights into vegetation vulnerability to drought at a small scale, knowledge on this topic is limited at a large scale. The Sudanian climatic zone in Burkina Faso encompasses most of the country’s protected forest area (MECV, 2007b), so it appears crucial to know this area's vulnerability to drought for accurate and consistent information building, which can lead to environmental sustainability management and community livelihood preservation by policymakers and protected forest managers. Previous studies have shown the relevance of using the Standardised Precipitation-Evapotranspiration Index (SPEI) (Wu et *al*., 2022; Sawadogo, 2022) and the Normalised Difference Vegetation Index (NDVI) (Hountondji, 2014; Boussougou et *al*., 2018) in analysing the relationship between rainfall, temperature and vegetation. This study aims to understand the spatiotemporal vulnerability of vegetation in the Sudanian climatic zone to rainfall and temperature variability from 2001 to 2022 using ERA 5, TAMSAT, and MODIS NDVI satellite data.

## 2.1 Material and Methods

### 2.1.1 Material

#### 2.1.1.1 Rainfall and Temperature Ground Data

Monthly average rainfall and temperature ground data were collected from the National Meteorological Agency (ANAM) free of charge. The data collected ranged from 1990 to 2022 and were recorded from 10 synoptic stations (Figure 5).

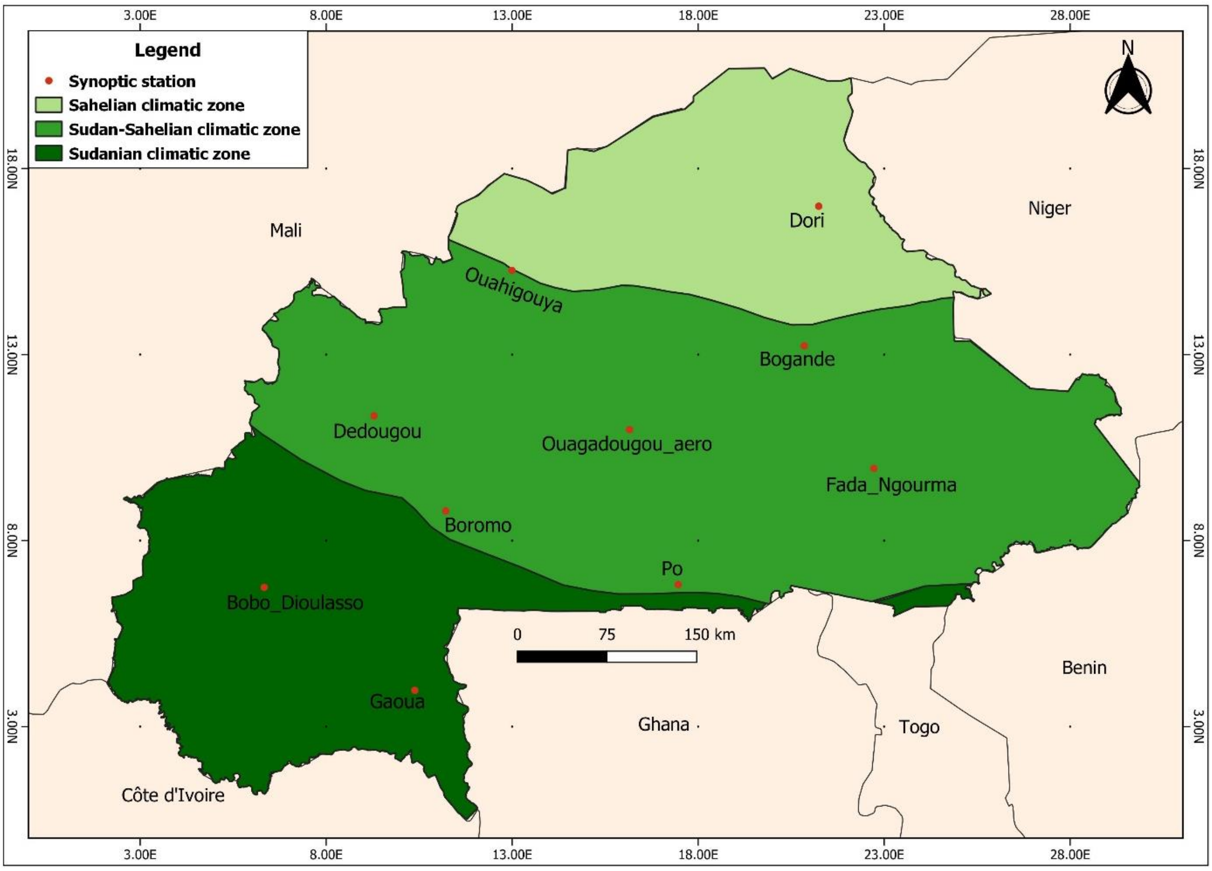


Figure 5: Spatial distribution of synoptic stations in the study area (Source: Millogo, 2024)

#### 2.1.1.2 Satellite TAMSAT (rainfall) data

The Tropical Applications of Meteorology using Satellite and ground-based observations (TAMSAT) version 3.1 monthly dataset was downloaded free of charge from the TAMSAT website (http://www.tamsat.org.uk) (Maidment et al., 2017). Table 1 shows the details of the TAMSAT data collected.

#### 2.1.1.3 Satellite ERA5 (Temperature) data

ERA5 is the latest climate reanalysis product from ECMWF. The ERA5 monthly temperature dataset was downloaded free of charge from the Copernicus website (https://climate.copernicus.eu/climate-reanalysis) (Muñoz-Sabater et al., 2021).

Table 1: TAMSAT (rainfall) and ERA5 (Temperature) datasets description

| Satellite | Temporal coverage | Spatial Resolution | Type | References |
|---|---|---|---|---|
| TAMSAT v 3.1 | 1983-01 to present | 0.0375° (~4 km) | TIR, Gauge (NMH) | (Maidment et al., 2017) |
| ERA5 | 1940 to present | 0.25° (~25 km) | Reanalysis | (Muñoz-Sabater et al., 2021) |

#### 2.1.1.4 MODIS NDVI data

The Normalised Difference Vegetation Index (NDVI) data collected were downloaded from the website (https://urs.earthdata.nasa.gov) using R script (Appendix 1) free of charge. The downloaded NDVI are MODIS MOD13Q1 from the sensor Terra with 250 m spatial resolution and 16 days temporal resolution (Boussougou et al., 2018). The downloaded data spans the period from 01/01/2001 to 31/12/2022.

### 2.1.2 Methods

Figure 6 illustrates the various steps involved in satellite data validation using ground data, the calculation of the Standardised Precipitation-Evapotranspiration Index (SPEI), and the analysis of the relationship between SPEI and NDVI. From their acquisition to computing statistical metrics and displaying results, the software R has been used.

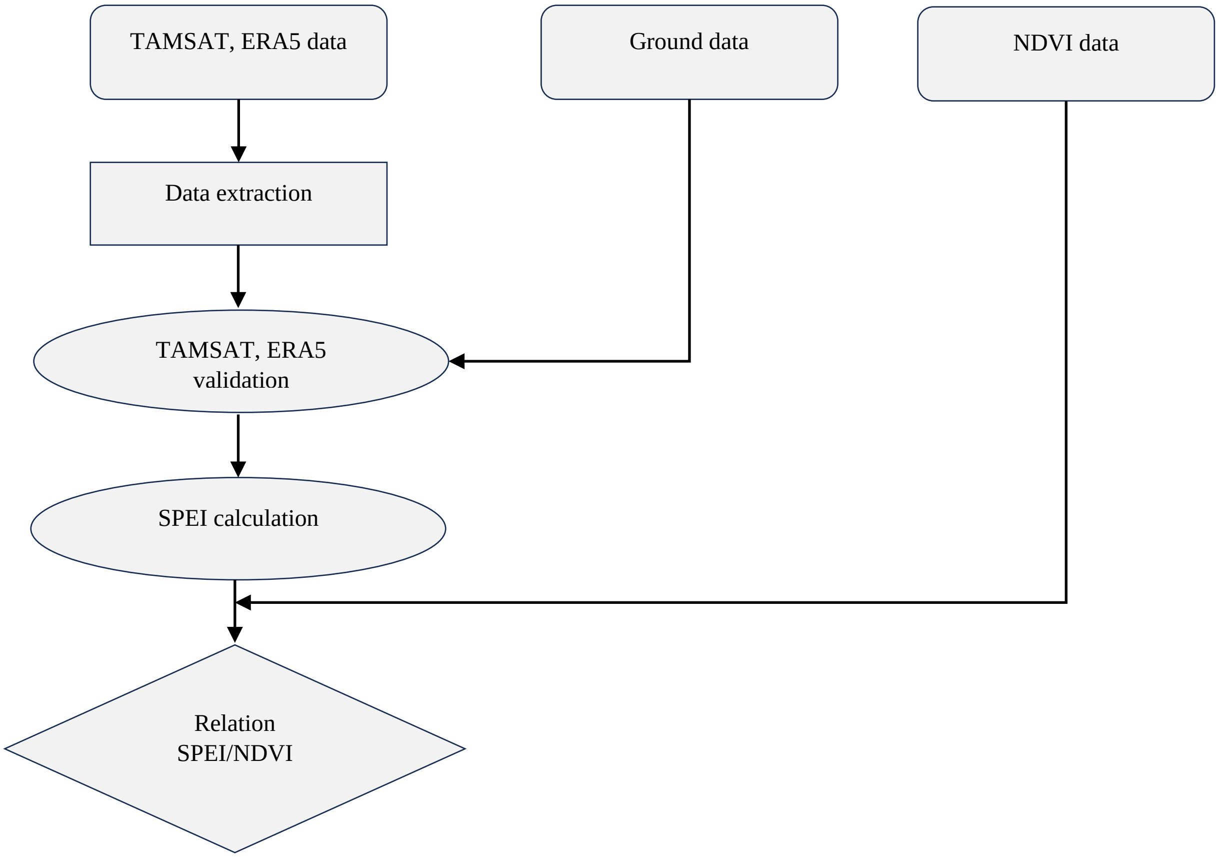


Figure 6: Relationship between rainfall, temperature and vegetation flowchart

### 2.1.2.1 TAMSAT and ERA5 validation

The TAMSAT and ERA5 data were validated at each synoptic station between 2001 and 2022. An analysis of ground point to pixel (Cohen Liechti et *al*., 2012; Thiemig et *al*., 2012) was achieved by extracting TAMSAT and ERA5 data at the same place on each synoptic station before proceeding to statistics indicator computing.

Some metrics have been calculated to evaluate the quality of satellite data in comparison to data recorded by synoptic stations (Table 2). The metrics include Pearson correlation (r), root mean square error (RMSE), average absolute error (MAE), standard deviation (SD), and bias. A Pearson correlation coefficient of 1 indicates a strong linear relationship between predicted satellite data and ground data. RMSE, MAE, and SD values close to zero suggest low error dispersion, while a bias of one indicates an absence of a non-systematic trend.

Other categorical metrics, including the probability of detection (POD) and the false alarm ratio (FAR), are calculated to evaluate the reliability of satellite data validation. A POD of one indicates that the model has a strong capacity to detect occurrences of an event, while a FAR of zero signifies the absence of false alarms.

Table 2: TAMSAT and ERA5 validation metrics formulas

| Statistical metrics | Formulas | Range | Perfect value | |
|---|---|---|---|---|
| Pearson's Correlation (r) | $r = \frac{\sum_{i=1}^{i=N}(G_i - \bar{G})\,(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{i=N}(G_i - \bar{G})^2}\,\sqrt{(S_i - \bar{S})^2}}$ | -1 to +1 | 1 | Equation (1) |
| The root mean square error (RMSE) | $RMSE = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(S_i - G_i)^2\right)}$ | 0 to +∞ | 0 | Equation (2) |
| The mean absolute error | $MAE = \frac{1}{N}(G_i - S_i)$ | 0 to +∞ | 0 | Equation (3) |
| Standard deviation (SD) | $\sigma = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(S_i - \bar{S})^2}$ | 0 to +∞ | 0 | Equation (4) |
| The bias | $Bias = \frac{\sum_{i=1}^{N}(S_i)}{\sum_{i=1}^{N}(G_i)}$ | 0 to +∞ | 1 | Equation (5) |
| Probability of Detection (POD) | $POD = \frac{H}{H + M}$ | 0 to +1 | 1 | Equation (6) |
| The False Alarm Ratio (FAR) | $FAR = \frac{F}{H + F}$ | 0 to +1 | 0 | Equation (7) |

Adapted from (Garba et *al*., 2023)

Notes: **Gi** represent ground rainfall or temperature measurement (mm); **G** is average ground rainfall or temperature measurement (mm); **Si** is satellite rainfall or temperature estimate (mm); S is average satellite rainfall or temperature estimate (mm); and **N** is the number of data pairs; **H** is the number of hits; **F** is the number of false alarms; and **M** is the number of misses.

### 2.1.2.2 Standardised Precipitation-Evapotranspiration Index (SPEI) calculation

The *SPEI* was computed with R using the following equation (Beguería et *al*., 2014):

$$SPEI = P - ET_0 \qquad \text{Equation (8)}$$

Where *P*= Precipitation and $ET_0$= the reference evapotranspiration.

The reference evapotranspiration was calculated using the Penman-Monteith Evapotranspiration method (Zotarelli et *al*., 2010).

The SPEI interpretation based on wet and dry categories was made using the description of Li et *al*., (2015). The October SPEI 6, which measures precipitation and evapotranspiration anomalies over six months, has been computed and used for the study purpose due to its relevance in assessing the impact on vegetation production. Table 3 shows the description of the SPEI categories computed.

Table 3: SPEI values and categories interpretation

| **SPEI values** | **Categories description** |
|---|---|
| From 2.00 to over | Extremely wet (EW) |
| From 1.50 to 1.99 | Very wet (VW) |
| From 1.00 to 1.49 | Moderately wet (MW) |
| From -0.99 to 0.99 | Near normal (NN) |
| From -1.00 to -1.49 | Moderately dry (MD) |
| From -1.50 to -1.99 | Severely dry (SD) |
| From less to -2.00 | Extremely dry (ED) |

Adapted from (Li et *al*., 2015)

#### 2.1.2.3 Normalised Difference Vegetation Index rescaling

To better illustrate the relationship between rainfall and temperature as indicated by the SPEI and vegetation as shown by the NDVI, it was necessary to have the SPEI and NDVI at the same scale. Therefore, the NDVI data extracted from the Sudanian climatic zone was rescaled using a Z-score approach. The z-score is a standardised measure of the distance between a specific value and the mean of a normally distributed data set. This enabled us to rescale the NDV from -2 to 2, similar to the SPEI. The z-score was calculated using the following equation:

$$Z - score := \frac{x-u}{\partial} \qquad \text{Equation (9)}$$

Note: x represents the NDVI variable, u the mean and $\partial$ the standard deviation.

## 2.2 Results and Discussion

### 2.2.1 Results

#### 2.2.1.1 TAMSAT (Rainfall) validation analysis

The statistical validation of TAMSAT data revealed a high correlation with ground rainfall data, with a correlation coefficient (CORR) ranging from 0.89 to 0.94 (Table 4). The bias data (BIAS) generally show low values, indicating strong agreement between TAMSAT data and ground observations. The synoptic stations at Dori, Gaoua, and Po displayed the highest probability of detection (POD) values of 1, indicating perfect event detection for these stations. Mean absolute errors (MAE) range from 15.48 to 27.96, with Dori exhibiting the lowest MAE, indicating high forecast accuracy for this station.

Regarding the root mean square errors (RMSE), the values range from 28.97 to 43.99, with Dori recording the lowest value, indicating a decrease in significant errors for this station. The false alarm rate (FAR) ranges from 0.21 to 0.39, with Bobo-Dioulasso exhibiting the lowest rate of 0.25, indicating better performance in avoiding false alarms. In conclusion, the TAMSAT data demonstrate strong overall performance, with Dori being the most accurate regarding MAE and RMSE, while Bobo-Dioulasso and Gaoua provide superior performance concerning the false alarm rate. These results indicate that TAMSAT data are consistent and reliable for most stations; however, adjustments may be necessary to optimise accuracy based on the specific characteristics of each station.

A strong relationship between TAMSAT (rainfall) and ground rainfall data is demonstrated by the linear regression, as indicated by the close distribution of the point cloud to the adjustment line (Figure 7).

Table 4: TAMSAT validation statistics metrics

| **Stations** | **Statistics metrics** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **CORR** | **BR2** | **BIAS** | **MAE** | **RMSE** | **POD** | **FAR** |
| **Bobo-Dioulasso** | 0.912 | 0.695 | 0.962 | 27.959 | 43.991 | 0.995 | 0.25 |
| **Bogandé** | 0.904 | 0.639 | 0.914 | 19.239 | 34.395 | 0.993 | 0.371 |
| **Boromo** | 0.942 | 0.755 | 0.943 | 21.282 | 33.855 | 0.989 | 0.272 |
| **Dori** | 0.909 | 0.667 | 0.925 | 15.482 | 28.976 | 1 | 0.394 |
| **Dédougou** | 0.941 | 0.687 | 0.87 | 22.288 | 36.953 | 1 | 0.32 |
| **Fada Ngourma** | 0.933 | 0.756 | 0.967 | 20.11 | 32.753 | 0.994 | 0.326 |
| **Gaoua** | 0.89 | 0.676 | 0.944 | 27.664 | 42.752 | 1 | 0.21 |
| **Ouagadougou** | 0.936 | 0.668 | 0.863 | 21.27 | 38.253 | 0.994 | 0.343 |
| **Ouahigouya** | 0.929 | 0.652 | 0.832 | 21.36 | 36.83 | 0.975 | 0.365 |
| **Po** | 0.939 | 0.701 | 0.868 | 24.499 | 39.138 | 1 | 0.293 |

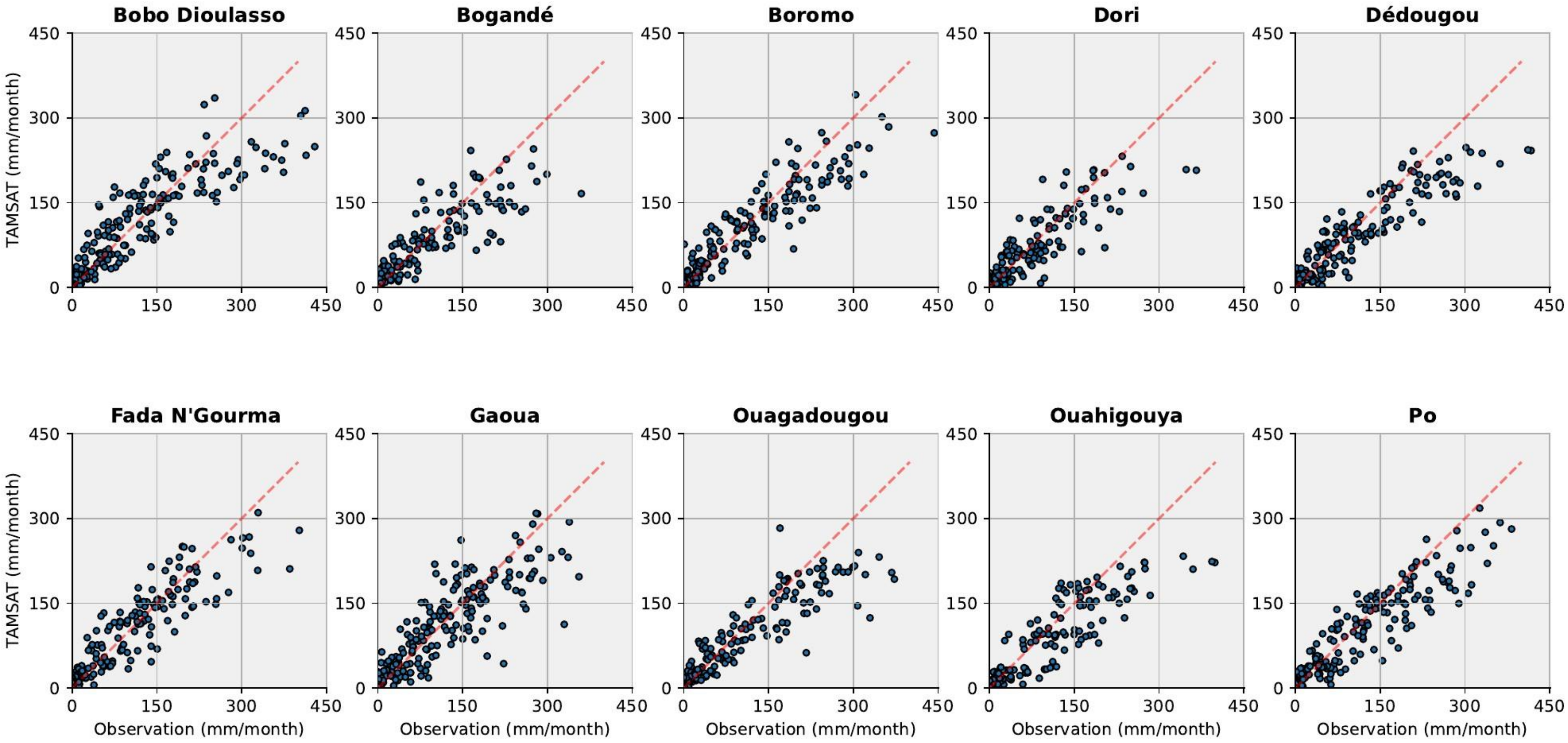


Figure 7: Point clouds distribution and linear regression between TAMSAT data and synoptic stations rainfall data

### 2.2.1.2 ERA5 (Temperature) validation analysis

Statistical metrics comparing ERA5 data to ground data indicate excellent overall agreement (Table 5). The correlation coefficient (CORR) metrics range from 0.91 to 0.99, indicating a strong correlation between ERA5 data and ground data. The bias (BIAS), close to 1, indicates that ERA5 data are generally well aligned with ground temperatures, with the lowest bias recorded for Bogandé (0.998) and the highest for the Gaoua (1.005) synoptic station.

The mean absolute errors (MAE) and root mean square errors (RMSE) demonstrate low values, with MAE ranging from 0.33 to 1.15 and RMSE from 0.42 to 1.27. The Bogandé synoptic station achieves the best performance with the lowest MAE (0.33) and RMSE (0.42) values. In contrast, the Ouahigouya synoptic station exhibits the highest MAE (1.15) and RMSE (1.27) values, indicating low accuracy for this station.

The ERA5 data are generally very accurate compared to ground data, showing particularly good results in Bogandé, Dédougou, and Fada Ngourma.

The linear regression indicates a strong relationship between ERA5 (temperature) and temperature data from synoptic stations, as shown by the point cloud distribution near the adjustment line (Figure 8).

Table 5: ERA5 validation statistics metrics

| **Stations** | **Statistics metrics** | | | | |
|---|---|---|---|---|---|
| | **CORR** | **BR2** | **BIAS** | **MAE** | **RMSE** |
| **Bobo Dioulasso** | 0.981 | 0.961 | 1 | 0.358 | 0.444 |
| **Bogandé** | 0.99 | 0.979 | 0.998 | 0.331 | 0.415 |
| **Boromo** | 0.973 | 0.942 | 0.995 | 0.497 | 0.597 |
| **Dori** | 0.99 | 0.973 | 0.994 | 0.451 | 0.559 |
| **Dédougou** | 0.988 | 0.971 | 0.994 | 0.374 | 0.456 |
| **Fada Ngourma** | 0.985 | 0.964 | 0.993 | 0.388 | 0.481 |
| **Gaoua** | 0.912 | 0.828 | 1.005 | 0.726 | 0.872 |
| **Ouagadougou** | 0.985 | 0.95 | 0.979 | 0.68 | 0.783 |
| **Ouahigouya** | 0.984 | 0.931 | 0.962 | 1.147 | 1.269 |
| **Po** | 0.978 | 0.955 | 1.002 | 0.421 | 0.517 |

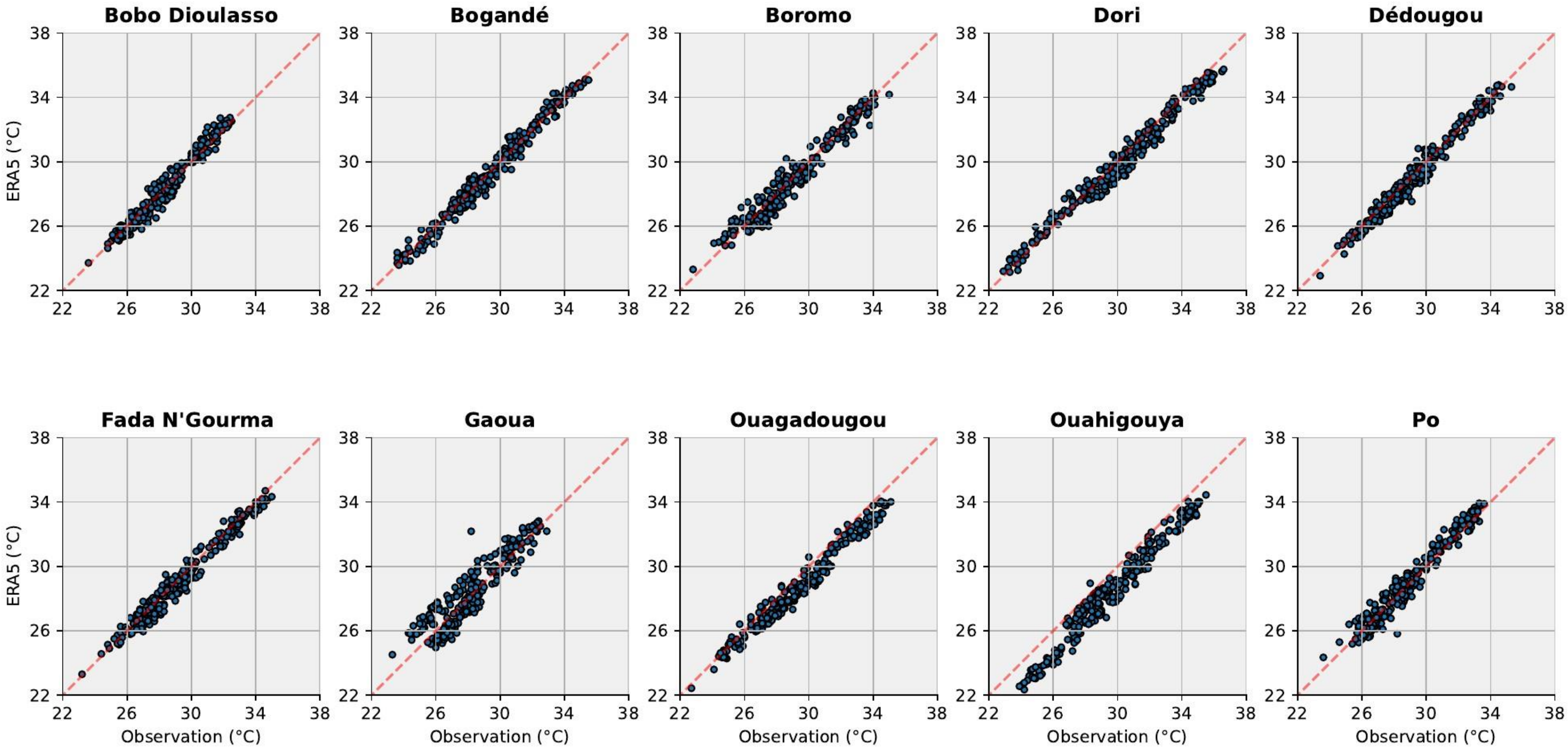


Figure 8: Distribution of point clouds and linear regression analysis between ERA5 data and temperature data from synoptic stations

#### 2.2.1.3 Spatialisation of average annual TAMSAT rainfall in climatic zones over the period 2001 to 2022

The spatial distribution of TAMSAT rainfall data within climatic zones from 2001 to 2022 indicates increasing rainfall along the climatic gradient from North to South. Variations in rainfall across climatic zones are highlighted (Figure 9). The Sahelian climatic zone in the North experiences the lowest average annual rainfall of less than 500 mm, indicating an arid to semi-arid climate characterised by a short rainy season. The Sudan-Sahelian climatic zone in the center displays moderate average annual rainfall, ranging from 500 to 1000 mm. The Sudanian climatic zone in the South experiences higher average annual rainfall, likely exceeding 1000 mm.

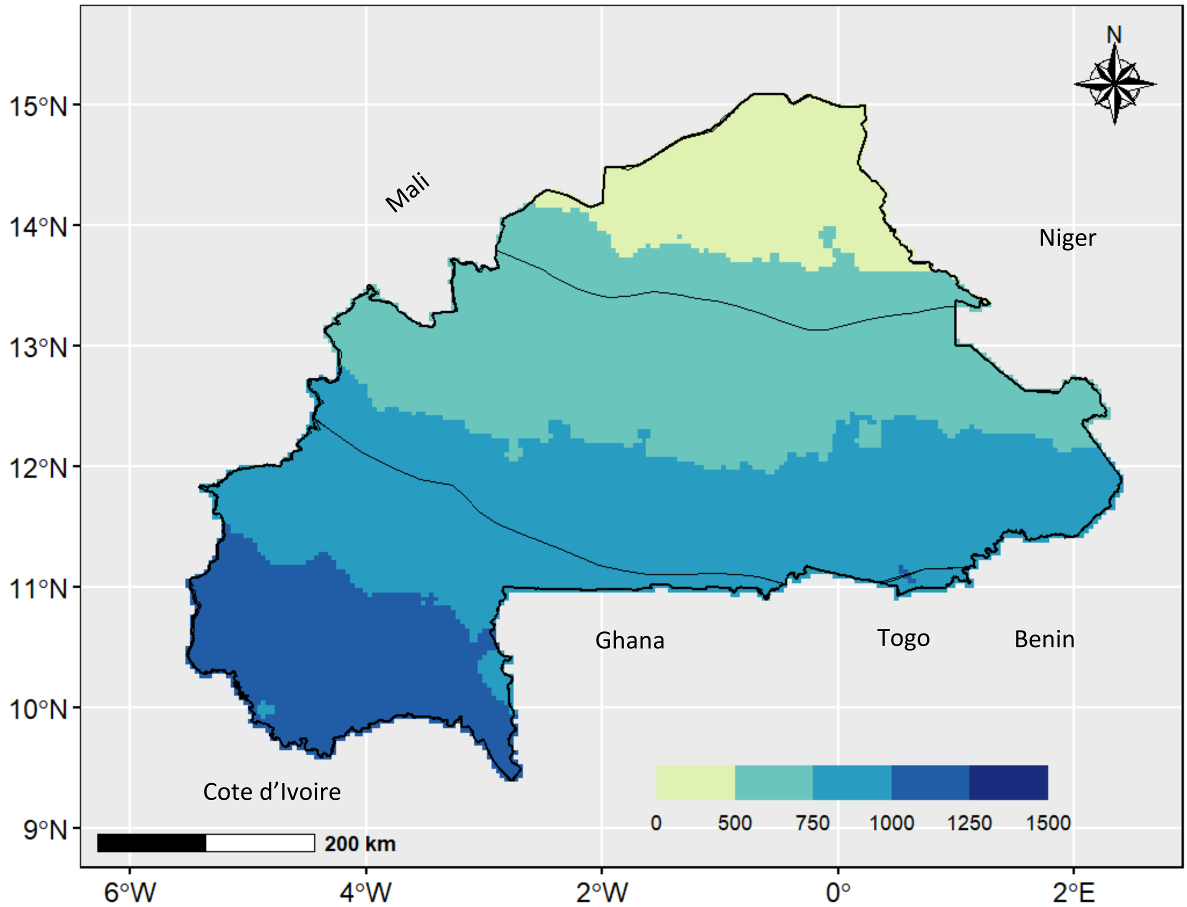


Figure 9: Spatial distribution of average annual TAMSAT rainfall (mm) in the climatic zones of Burkina Faso for the period from 2001 to 2022

#### 2.2.1.4 Spatialisation of average annual ERA5 temperature in climatic zones over the period 2001 to 2022

The spatial distribution of temperature across climatic zones from 2001 to 2022 exhibits variability, with temperatures decreasing from North to South. The variability in temperature across the country's climatic zones is illustrated in Figure 10. The Sahelian climatic zone features a higher average annual temperature, especially in its northern and northeastern areas. The temperature in the Sahelian climate zone varies between 30 and 31°C. The Sudan-Sahelian climatic zone in the middle exhibits a moderate average annual temperature ranging from 28 to 29 °C. The Sudanian climatic zone, with an average annual temperature ranging from 27 to 28°C, is the coolest of the three climatic zones, especially in its southwestern area.

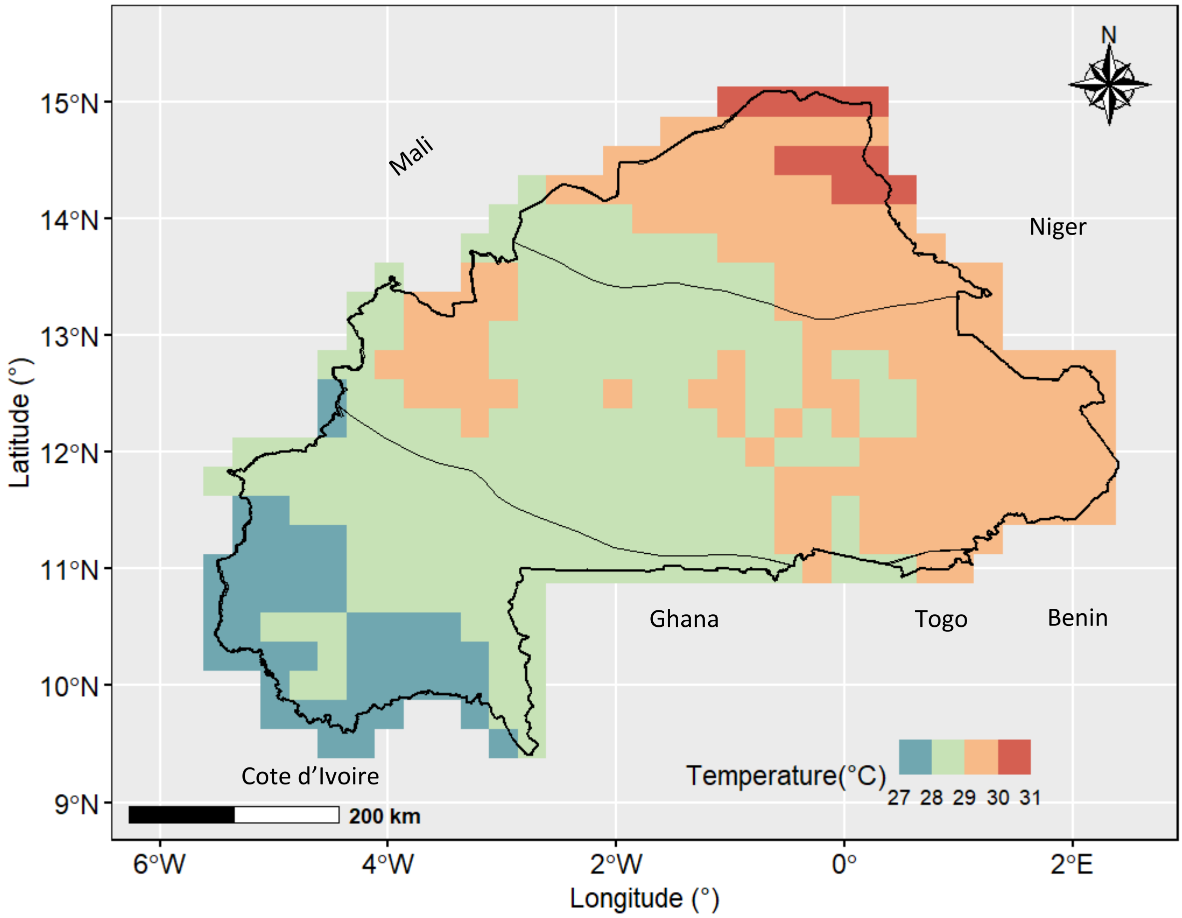


Figure 10: Spatialisation of average annual ERA5 temperature (°C) in Burkina Faso climatic zones for the period 2001 to 2022

### 2.2.1.5 TAMSAT rainfall seasonal variability

The monthly average rainfall across Burkina Faso's climatic zones, estimated using TAMSAT data, is illustrated and underscores the country's notable seasonality (Figure 11). Several phases are observed in the seasonal variability of rainfall. Firstly, the dry season lasts from November to April, generally occurring in the Sudan-Sahelian and Sahelian climatic zones. Secondly, the onset of the rainy season. The rainy season begins in May and becomes fully established in June, primarily in the southern part of the country, within the Sudanian climatic zone. Thirdly, the peak rainy season occurs from July to September, during which the country experiences its highest rainfall, with August having the most precipitation at up to 400 mm. The wettest areas are most noticeable in the Sudanian climatic zone, particularly in the southern and southwestern regions of the country in August, followed by the Sudan-Sahelian climatic zone, which receives 200 to 300 mm of precipitation. Fourthly, the end of the rainy season begins in October, characterised by decreasing rainfall. This conclusion of the rainy season is first observed in the Sahelian climatic zone.

In summary, Burkina Faso has two distinct seasons: the rainy season from May to October and the dry season from November to April.

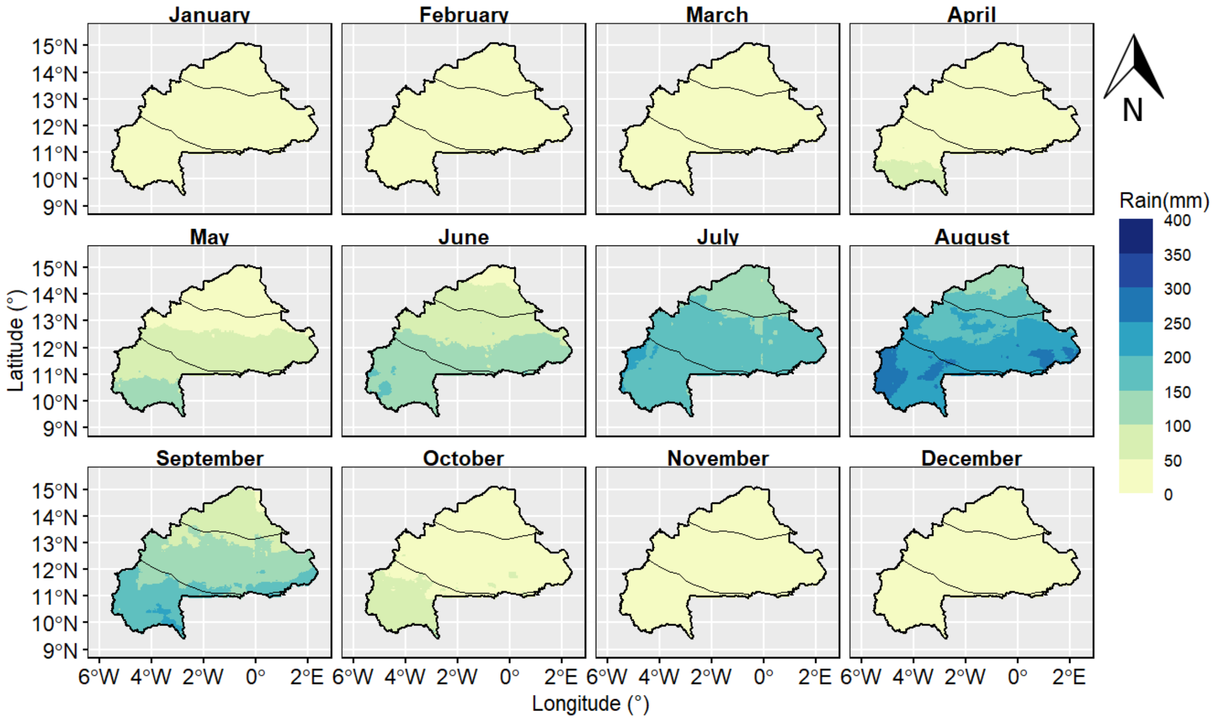


Figure 11: Monthly variability of TAMSAT rainfall average

### 2.2.1.6 ERA5 Temperature seasonal variability

The variability of average monthly temperatures in Burkina Faso's climatic zones is highlighted, with temperatures ranging from 27 to 31°C (Figure 12). The entire climatic zone experienced high temperatures between 30 and 31°C from January to April. The hottest months are observed in March and April, especially in the Sahelian and Sudan-Sahelian climatic zones. As the rainy season begins in May, temperatures will start to decrease slightly, particularly in the Sudanian climatic zone. The temperature will continue to decline until it reaches its peak in July and August, with the average temperature varying between 27 and 29°C.

Due to the onset of the end of the rainy season, temperatures will begin to rise slightly starting in September. A notable increase is observed in October, particularly in the Sahelian and Sudan-

Sahelian climatic zones, with temperatures lower than those recorded in March and April. From November to December, temperatures will decrease from 27 to 29°C.

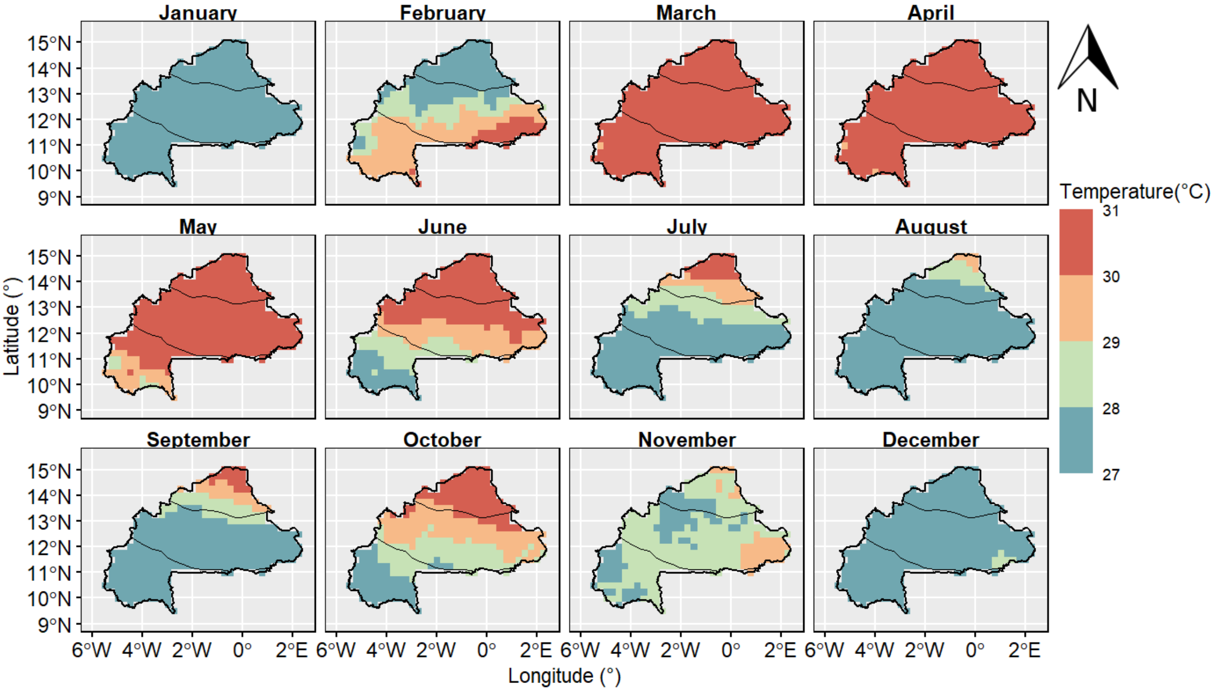


Figure 12: ERA5 average monthly temperature variability

### 2.2.1.7 TAMSAT rainfall annual variation from 2001 to 2022

Significant interannual variability in rainfall is illustrated (Figure 13). The areas in the south and southwest of the Sudanian climatic zone are the wettest, receiving rainfall of up to 1500 mm. In contrast, the Sahelian climatic zone in the northern part of the country is dry, with annual rainfall of less than 500 mm. The rainiest years, with 1500 mm of rainfall, were observed in 2007, 2010, and 2018. Inversely, some years, including 2004, 2014, and 2021, reveal low rainfall and poor spatial distribution. In summary, there was significant interannual rainfall variability from 2001 to 2022.

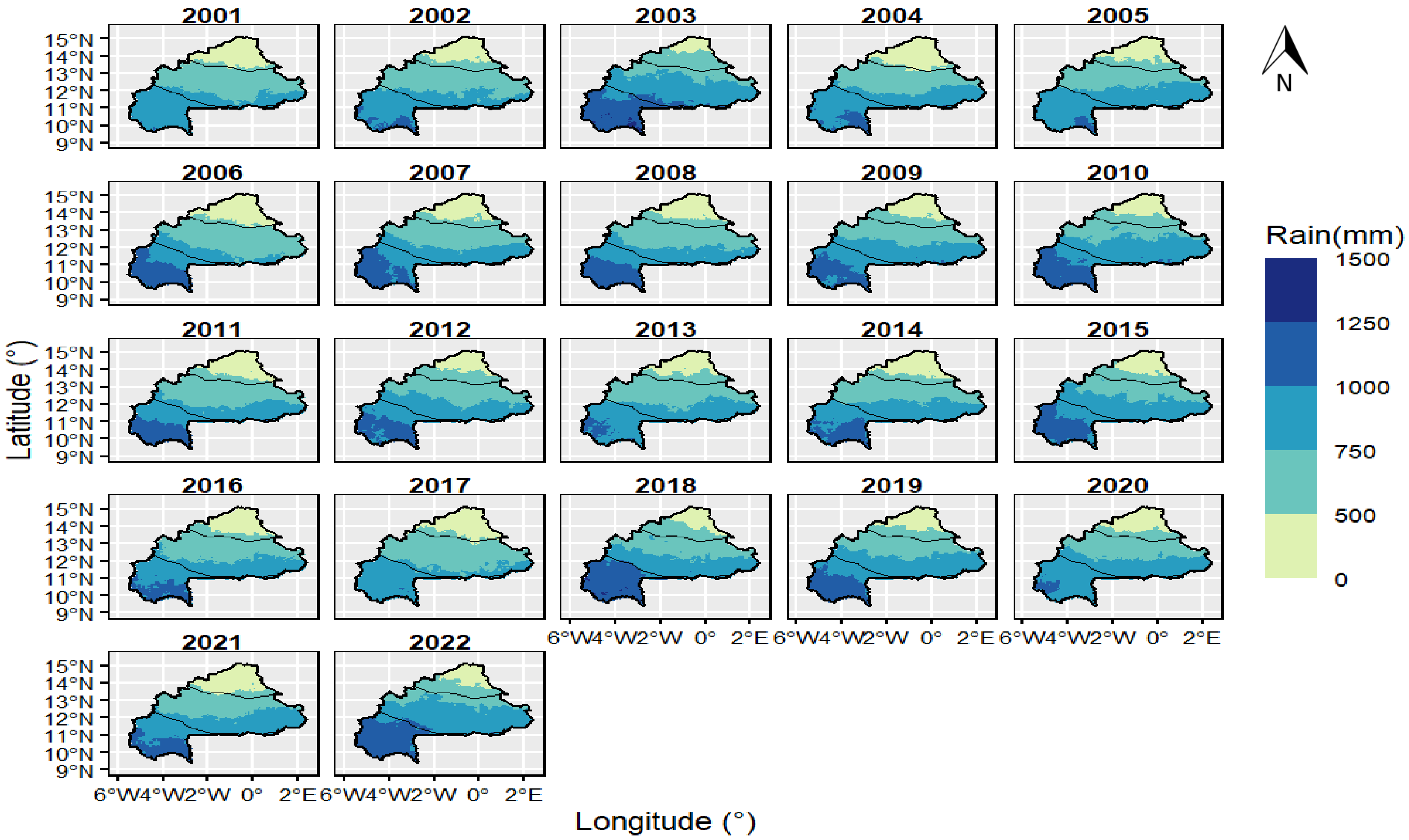


Figure 13: TAMSAT rainfall variability from 2001 to 2022

#### 2.2.1.8 ERA5 Temperature annual variability from 2001 to 2022

The years show a stable spatial distribution of temperature (Figure 14). The Sahelian and Sudan-Sahelian climatic zones are consistently characterised by high temperatures between 30 and 31℃. In contrast, the Sudanian climatic zone is characterised by the lowest temperatures, ranging from 27 to 29 °C. Some years, including 2006, 2010, 2016, and 2021, exhibit a slight temperature decrease in the southern and western regions. To summarise, the interannual temperature variability from 2001 to 2022 in Burkina Faso's climatic zones is characterised by the relative stability of high-temperature values, particularly in the Sahelian and Sudan-Sahelian climatic zones, with most temperature readings ranging from 30 to 31℃.

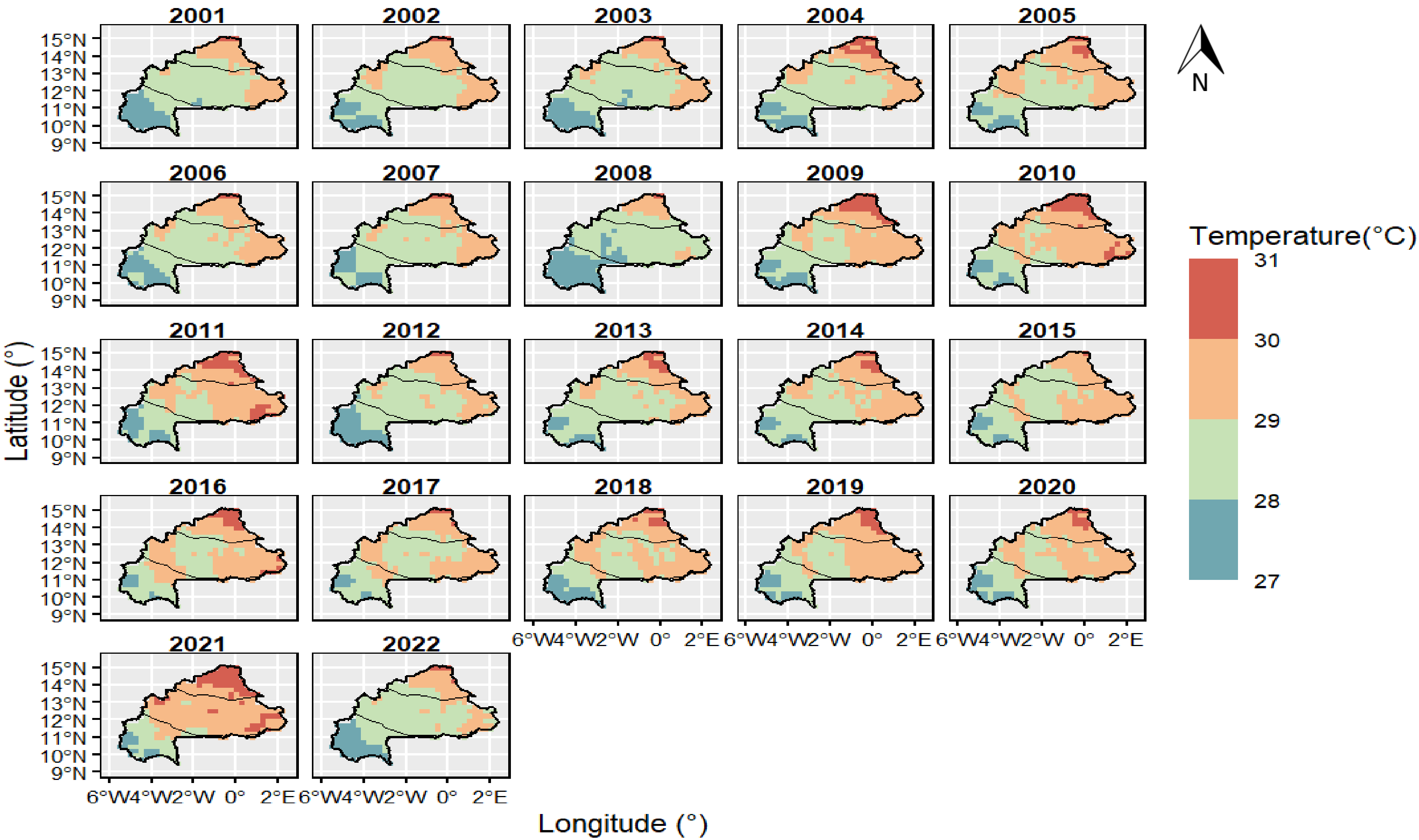


Figure 14: ERA5 temperature interannual variability across Burkina Faso's climatic zones from 2001 to 2022

### 2.2.1.9 Spatial distribution of vegetation (MODIS NDVI) from 2001 to 2022

The spatial distribution of vegetation across Burkina Faso's climatic zones from 2001 to 2022 highlights variability from North to South (Figure 15). The Northern Sahelian region exhibits low plant density, with NDVI values ranging from 0.0 to 0.2. In contrast, the southern part of the country, primarily within the Sudanian climatic zone and the southern section of the Sudan-Sahelian climatic zone, demonstrates high NDVI values between 0.4 and 0.6.

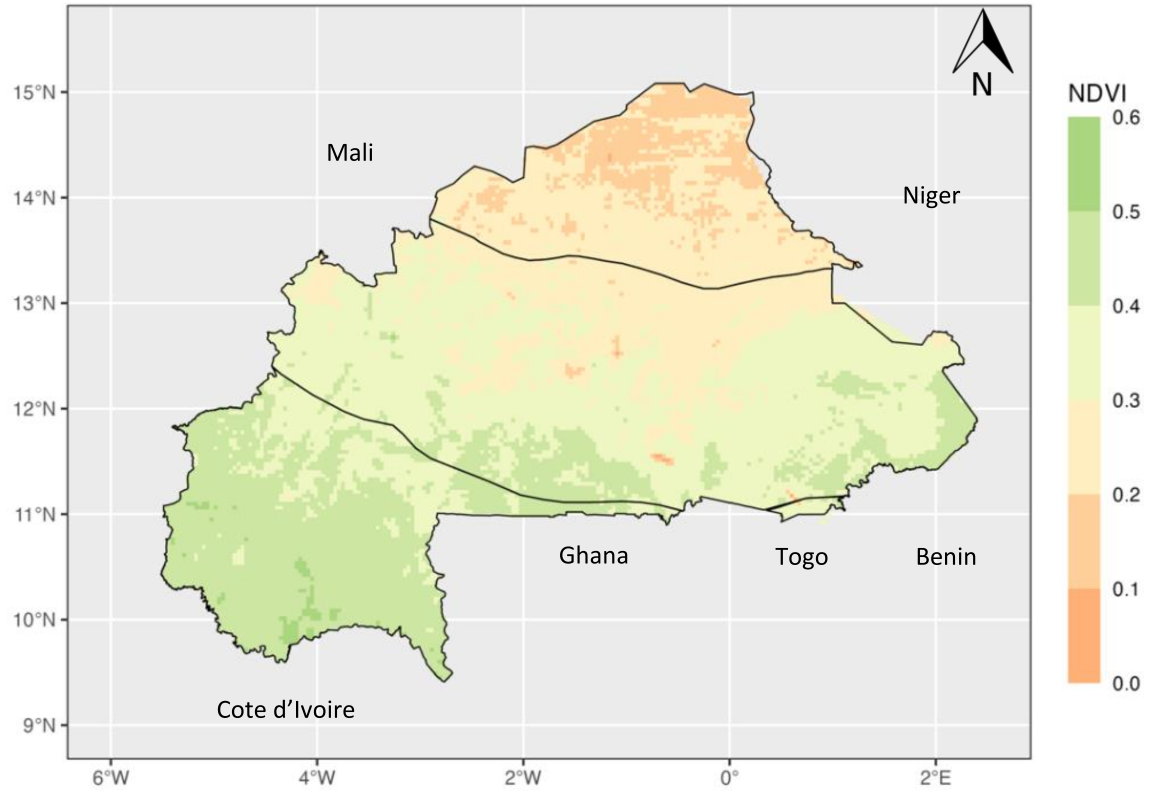


Figure 15:Vegetation (MODIS-NDVI) spatialisation from 2001 to 2022

### 2.2.1.10 Vegetation (MODIS NDVI) annual variability

The interannual spatial variability of vegetation in climatic zones from 2001 to 2022 is illustrated (Figure 16). This interannual spatial variability is characterised by a constancy of gradients in the North-South direction. The northern regions, particularly the Sahelian climatic zone and the northern part of the Sudan-Sahelian climatic zone, exhibit low NDVI values, whereas high NDVI values characterise the southern areas in the Sudan-Sahelian and Sudanian climatic zones. Despite the relative constancy observed in the North-South gradient, some interannual variations in the years 2007, 2010, and 2015 indicate an improvement in vegetation in the Sahelian and northern regions of the Sudan-Sahelian climatic zones.

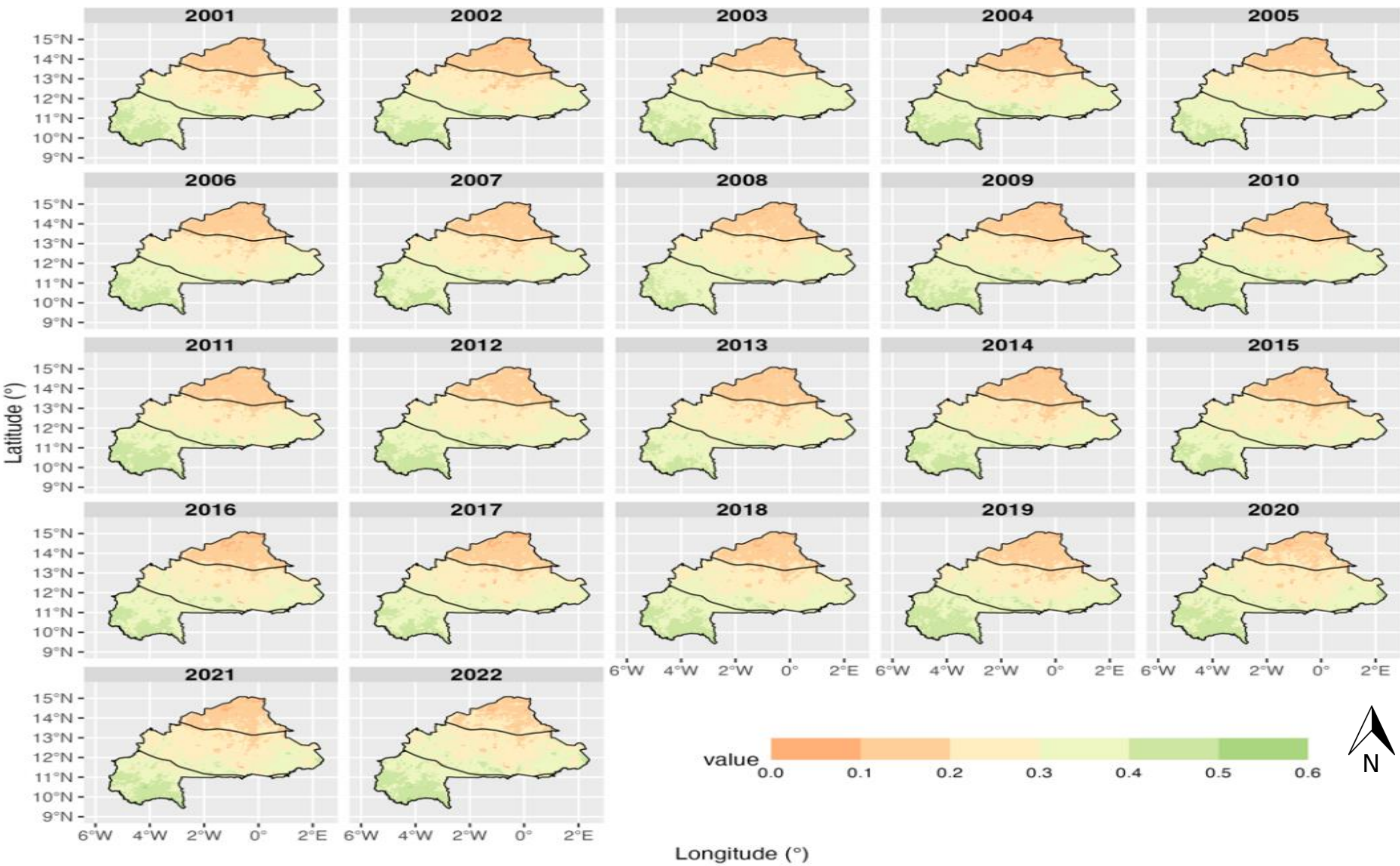


Figure 16: Variability of interannual spatial vegetation (MODIS-NDVI) from 2001 to 2022

### 2.2.1.11 Vegetation (MODIS NDVI) seasonal variability

The results of the seasonal vegetation analysis indicate significant variability (Figure 17). NDVI values are generally low from January to May, with significant differences between the northern and southern climatic zones.

From June onward, NDVI gradually increases, peaking in August. This is especially evident in the Sudanian climatic zone at the onset of the rainy season. In contrast, the north remains less green, though NDVI values are also increasing there, indicating a limited response of drier ecosystems to heightened humidity. A transition is observable in September, showing a gradual decline in NDVI until December. The seasonal cycle of the NDVI demonstrates a close synchronisation with rainfall.

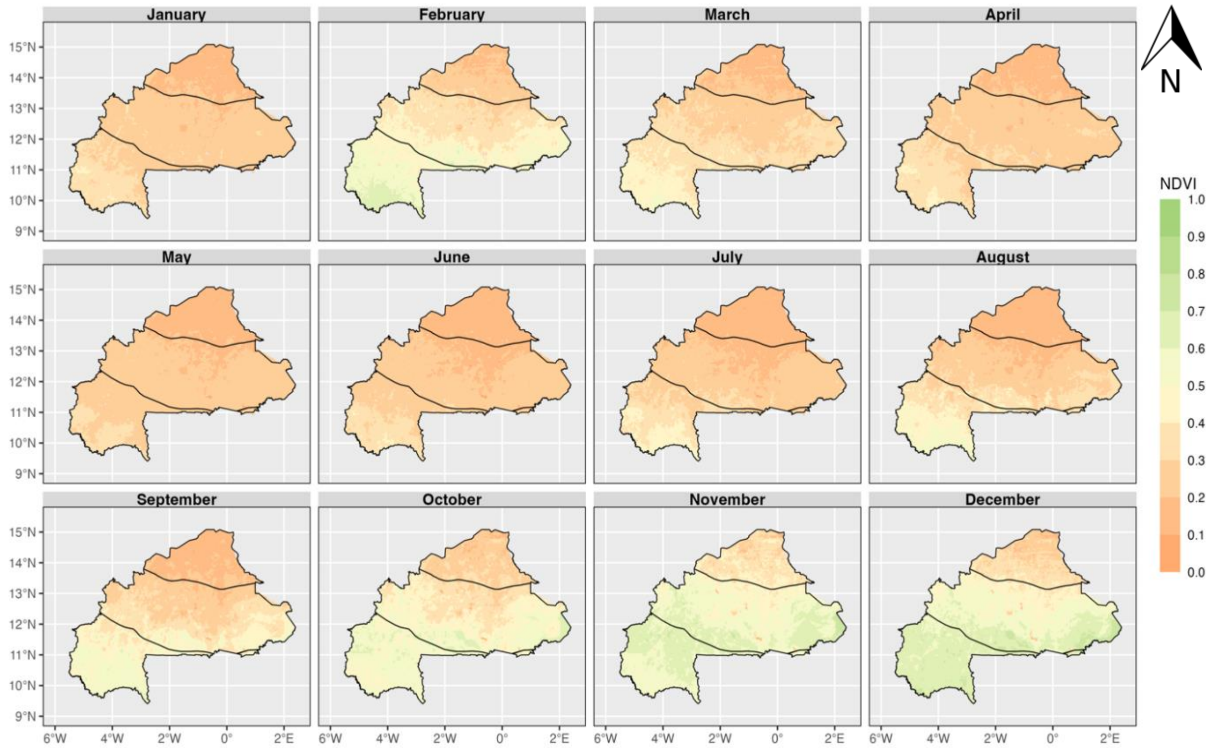


Figure 17: Annual evolution of Standard Precipitation-Evapotranspiration Index (SPEI) in Burkina Faso

### 2.2.1.12 Annual evolution of Standard Precipitation-Evapotranspiration Index (SPEI) in Burkina Faso.

The annual evolution of SPEI 6 across climatic zones from 2001 to 2022 is illustrated (Figure 18). Some years, such as 2004, 2013, 2014, 2017, and 2021, were concerned by extreme and severe drought, which probably impacted vegetation production. The results shown in Figure 18 indicate that droughts occurred regularly from 2001 to 2022, impacting all vegetation across every climatic zone.

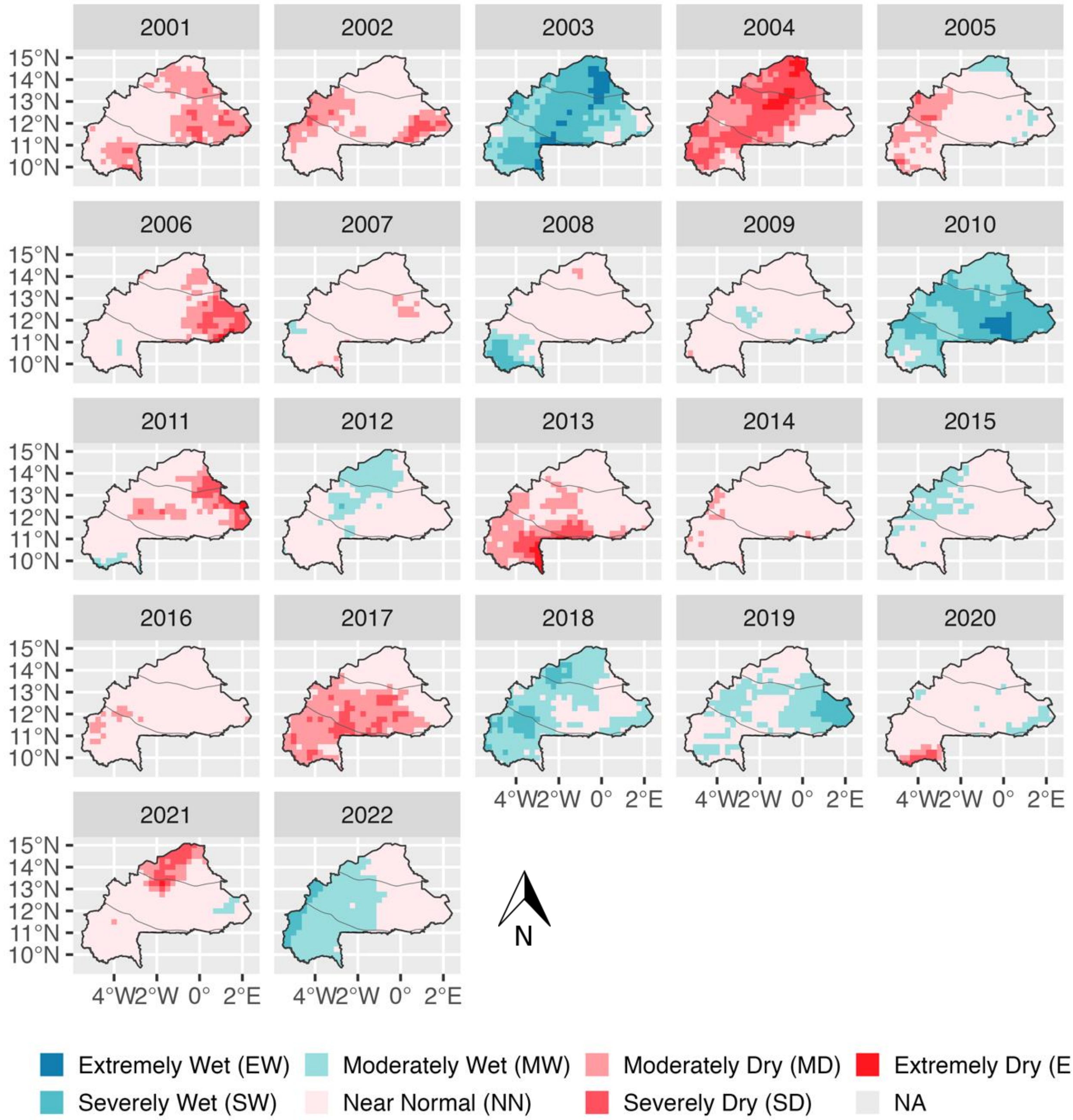


Figure 18: Annual evolution of Standard Precipitation-Evapotranspiration (SPEI 6) in Burkina Faso from 2001 to 2022

### 2.2.1.13 Temporal evolution of SPEI 6 in the Sudanian climatic zone

The temporal evolution of SPEI 6 in the Sudanian climatic zone from 2001 to 2022 shows a consistent alternation between drought and humidity periods (Figure 19). From 2001 to 2005, persistent drought, indicated by negative SPEI 6 values, signifies a water deficit. Following this period of drought, an improvement in water conditions was observed from 2007 to 2011, indicated by the rise in SPEI 6 positive values. This indicates that humidity levels rose, particularly between 2009 and 2011. However, this humid phase will be succeeded by a new period of drought events from 2013 to 2016, peaking between 2015 and 2016. Another wet period will occur from 2018 to 2020, preceding a less pronounced drought event starting in 2020. These climate fluctuations, especially drought events in the Sudanian climatic zone, highlight the vulnerability of vegetation in that area.

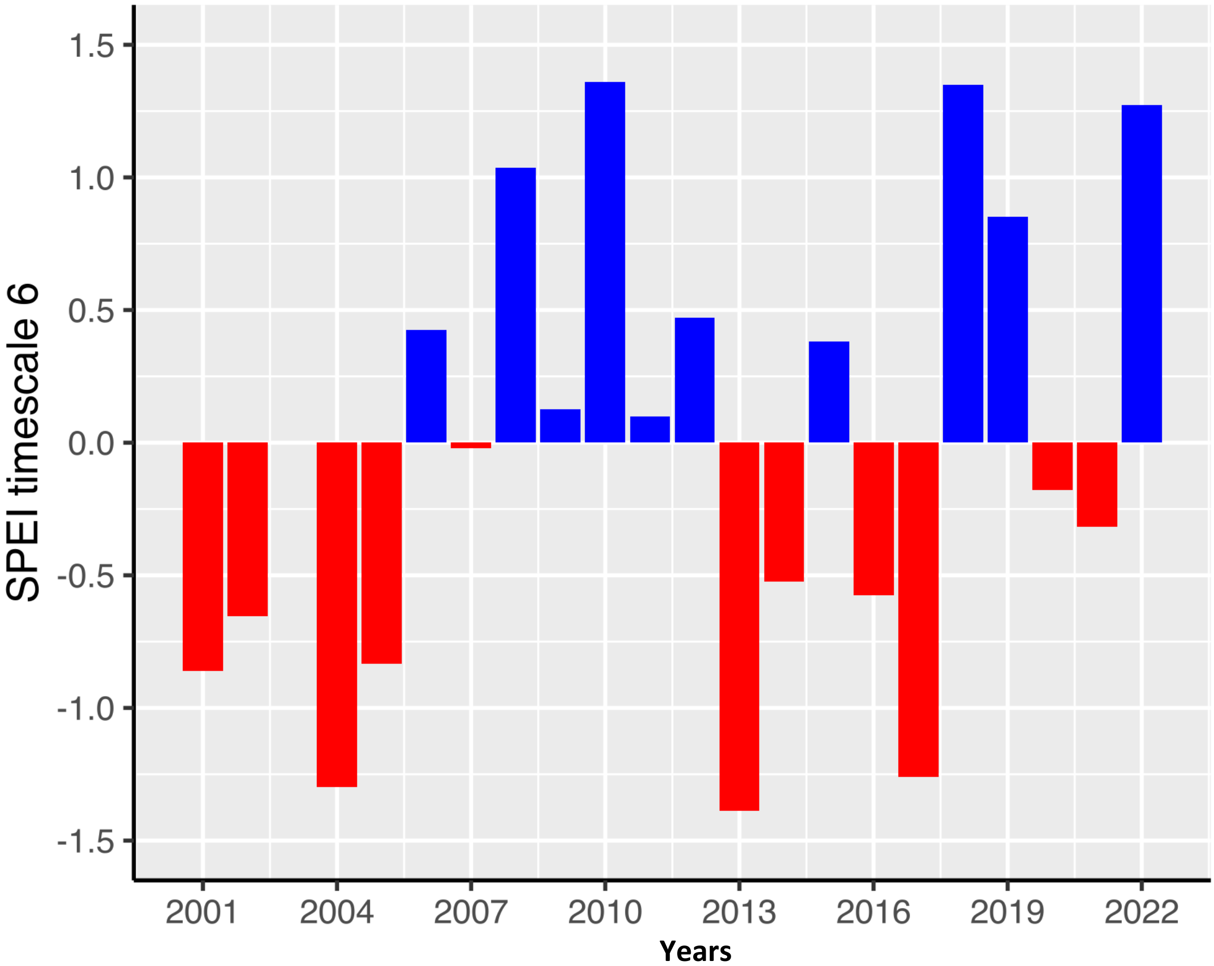


Figure 19: The temporal evolution of Standard Precipitation-Evapotranspiration Index (SPEI 6) in the Sudanian climatic zone

#### 2.2.1.14 Correlation between Vegetation (NDVI) and drought (SPEI 6) in the Sudanian climatic zone

The Pearson correlation test between NDVI and SPEI 6 in the Sudanian climatic zone from 2001 to 2022 shows a significant correlation between NDVI and SPEI 6 (Figure 20). The correlation coefficient, $r = 0.61$, indicates a moderate positive relationship between vegetation (NDVI) and the drought index (SPEI 6). To evaluate the consistency of the correlation, a t-test was conducted, producing a t-statistic of 3.42 with 20 degrees of freedom and a p-value of 0.0027. This result confirms that the correlation between NDVI and SPEI 6 is statistically significant at the 5% level. The 95% confidence interval for the correlation ranges from 0.25 to 0.82, reinforcing the robustness of this relationship.

The comparison between the vegetation and the SPEI (Figure 21) reveals that positive SPEI 6 values generally correspond to increased vegetation, indicating that humid periods enhance vegetation growth. Conversely, the decline in SPEI 6 values corresponds with a reduction in vegetation, indicating that drought events in the Sudanian climatic zone have contributed to the degradation of the area's vegetation. The negative impact of drought events on vegetation was especially evident between 2011 and 2012, highlighted by a significant decrease in NDVI and SPEI 6. Overall, the synchronisation between the two curves is evident, though minor shifts can be observed from 2015 to 2018.

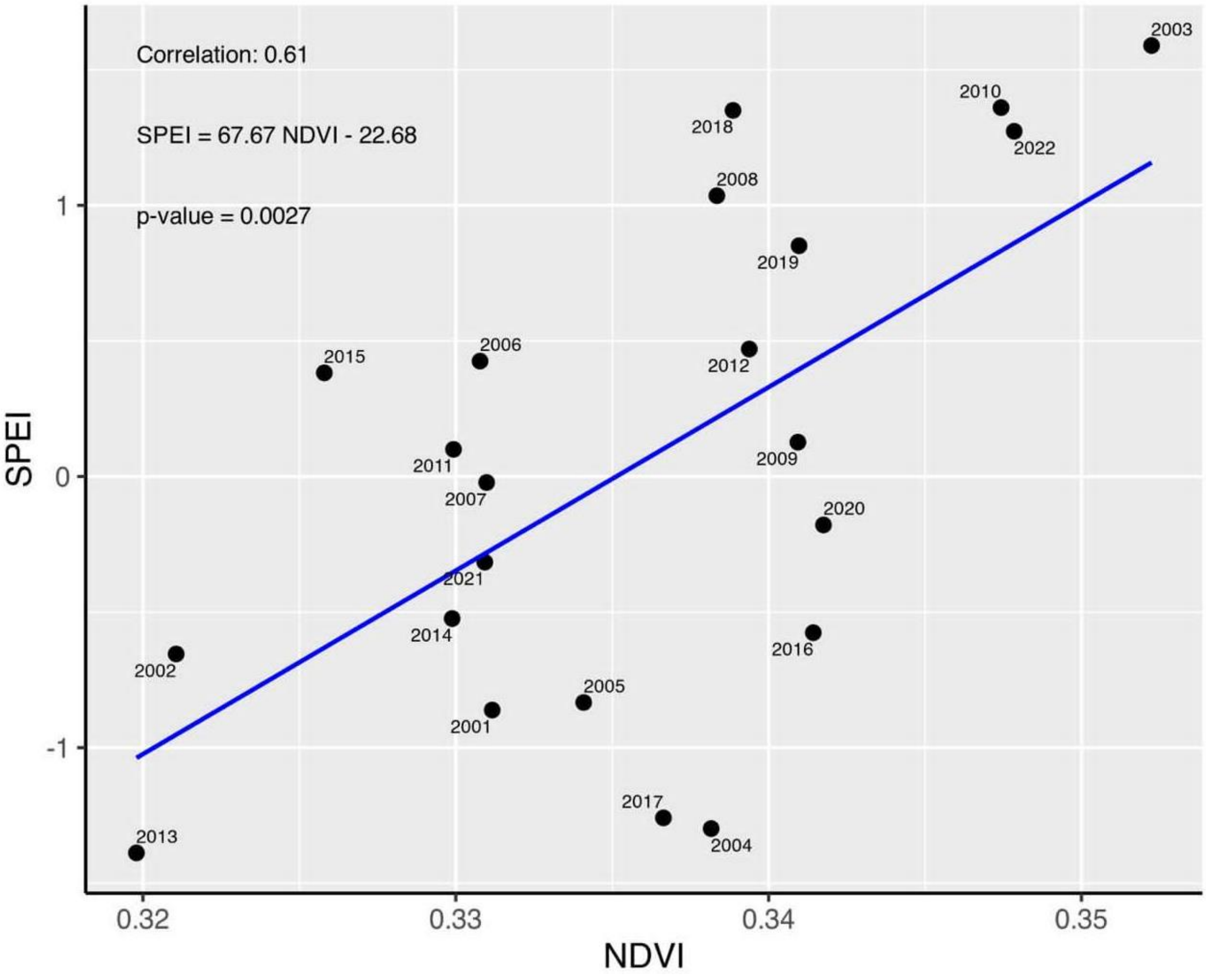


Figure 20: Correlation of NDVI and SPEI in the Sudanian climate zone from 2001 to 2022

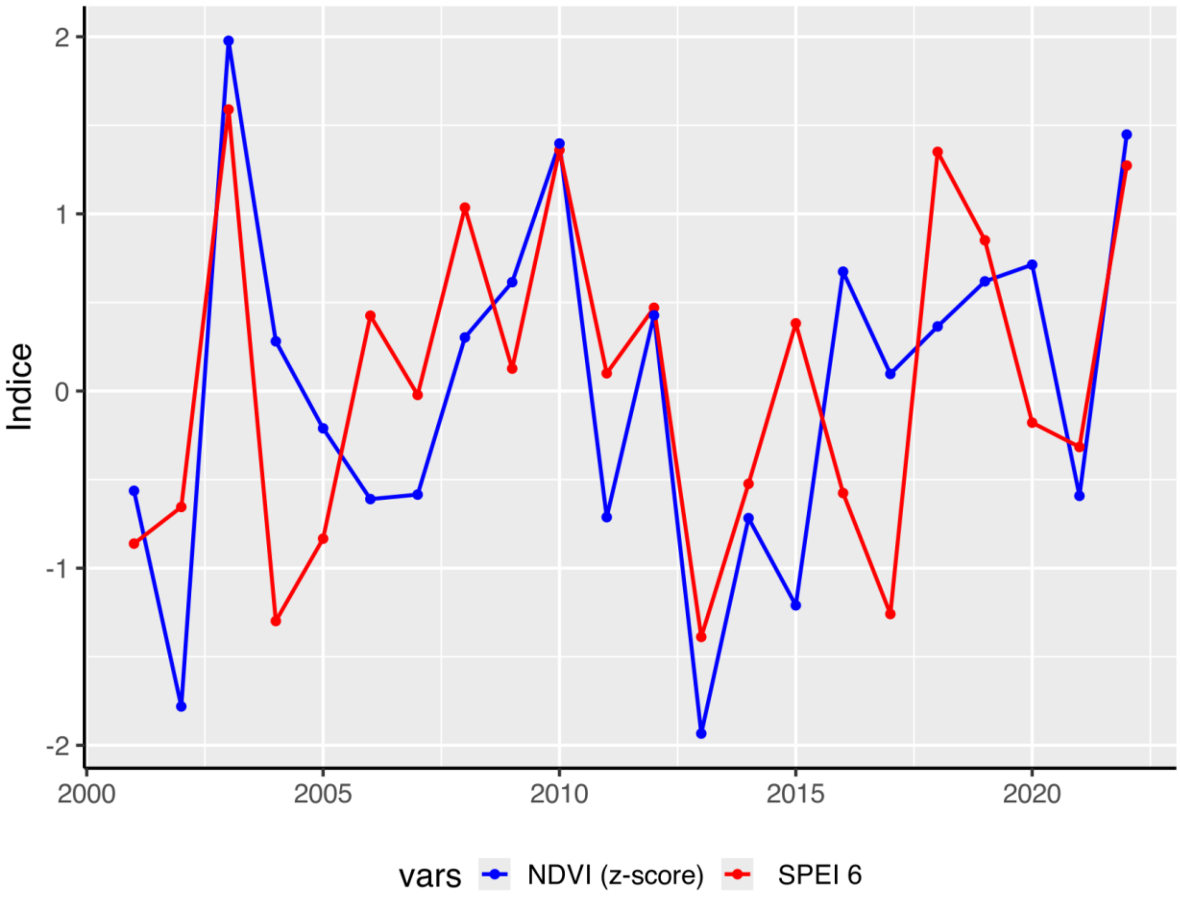


Figure 21: Relation between NDVI and SPEI 6 in the Sudanian climatic zone from 2001 to 2022

## 2.2.2 Discussion

### 2.2.2.1 TAMSAT and ERA5 data validation

The validation of TAMSAT data against synoptic station rainfall data revealed a strong agreement between the two datasets, indicated by a correlation coefficient that ranged from 0.89 to 0.94 with low bias. This result demonstrates the effectiveness of using TAMSAT data to estimate rainfall in Burkina Faso. This finding is consistent with the research findings of Nabassebeguelogo et *al*., (2023), who conclude that the TAMSAT dataset can serve as an alternative source of ground rainfall data in Burkina Faso for various purposes. This study's conclusion is also consistent with Novella & Thiaw (2009) findings that highlight using TAMSAT data as an estimator for rainfall in Burkina Faso is suitable due to low bias and fewer systematic errors associated with it.

#### 2.2.2.2 Spatiotemporal variability of rainfall

The spatiotemporal variability of rainfall revealed differences across the climatic zones. Some studies have noted this specific aspect of rainfall's spatiotemporal variability observed in Burkina Faso (SP/CONEDD, 2012; Karambiri & Gansaonre, 2023). The findings of Yameogo et *al*., (2023) highlighted the significant spatiotemporal variability of rainfall in the Nakanbe-Wayen watershed in Burkina Faso.

The spatial distribution of rainfall showed a clinal variation, characterised by an increase in rainfall from the Sahelian climatic zone to the Sudanian climatic zone. This aligns with the delineation of climatic zones concerning climate parameters like rainfall. This trend of decreasing rainfall from the Sudanian to the Sahelian climatic zone has been highlighted in the study of SP/CONEDD (2012), utilising rainfall data from 1990 to 2010.

The analysis of seasonal rainfall variability has highlighted two seasons: a brief rainy season from May to September, peaking in August, and an extended dry season from November to April. This rainfall regime, characterised by a brief rainy season and an extended dry season typical of Sahelian countries, has also been mentioned by Tano et al. (2023), who highlighted the same seasonal rainfall patterns for Burkina Faso, Mali, Niger, and Mauritania.

Generally, the spatial variability of rainfall in Burkina Faso is linked to the movements of the Intertropical Convergence Zone (ITCZ), which accounts for the decrease in rainfall from the southern to the northern part of the country. Additionally, it is important to highlight the significance of vegetation cover. Vegetation cover plays a role in creating local climate variations. Indeed, the southern part of Burkina Faso contains many protected areas, which may explain why the rainfall is more significant in this region compared to the northern part of the country.

The temporal variability of rainfall can be explained seasonally by the country's unimodal rainy season, which typically features a dry season that is longer than the rainy season. The interannual variability of rainfall is attributed to climate variability, with some fluctuations in rainfall observed from year to year.

#### 2.2.2.3 Spatiotemporal variability of temperature

The analysis of temperature has revealed a stable spatial variability. In contrast to rainfall, there is no significant variability in temperature across the different climatic zones. This is confirmed by the average temperature ranging from 27 to 31℃. However, there is a clear trend of increasing temperatures from the Sudanian climatic zone to the Sahelian climatic zone in the northern part of the country. The temperature increases when transitioning from the Sudanian climatic zone to the Sahelian climatic zone, clearly indicating a spatial variability of temperature that relates to latitudinal variability and the impact of land cover. In the Sudanian climatic zone of Burkina Faso, the vegetation is denser than in the Sahelian climatic zone, which likely contributes to the reduced evapotranspiration effect, explaining the lower temperatures observed in the Sudanian climatic zone. This result aligns with the SP/CONEDD (2012) study result, which also mentioned this same trend of temperature variability from the Sudanian climatic zone to the Sahelian climatic zone.

The observed temporal variability of temperature can be explained at the seasonal level by the alternation of dry and rainy seasons within the same year, along with some variability. The dry season consists of two temperature stages: the cool, dry season from November to February, when temperatures are generally low due to the harmattan's dry and cool winds, and the hot, dry season from March to May, which records higher temperatures during the journey. During the rainy season, cloud cover and increased humidity contribute to a decrease in temperature during this period. The interannual variability could be explained by climate variability and climate change that the country has experienced for many years, characterised by rising temperatures each year.

#### 2.2.2.4 Vegetation spatiotemporal variability

The spatiotemporal analysis of vegetation highlighted variability based on the type of climatic zone. Indeed, the results showed higher NDVI values from the Sahelian to the Sudanian climatic zone. This variability in vegetation from north to south should be linked to the corresponding variability in rainfall, which also increases from the Sahelian to the Sudanian climatic zone, indicating a relationship between vegetation and rainfall (Herrmann et *al*., 2005; Zoungrana et *al*., 2018). This result aligns with similar studies conducted in the Sudan-Sahelian climatic zone of Burkina Faso by Lind & Fensholt (1999), highlighting a significant relationship between rainfall and NDVI. According to Mohamed & Bannari (2016), who also highlighted a strong correlation between rainfall and vegetation quantity, they recommended using NDVI to map rainfall variability.

#### 2.2.2.5 Standard Precipitation -Evapotranspiration Index (SPEI 6) spatiotemporal variability

The spatiotemporal analysis of SPEI 6 revealed its occurrence across all climatic zones from 2001 to 2022, indicating that the country remains under the threat of drought. This finding aligns with numerous studies highlighting the persistence of drought events in Burkina Faso. (SP/CONEDD, 2012; Karambiri & Gansaonre, 2023).

The spatiotemporal analysis of SPEI 6 highlights that numerous drought events occurred in the Sudanian climatic zone from 2001 to 2022. This finding differs from Karambiri & Gansaonre (2023) findings, which suggested that the Sudanian climatic zone experienced few drought events (1983, 2011, 2017) from 1921 to 2018. This difference in estimating drought events in the Sudanian climatic zone may be attributed to the sensitivity of the SPEI drought estimator used in the current study. This estimator considers both rainfall and temperature, whereas the SPI used in the other study relies only on rainfall as the measure for drought events. The sensitivity of SPEI to temperature has been noted in a previous study by Zarei et *al*., (2021), which found that the SPEI is the most effective drought estimator compared to the SPI in regions with hyper-arid, semi-arid, Mediterranean, and humid climate conditions.

#### 2.2.2.6 Relation between Vegetation and Standard Precipitation-Evapotranspiration Index in the Sudanian climatic zone

The correlation between the SPEI and the NDVI in the Sudanian climatic zone shows a strong positive relationship. The t-test statistic with a P-value of 0.0027 emphasised the strong positive correlation's consistency and reliability from 2001 to 2022. Many research studies have emphasised the importance of using the SPEI to monitor the spatiotemporal dynamics of vegetation (Li et *al*., 2016; Zarei et *al*., 2021; Nejadrekabi et *al*., 2022; Ma et *al*., 2023). Besides the suitability of using SPEI instead of SPI to monitor vegetation dynamics in arid, semi-arid, and Mediterranean areas, as mentioned by Zarei et *al*., (2021), The observed positive correlation between the SPEI and vegetation in the current study is related to the fact that the study area, recognised as an arid and semi-arid zone, faces soil water constraints. Thus, the response of vegetation primarily relates to the rainfall recorded during the rainy season in the study area. This finding aligns with previous studies (Li et *al*., 2016; and Liu et *al*., 2017). The slight shifts observed from 2015 to 2018 could be attributed to the delayed response of vegetation to climate change, influenced by variability in the phenology of plant species. This delayed response of vegetation to climate change has been highlighted in previous studies (Svenning & Sandel, 2013; Wu et *al*., 2015; Boussougou et *al*., 2018). This phenomenon, also known as the vegetation lag effect, refers to the time required for vegetation to adjust to climate changes.

This vegetation lag effect involves several factors, including soil moisture and its ability to store water, the life cycle of vegetation, ecophysiological adaptation factors of vegetation, interactions between vegetation and the biotic environment, disturbance events (such as firewood and land use), and soil fertility. The high number of drought events identified in the current study within the Sudanian climatic zone compared to the findings of Karambiri & Gansaonre (2023) in the same location may also relate to the amount of meteorological data used to achieve the analysis. In the current study, data from multiple synoptic stations in the Sudanian climatic zone have been considered in the analysis, compared to the previous study conducted by Karambiri & Gansaonre (2023), which utilised synoptic data from Bobo-Dioulasso for their study. According to Páscoa et *al*., (2018), more meteorological stations are needed to provide sufficient data for a better understanding of drought impacts on vegetation.

# CONCLUSION

The analysis of the relationship between rainfall and temperature on vegetation in the Sudanian climatic zone from 2001 to 2022 highlights the vulnerability of this vegetation to severe and extreme drought events, similar to other climatic zones in Burkina Faso. The use of SPEI from TAMSAT and ERA5 datasets, along with MODIS-NDVI, has demonstrated that SPEI 6 is effective for vegetation monitoring in Burkina Faso, particularly in the Sudanian climatic zone, based on the strong positive correlation observed between SPEI 6 and NDVI. This study's findings also highlighted that the Sudanian climatic zone experienced numerous drought events from 2001 to 2022, indicating that the vegetation, particularly the forest areas in that zone, has been adversely impacted by these drought events. Monitoring the spatiotemporal response of vegetation to climate factors, including rainfall and temperature from validated satellite data, is crucial for accurately assessing the potential impacts of drought on vegetation. This is essential for sustainable forest management and the preservation of livelihoods in African countries with limited coverage of meteorological stations, especially in the context of climate change.

# CHAPTER 3: SPATIOTEMPORAL ANALYSIS OF LAND USE AND LAND COVER DYNAMICS OF DINDERESSO AND PENI FORESTS IN BURKINA FASO


## Abstract

The sustainable management of protected areas has become increasingly difficult due to inadequate information on changes in land use and land cover resulting from human activities. This study investigates the spatiotemporal dynamics of the Dinderesso and Peni classified forests in Burkina Faso from 1986 to 2022. First, a data-driven method was adopted to investigate the degradation dynamics of these forests. Relevant Landsat image data were collected, segmented, and analysed using the Random Forest algorithm in the QGIS SCP plugin. A second investigation involving field trips, literature review, and meetings with forest managers enabled the identification of anthropogenic forest degradation and deforestation drivers. The results of the land use and land cover classification analysis showed overall accuracies adjusted and a Kappa coefficient of over 90%. The analyses showed significant degradation and deforestation, with clear forest and wooded savannah classes converging into shrub savannah and agroforestry parklands expanding at annual rates of 3.86% and 3.09%, respectively, in Dinderesso forest, and at rates of 358.54% and 0.95%, respectively, in Peni forest. The anthropogenic drivers accounting for over 90% of both the Dinderesso and Peni classified forest degradations include agricultural expansion, excessive logging, overgrazing, charcoal production, and bushfires. These findings underscore the urgent need for improved management to enhance these protected areas.



**Keywords:** Anthropogenic factors; Burkina Faso; Dinderesso and Peni forest; land use land cover; Random Forest

# INTRODUCTION

Forest resources, particularly the changes in land use and land cover in protected areas caused by human activities, have long been a global concern, especially in West African countries. (FAO, 2020a; Thiombiano & Kampmann, 2010). These changes present substantial challenges to biodiversity conservation and the preservation of local populations' livelihoods. In this context, Geographic Information Systems (GIS), combined with satellite imagery, present a valuable opportunity to analyse land use and land cover in protected areas. Such analyses can improve monitoring efforts by managers and guide sustainable policy investments, ultimately resulting in better outcomes for biodiversity conservation and the protection of community livelihoods (Falcucci et *al*., 2007; Sánchez-Reyes et *al*., 2017).

Numerous satellite imagery studies have shown its effectiveness in detecting changes in land use and cover within protected areas (Dimobe et *al*., 2015; Millogo et *al*., 2017). These findings highlight the value of this technology in monitoring and managing forest areas increasingly threatened by human activities, which jeopardise both biodiversity and the well-being of neighboring communities.

Situated near several rural municipalities and the urban municipality of Bobo-Dioulasso, the Dinderesso and Peni classified forests are consistently exposed to various illegal resource exploitations and banned human activities (Djiguemde et *al*., 2023; MECV, 2007b). All these human activities, falling outside the legal regulations governing the Dinderesso and Peni classified forests, contribute to changes in land use and land cover, obstructing their primary function of biodiversity conservation and their secondary function of socio-economic development.

The sustainable management of the Dinderesso and Peni classified forests faces significant challenges due to various anthropogenic pressures. Since they have been recognised as classified forests, which grants them a protective status to manage human encroachments, several studies related to the drivers of forest degradation, flora composition, and forest structure have been conducted using surveys and inventories (Djiguemde et *al*., 2023; Yaméogo et *al*., 2020). Recognising the relevance of these studies to Dinderesso and Peni's classified forest sustainable management, their implementation requires numerous resources and does not provide detailed information on land use and land cover patterns globally. Sadly, there is no understanding of the spatial-temporal land use and land cover dynamics of Dinderesso and Peni classified forests, which complicates sustainable management. Research on land use and land cover dynamics in the Sudanian climatic area has highlighted the key role of anthropogenic drivers in the land use and land cover changes in those forests. Indeed, the Toessin classified analysis of forest land use and land cover dynamics from 1986 to 2010 has revealed that vegetation classes are decreasing due to human activities (Belem et *al*., 2019). Conducting the same analysis in the Tiogo classified forest from 1986 to 2006, Millogo et *al*., (2017) findings highlighted that the forest loses 0.49% of its vegetation cover each year. Many other studies have also noted the role of anthropogenic drivers in land use and land cover change in protected areas (Dimobe et *al*., 2015; Savadogo, 2021).

Given the evidence of threats to protected areas from human activities in the study area, it is essential to address the knowledge gap regarding the spatiotemporal land use and land cover dynamics of Dinderesso and Peni classified forests in order to provide consistent and large-scale information for their sustainable management.

This study aims to analyse the land use and land cover dynamics of Dinderesso and Peni classified forests from 1986 to 2022 and to identify anthropogenic drivers of land use and land cover change.

## 3.1 Methods

The overall methodology of the study is illustrated in Figure 22. It includes Landsat images and assessments of land use and land cover.

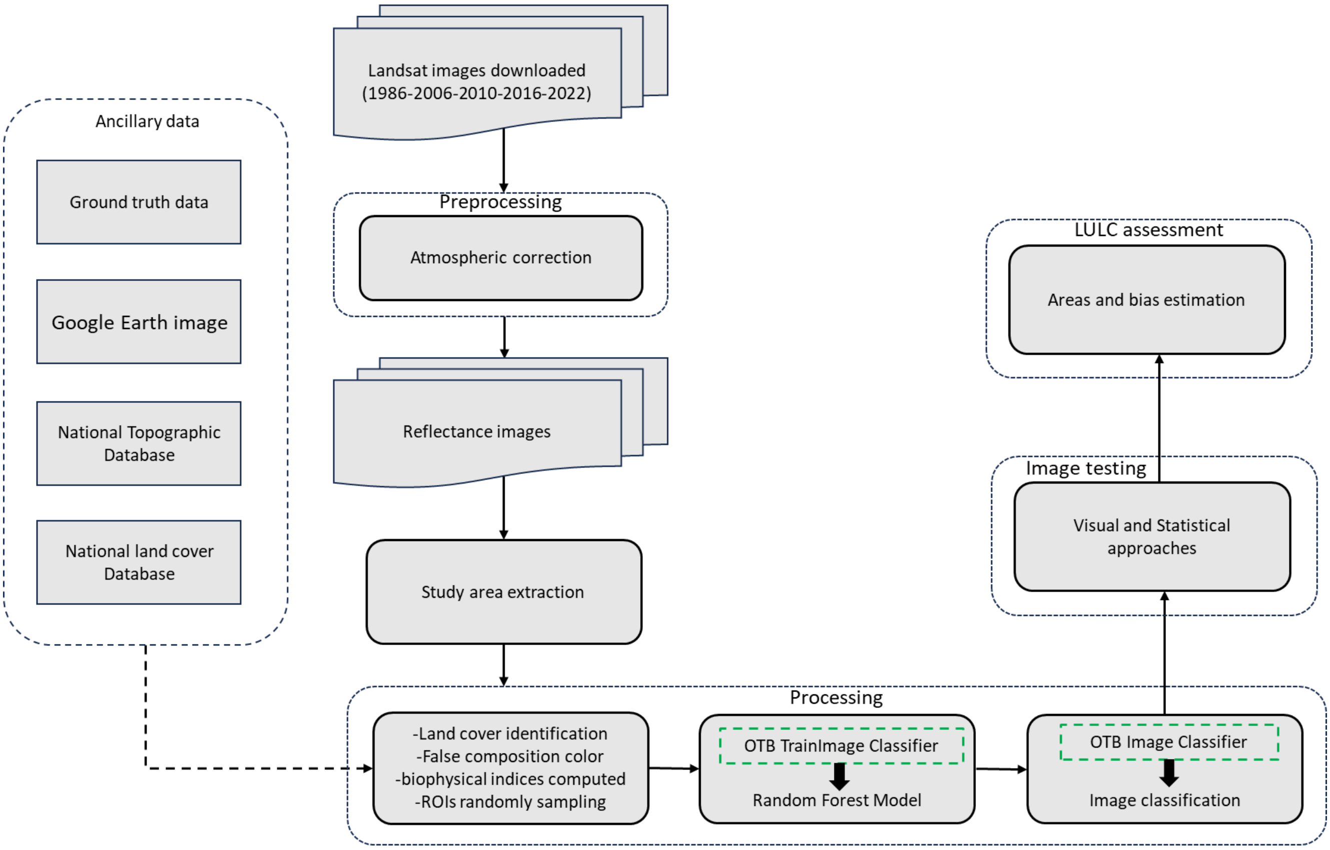


Figure 22: Landsat land use and land cover assessment flowchart

### 3.1.1 Landsat Data Collection

For land use land cover dynamic assessment, a set of five multi-temporal Landsat images covering path 197/52 were downloaded from the United States Geological Survey (USGS) website (available at:http://earthexplorer.usgs.gov/) for the years 1986, 2006, 2010, 2016, and 2022 (Table 6). The images were selected during the same year period (October to November) with image availability and cloud cover per cent criteria to minimise the biases linked to solar angle, vegetation phenological change, and soil humidity variation (Tankoano et *al*., 2015). Twenty (20) ground truth Global Positioning System (GPS) data were collected through a stratified random sampling approach with at least 1 km between two points from each land cover class during the field trips from 23 August 2023 to 27 August 2023 in Dinderesso classified forest and from 8 December 2023 to 9 December 2023 in Peni classified forest. The national topographic database (BNDT) and the national land cover database for 2012 from the Burkinabe Geographic Institute (IGB) were also used for improving the study area knowledge and the land cover classes identification.

Table 6: Landsat image characteristics

| Forest | Landsat N | Date Acquired | Sensor_ID | Cloud Cover | Path | Row |
|---|---|---|---|---|---|---|
| **Dinderesso** | 5 | 16 November 1986 | TM | 0 | 197 | 52 |
| | 5 | 7 November 2006 | TM | 0 | 197 | 52 |
| | 5 | 18 November 2010 | TM | 0 | 197 | 52 |
| | 8 | 17 October 2016 | OLI_TIRS | 0.17 | 197 | 52 |
| | 8 | 18 October 2022 | OLI_TIRS | 0 | 197 | 52 |
| **Peni** | 5 | 16 November 1986 | TM | 0 | 197 | 52 |
| | 5 | 7 November 2006 | TM | 0 | 197 | 52 |
| | 5 | 18 November 2010 | TM | 2 | 197 | 52 |
| | 8 | 17 October 2016 | OLI_TIRS | 0.17 | 197 | 52 |
| | 8 | 18 October 2022 | OLI_TIRS | 0 | 197 | 52 |

### 3.1.2 Land use and land cover classes identification

Seven and six LULC classes were identified in the classified forests of Dinderesso and Peni, respectively (Figure 23). These classes are related to Water Body/Wetland Area (WB/WA), Gallery Forest (GF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS). Due to the difficulty in clearly identifying certain LULC classes with very similar spectral signatures, some classes, such as Water Body and Wetland Area, Wooded Savannah and Tree Savannah, and Built Area and Bare Soil, have been merged.

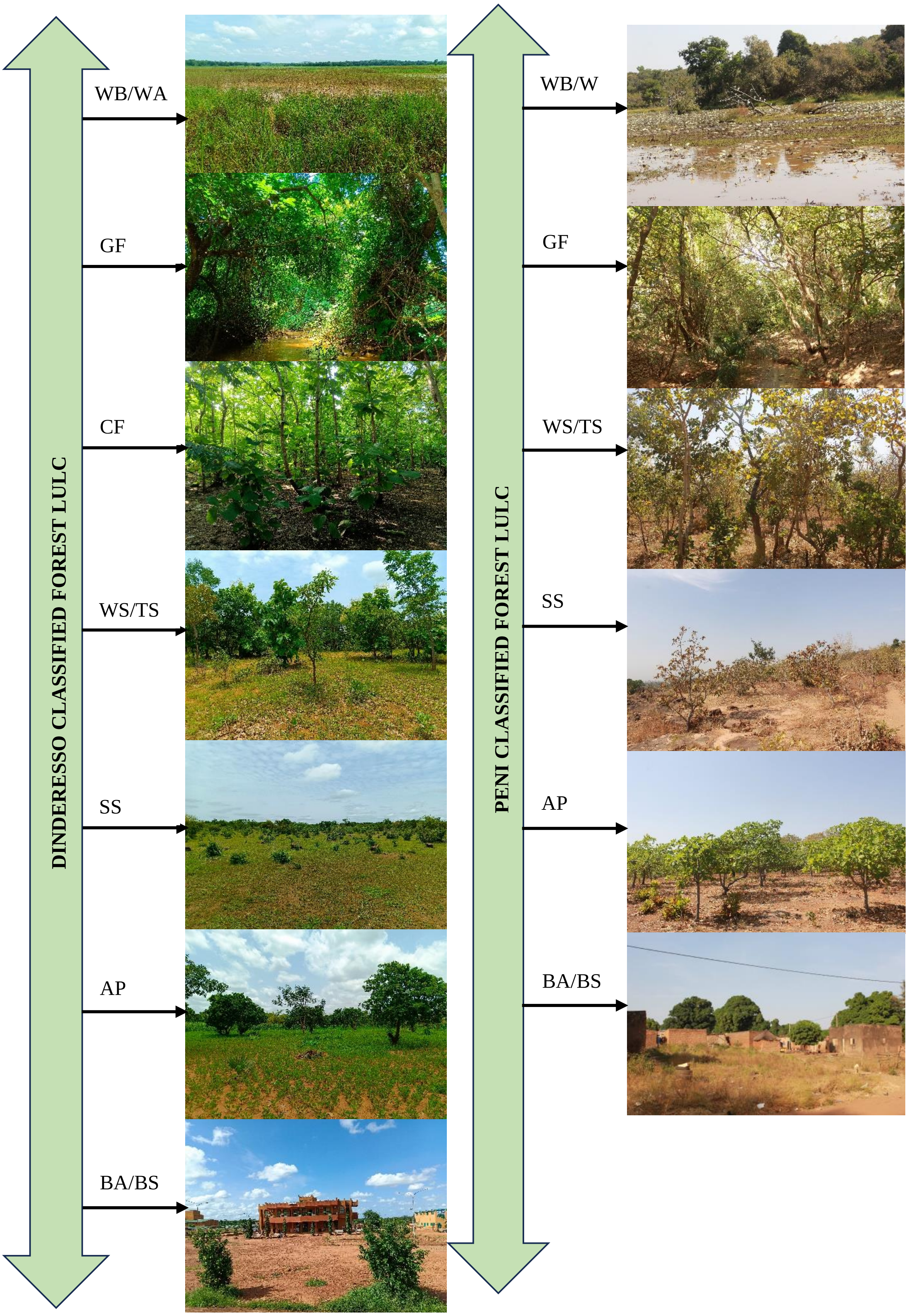


Figure 23: Land use and land cover classes in Dinderesso and Peni classified forests

### 3.1.3 Digital Preprocessing of Landsat Images

All the downloaded Landsat images were already georeferenced to Universal Transverse Mercator (UTM) zone 30 North within the Coordinate Reference System WGS84. Atmospheric correction using the QGIS Semi-automatic Classification Plugin (SCP) was applied to convert images from Digital Numbers (DN) to reflectance. The reflectance images of each respective study year were stacked before extracting the study area using forest masks from the national topographic database.

### 3.1.4 Digital Image Processing

The different studied years' panchromatic band sets obtained after the data pre-processing step were uploaded to the QGIS SCP for image classification. Auxiliaries data, including false color composition (5-4-3 and 4-3-2, respectively, for OLI_TIRS and TM band sets); biophysical indices, which are Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), and Normalised Difference Water Index (NDWI); the national land use database; Google Earth high-resolution image; and the ground truth data were used along the images classification, as shown in Figure 22, to improve the identification of land cover classes, respectively, for Dinderesso and Peni classified forests with their periphery. Based on the particularity of the colored composition image to highlight each land cover class spectral signature (Tempa & Aryal, 2022), 563 and 377 regions of interest (ROI) polygons were selected randomly and homogeneously from the reference 2022 multispectral image in false color composition. Each ROI selected was assigned the corresponding land class (Tempa & Aryal, 2022). For each ROI random sample selected, 2/3 (60% for model training and 40% for model validation) was used for Random Forest model training and 1/3 for the testing (Denis, 2020). A total of 377 and 256 training ROIs were used as input data into the Orfeo ToolBox (OTB) "TrainImagesClassifier" program to train and generate the classification model. Then, the Random Forest model was used as input with the reference multispectral image to perform the whole image classification into the OTB "ImageClassifier" program. The supervised Random Forest classification was also applied to 1986, 2006, 2010, and 2016 multi-spectral images based on ROIs selected from identified land cover class areas that stayed stable over the years (Denis, 2020).

### 3.1.5 Testing of Classified Images

The classified images were validated using visual and statistical approaches (Denis, 2020). The visual comparison of the Random Forest classified image with the false color composition image revealed a high similarity between the two images. This visual testing, recognised as a subjective method, was used as a first step in the classification testing before applying the statistical testing, which is more accurate. The ROIs testing polygons were used to validate the Random Forest classified image into the QGIS SCP "Accuracy" program (Denis, 2020). The statistical classification testing generated confusion matrices for each classified image in an Excel spreadsheet that was used to assess the classification accuracy by computing the overall accuracy, producer and user accuracy, and kappa coefficient (Dimobe et *al*., 2015; Ghosh et *al*., 2014).

The producer accuracy of land cover classes was measured by dividing the total number of perfectly classified pixels within the testing zone of the given class by the total number of pixels in the testing zones of said class. The user's accuracy was calculated for each class by dividing the total number of pixels correctly classified in the given class in all testing areas of the said class by the total number of pixels classified in that class in the given class within all testing zones for all LULC classes. For more reliability to the Random Forest classification described as an outperformer classifier model Traoré et *al*., (2024), other metrics, including the accuracy, the recall, and the F1-score, were computed. They were computed based on the true positive (*TP*) for recognised objects, false negative (*FN*) for non-detected objects, and false positive (*FP*) for incorrectly identified objects. The following equations (Tam et al., 2020) were used to assess these metrics:

$$Accuracy = \frac{TP}{TP+FP}$$ Equation (10)

$$Recall = \frac{TP}{TP+FN}$$ Equation (11)

$$F1 - score = \frac{Accuracy * Recall}{Accuracy + Recall}$$ Equation (12)

In addition to previous metrics computing, the accuracy assessment good practices recommended by Olofsson et *al*., (2014) were considered to highlight the misclassification bias by adjusting producer, user accuracy, and estimated areas. This adjustment was achieved using Card's confusion matrix correction (Card, 1982) using a Microsoft Excel version 2408 spreadsheet (Obodai et *al*., 2019).

For post-classification processing, the SCP "Classification sieve" algorithm was applied to the classified images to clean isolated pixels and thus improve their sharpness. Following this processing and the various analyses relating to the dynamics of LULC, the images were vectorised before their mapping in QGIS.

### 3.1.6 Evaluation of Land Use Land Cover Dynamics

For this analysis, we once again used the shapefiles of the two forests to extract the data relating to each of the forests. The images extracted after cleaning the isolated pixels were used as input data in the SCP "Land cover change" algorithm to generate the transition matrices. The SCP's "Classification report" algorithm was subsequently used to generate, in Excel format, information relating to the areas of the different LULC classes for each study period. These data made it possible to calculate the average annual rate of land cover change between two periods using the following formula from (Long et *al*., 2007):

$$C = \frac{\left(\frac{(B2 - B1)}{B1} * 100\right)}{T2 - T1} \quad \text{Equation (13)}$$

where $C$ is the average annual rate of change; $B1$ is the amount of land cover type in time 1 ($T1$); and $B2$ is the amount of land cover type in time 2 ($T2$).

### 3.1.7 Identification of anthropogenic factors of forest degradation and deforestation

Three conceptual approaches were used to identify the anthropogenic factors contributing to degradation and deforestation in the Dinderesso and Peni classified forests. This involved a literature review, including previous research works and technical reports conducted in the study area related to degradation and deforestation drivers. Four meetings with four resource people in charge of Dinderesso and Peni classified forest management have been held to identify the main drivers of forest degradation and deforestation drivers. The resource people involved in these meetings included the Houet province Director in charge of Dinderesso and Peni classified forests, the departmental chief in charge of Dinderesso and Peni classified forest management, the Director of the national forestry school, and the Coordinator of Dinderesso associations involved in Dinderesso forest management. In addition to the literature review and meetings, field observation was performed through visits to Dinderesso and Peni classified forests to track anthropogenic drivers of studied forest degradation and deforestation.

## 3.2 Results

### 3.2.1 Classification testing

The details of both Dinderesso and Peni classified image overall accuracy, the kappa coefficient, producer user accuracy, and user accuracy are highlighted by Appendix 2 and 3.

The overall accuracy unadjusted of Dinderesso classified images ranges from 92.81% to 94.32% for 2006 and 2010. The kappa coefficient ranges from 0.90 for 2006 to 0.92 for 1986, 2010, and 2022. The lowest producer accuracy unadjusted of Dinderesso classified forest land cover classes is 81.48% for WS/TS. The lowest user accuracy unadjusted is 80% for AP.

For the Peni classified forest, the overall accuracy unadjusted ranges from 94.85% to 99.76% for 2010 and 2006, respectively. The kappa coefficient ranges from 0.92 to 0.995 for 2010 and 2006, respectively. The lowest producer accuracy unadjusted of Peni classified forest land cover classes is 90.48% for BA/BS. The lowest user accuracy unadjusted is 90% for WB/WA.

The metric values obtained from the RF confusion matrix are presented, with Dinderesso's accuracy values ranging from 0.95 in 2016 to 0.98 in 2006 (Table 7). Peni's classified forest accuracy values range from 0.96 to 0.99 for 1986 and 2006. All these high values suggest a high overall performance of image classification.

The recall values of Dinderesso classified forest range from 0.95 to 0.97, respectively, for 2016 and 2006. Peni classified forest recall values range from 0.97 to 0.99 for 2010, 1986, and 2016, respectively. The recall values in both Dinderesso and Peni classified forests are high, attesting to reliable performance in class identification.

Dinderesso classified forest F1-score values fluctuate from 0.95 to 0.97 for 2016 and 2010, respectively. Peni classified forest F1-score ranges from 0.97 to 0.99 for 2022, 2006, and 2016, respectively. The high F1-score values in both forests indicate a good balance between accuracy and recall, showing the performance of the RF classification model.

Appendix 4 and 5 present the 1986 and 2022 bias-adjusted confusion matrix by Card's method derived from sample counts and the proportion of LULC class areas in the raw confusion matrix available in the complementary data. The adjusted metrics show similarity with unadjusted metrics concerning overall accuracy, which is over 90%, and user adjusted accuracy metrics, which are at least equal to 80% for all the different year map classifications.

Conversely to user accuracy, the producer accuracy adjusted results decreased considerably compared to unadjusted producer accuracy with low values under 50%, particularly for the Built Area/Bare Soil LULC class for Dinderesso classified forest 1986, 2016, and 2022 maps and for the Water Body/Wetland Area 2016 map. In the Peni classified forest, these low values of producer accuracy are only related to the Built Area/Bare Soil LULC class for the 2010, 2016, and 2022 maps.

Table 7: Accuracy, recall, F1-score, and kappa Land classification testing metrics for Dinderesso and Peni classified forests

| Forest | Year | Accuracy | Recall | F1-Score | Kappa |
|---|---|---|---|---|---|
| Dinderesso | 1986 | 0.97 | 0.96 | 0.96 | 0.92 |
| | 2006 | 0.98 | 0.97 | 0.97 | 0.9 |
| | 2010 | 0.97 | 0.96 | 0.97 | 0.92 |
| | 2016 | 0.95 | 0.95 | 0.95 | 0.91 |
| | 2022 | 0.96 | 0.96 | 0.96 | 0.92 |
| Peni | 1986 | 0.96 | 0.99 | 0.98 | 0.97 |
| | 2006 | 0.99 | 0.98 | 0.99 | 0.99 |
| | 2010 | 0.97 | 0.97 | 0.98 | 0.92 |
| | 2016 | 0.99 | 0.99 | 0.99 | 0.97 |
| | 2022 | 0.98 | 0.98 | 0.97 | 0.96 |

### 3.2.2 Dynamics of Land Use in the Classified Forests of Dinderesso and Peni from 1986 to 2022

The distribution of LULC classes of both Dineresso and Peni classified forests over 1986, 2006, 2010, 2016, and 2022 is highlighted in Figures 25, 26 and, 27, 28, respectively. The distribution of these LULC classes during the studied years in the Dinderesso and Peni classified forests show some changes. Figures 29 and 30 show the LULC classes' evolution over time. It can be seen that Dinderesso classified forest vegetation classes, including Clear Forest (CF) and Wooded Savannah/Tree Savannah (WS/TS), have been changing to Shrub Savannah (SS) and Agroforestry Parkland (AP) from 1986 to 2022. The same observation is made also in the Peni classified forest where Wooded Savannah/Tree Savannah (WS/TS) and Gallery Forest (GF) have been changing to Shrub Savannah (SS) and Agroforestry Parkland (AP). The annual growth area rate for Shrub Savannah (SS) and Agroforestry Parkland (AP) in the Dinderesso classified forest is 3.86% and 3.09%, respectively (Appendix 6). In the Peni classified forest, the Shrub Savannah (SS) growth area rate per annum is assessed at 358.54% and 0.95% for the Agroforestry Parkland (AP) growth rate per annum (Appendix 7). The Shrub Savannah in the Peni classified forest changed from 1.49 ha in 1986 to 193.81 ha in 2022, which explains the too-large growth rate per annum observed.

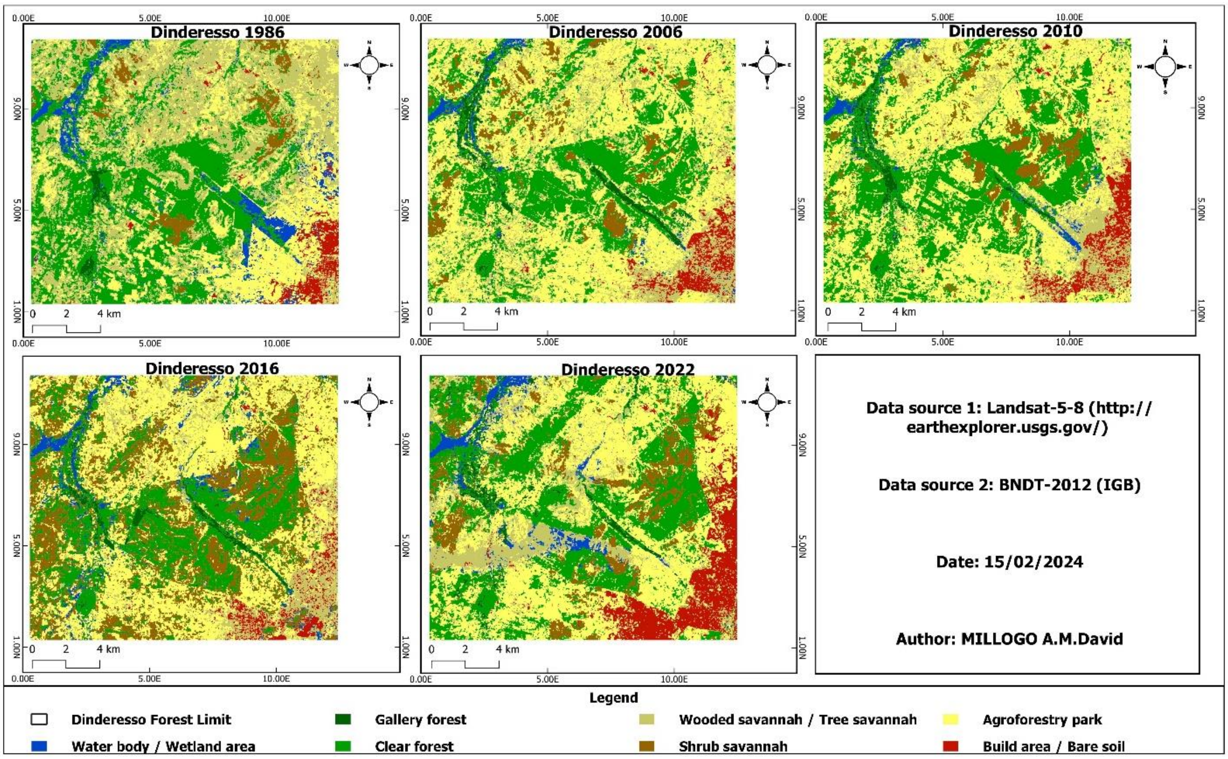


Figure 24: Land use land cover map of Dinderesso classified forest in 1986, 2006, 2010, 2016, and 2022 without forest mask

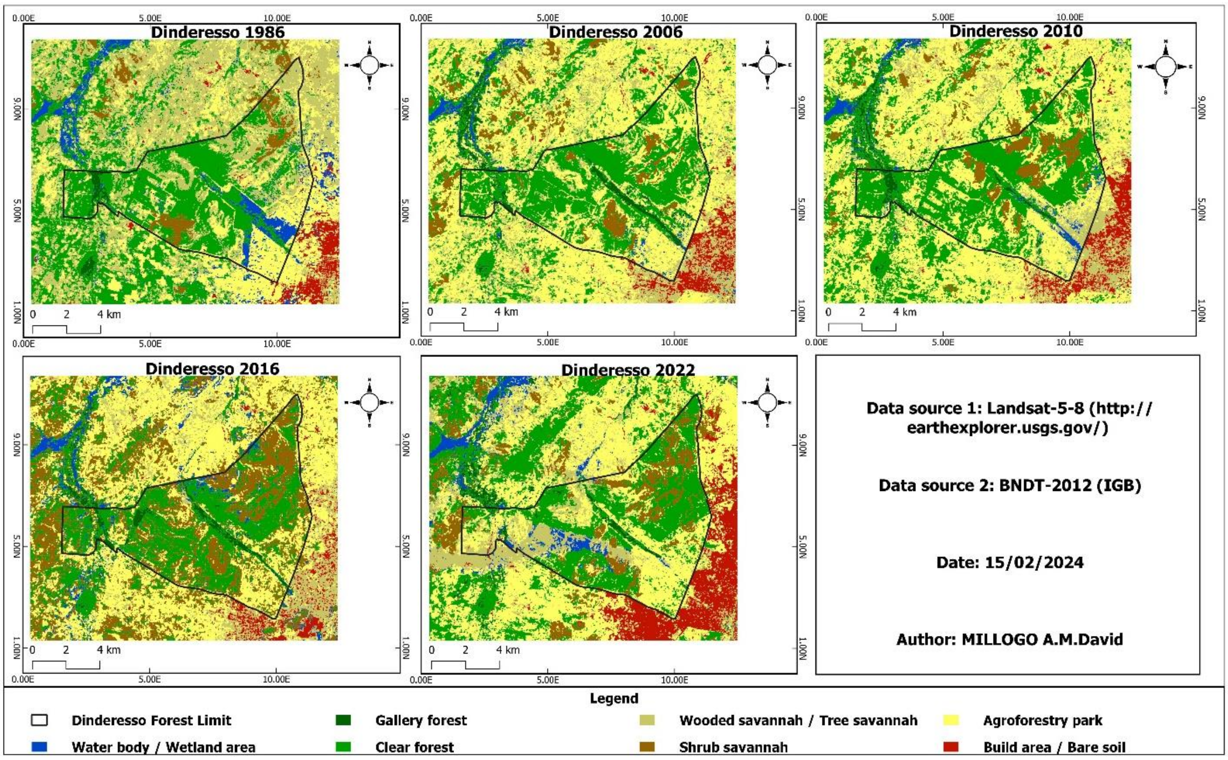


Figure 25: Land use and land cover map of Dinderesso classified forest and its periphery in 1986, 2006, 2010, 2016, and 2022 with mask

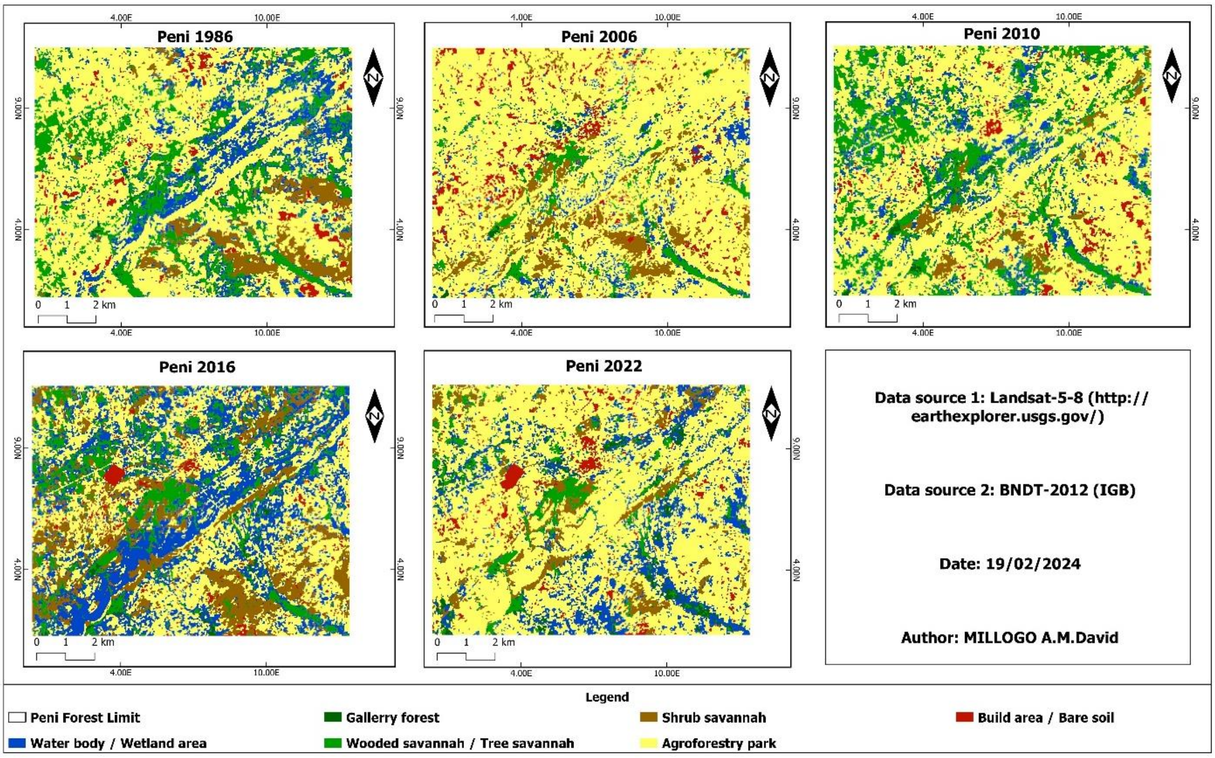


Figure 26: Land use and land cover map of Peni classified forest and its periphery in 1986, 2006, 2010, 2016, and 2022 without mask

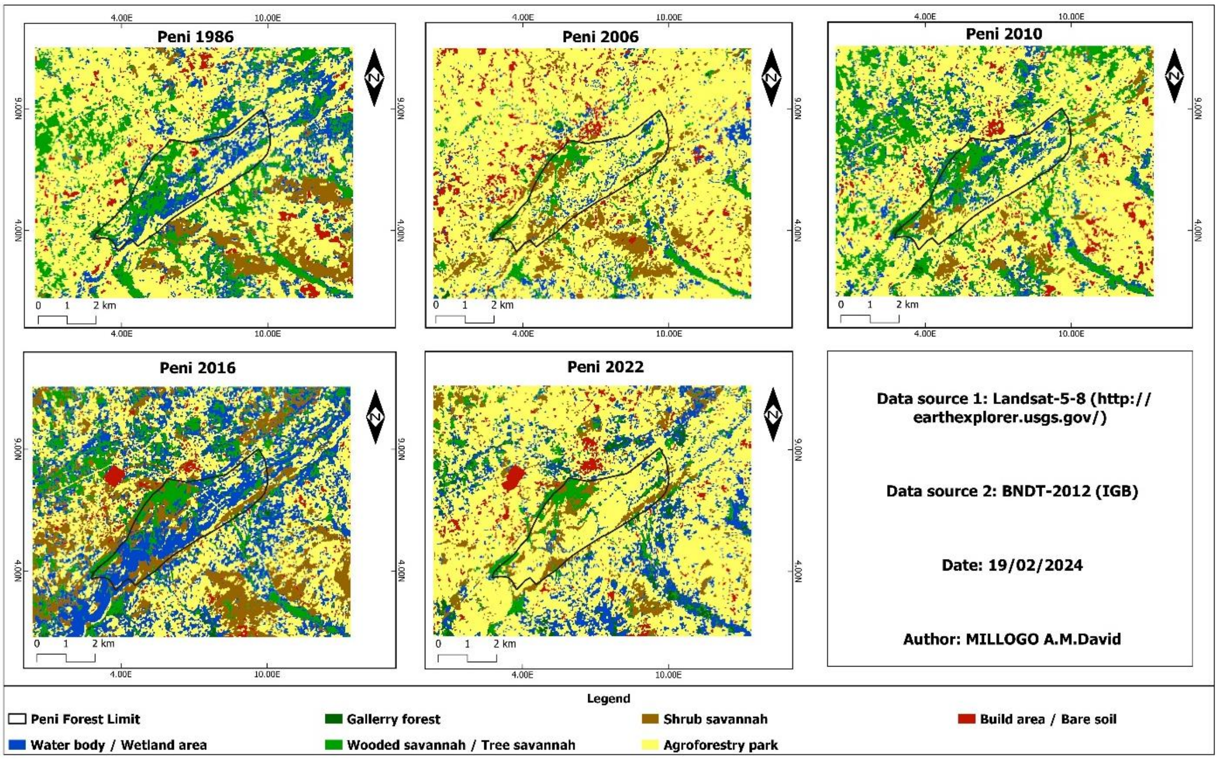


Figure 27: Land use and land cover map of Peni classified forest and its periphery in 1986, 2006, 2010, 2016, and 2022 with mask

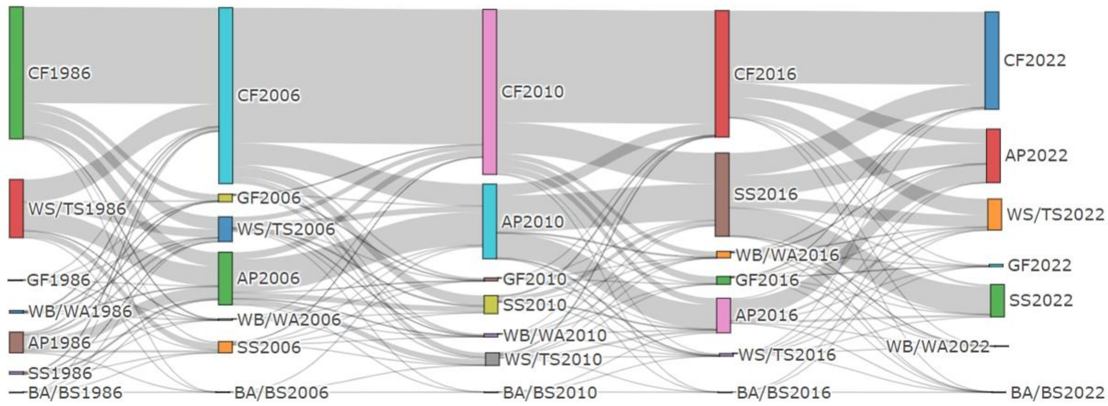


Figure 28: Land use and land cover change in the classified forest of Dinderesso in 1986, 2006, 2010, 2016, and 2022

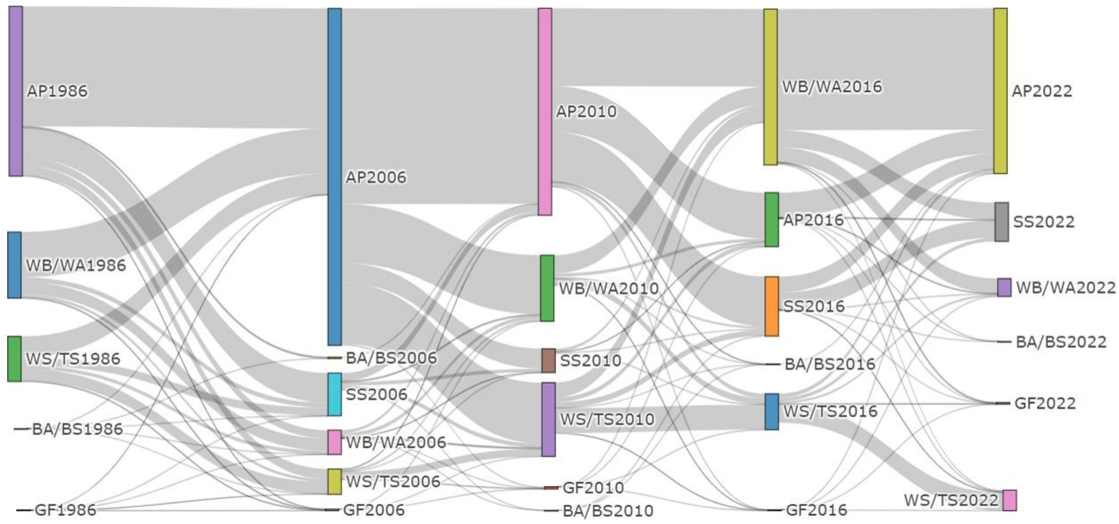


Figure 29: Land use and land cover change in the classified forest of Peni in 1986, 2006, 2010, 2016, and 2022

***Note:*** *Each cloured bar represents a given forest vegetation class area in a given studied year (e.g. AP1986 referred to agroforestry parkland area in 1986).*

### 3.2.3 Forest degradation and deforestation anthropogenic drivers from field observation and meetings with resource persons

The field trip in both Dinderesso and Peni classified forests, as well as their surrounding areas, revealed that human activities primarily contribute to their degradation and deforestation. Figure 31 illustrates these anthropogenic drivers, which include clearing land for crops and orchards, cutting trees for fuelwood and charcoal production, overgrazing by livestock, improper harvesting of non-timber forest products, and bushfires. These observations align with the main anthropogenic drivers of forest degradation and deforestation highlighted by resource persons during meetings, including unsustainable wood cutting for firewood, charcoal production, mortar production, poaching, overgrazing, agriculture, and urbanisation.

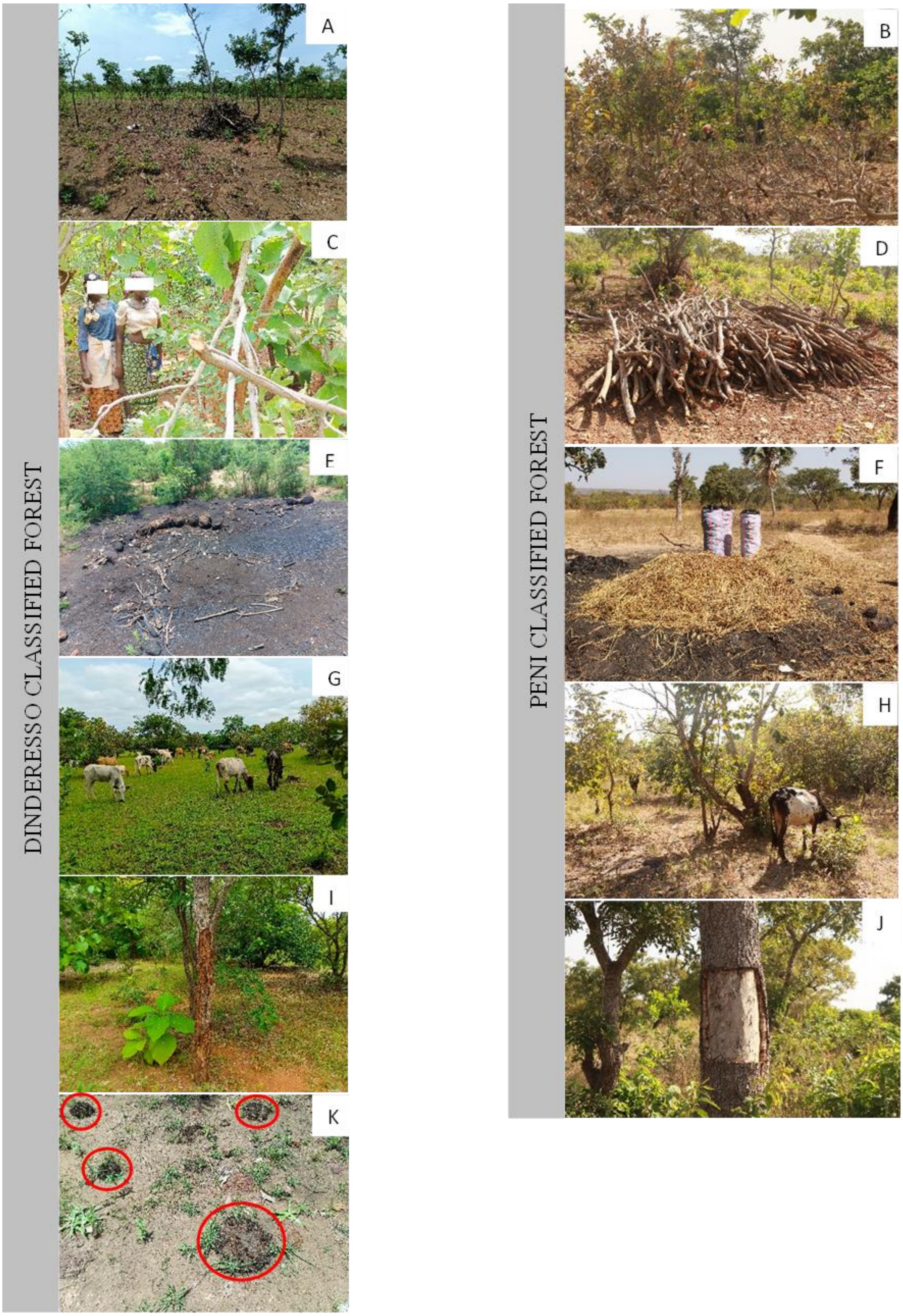


Figure 30: Anthropogenic drivers of Dinderesso and Peni classified forest degradation and deforestation (***Note:*** *Extensive agriculture (A, B), Firewood harvesting (C, D), Charcoal sites production (E, F), Cattle overgrazing (G, H), Poor bark harvesting (I, J), traces of bushfire circled in red (K)).*

## 3.3 Discussion

### 3.3.1 Peni land use land cover classes and Landsat images analysis

The Landsat images classification of Dinderesso and Peni classified forests allowed the identification of seven land use land cover classes. These classes, including Water Body/Water Area (WB/WA), Gallery Forest (GF), Clear Forest (CF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS), align with the national LULC database and are consistent with many authors' LULC descriptions in the Sudanian climatic zone (Dimobe et *al*., 2015; Savadogo, 2021; SE/CCNUCC, 2020). The supervised random forest classification approach provided high overall accuracy, kappa coefficient, producer accuracy, and user accuracy statistics. These statistic accuracies are consistent with other land use land cover studies achieved using Random Forest (Tempa & Aryal, 2022; Ghosh et *al*., 2014).

The high values of classification overall accuracy and the kappa coefficient suggest a high agreement between the classified thematic maps and the reference image used to generate the classification (Mohd Hasmadi et *al*., 2009). According to Tankoano et *al*., (2016), these high statistical results could be explained by training and testing pixels that are homogeneously chosen within LULC classes and well identified. These statistics values are also supported by the metrics, including the recall and the F1-score, which highlighted the Random Forest model's high performance and reliability in classified images. Despite the high accuracy statistics obtained, some confusion between LULC classes are highlighted by the producer and user accuracy statistics, which are not all 100%. The confusion observed between LULC classes could be related to the difficulties in choosing training ROIs among classes with very close spectral signatures. These confusions are common in the Sahel area, where vegetation class heterogeneity associated with Landsat image spatial resolution may affect the correct identification of LULC classes (Dash et *al*., 2023). Research conducted by Aka et *al*., (2022) in the Ivory Coast revealed the limits of Landsat-8 image spatial resolution by distinguishing some land cover classes where Sentinel-2 images with a better spatial resolution proved more successful. According to Khatami et *al*., (2017), the confusion between LULC classes could also belong to pixel sampling. According to Traoré et *al*., (2024), who compared the performance between Random Forest and the SVM models, the Random Forest is sensitive to the number of pixels. This case may concern the land cover class Water Area/Wetland Body (WA/WB) and Built Area/Bare Soil with low producer accuracy adjusted values in our study, where it was difficult to sample many training and testing polygons ROIs covering many pixels related to that particular class. This study, compared to previous LULC assessment studies conducted in Burkina Faso (Belem et *al*., 2019; Tankoano et *al*., 2016), highlighted the relevance of recall and F1-score metrics and the accuracy assessment by applying Olofsson's Olofsson et *al*., (2014) and Card (1982) methodology in the classification testing approach.

### 3.3.2 Land use and land cover dynamic

The main change observed in land use and land cover dynamics in both Dinderesso and Peni classified forests from 1986 to 2022 is the decreasing area of high-vegetation classes, including clear forest wooded savannah/tree savannah, and the increasing area of low-vegetation classes, including shrub savannah and agroforestry park. These results reflect the trend towards Dinderesso and Peni classified forests degradation and deforestation, characterised by high-vegetation classes replacement into low-vegetation classes. These results are consistent with those of MECV (2007c), who highlighted Dinderesso and Peni classified forests degradation and deforestation. Similar research studies achieved in the Sudanian area have also highlighted protected forest degradation and deforestation. A similar study conducted in the classified Koulbi forest in the Sudanian area showed that clear forest and tree savannah areas are being replaced by shrub savannah and cropland (Sanon et *al*., 2019). Other research studies conducted in the Sudanian area in Burkina Faso (Tankoano et *al*., 2016; Savadogo, 2021) and in West Africa (Atakpama et *al*., 2024; Boukeng & Elvire, 2021; N'Guessan et *al*., 2019) mentioned the increasing of agroforestry parkland and shrub savannah classes area in the forest. Many factors, including human activities and climate change, could explain the decrease in vegetation class areas observed in Dinderesso and Peni classified forests. The contribution of human activities in protected areas degradation and deforestation has been recognised by many authors (Sanou, 2023; Tindano et *al*., 2024). The proximity of Dinderesso and Peni classified forests to Bobo-Dioulasso city makes them ideal sources for fuelwood supply. According to Tankoano et *al*., (2016), the population harvests trees for fuelwood in forest and wooded savannah/tree savannah, where the largest trees are located. Overlogging of trees has been identified among the most common causes of the Dinderesso classified forest degradation and deforestation (Djiguemde et *al*., 2023). The demographic pressure, land tenure, and rural population poverty could explain the increase in agroforestry parklands in both forests. A survey conducted in Zambia revealed that population growth, loss of soil fertility, land tenure management, and lack of laws are the leading causes of agricultural expansion into Zambia's forest areas (Phiri et *al*., 2023). According to Miyamoto (2020), agricultural land inaccessibility due to population poverty contributes to agricultural expansion in forest areas. Climate change also contributes to forest degradation and deforestation. Some studies have highlighted the influence of climate change through drought events on forest degradation and deforestation (FAO, 2020a). The findings of Gaisberger et *al*., (2017) revealed that the main challenge in the long term for sixteen food tree species in their natural habitat in Burkina Faso is related to climate change. Beyond the threats of human activities and climate change impact, this study's findings raise crucial points related to biodiversity conservation in Dinderesso and Peni classified forests and the sustainability management system suitable for these protected areas. The conversion of high-vegetation classes into low-vegetation classes negatively affects plant species and their habitat, which can lead to the extinction of some plant species. According to Savadogo et *al*., (2019), the overexploitation of medicine plant species, such as *Securidaca longipedunculata*, negatively affects the availability of adult plants in their natural habitat. The changes observed in Dinderesso and Peni classified forests, despite their protected status, highlight the inefficiency of the current management system due to high threats from human activities. Some authors have suggested improving the management of protected forests for their sustainability (Dimobe et *al*., 2015; Savadogo, 2021). A suitable management system for protected forest areas should be developed based on sustainable biodiversity conservation and the preservation of the livelihoods of the riparian population.

### 3.3.3 Anthropogenic drivers of land use land cover degradation

The results of field observation made during the classification validation in both Dinderesso and Peni classified forests showed agroforestry parks installed or in the process of being installed within forests, the presence of trees cut down for fuel wood and other uses, charcoal sites production, overgrazing, poor harvesting practices for non-timber forest products, and bushfires, showed that human activities could explain the degradation and deforestation of studied forests. These observations align with those of several authors who have highlighted the responsibility of human activities in the degradation and deforestation of protected areas (FAO, 2020b; Fritz et *al*., 2022; MEEEA, 2022; MEEVCC, 2020a). The people living near the Dinderesso and Peni classified forests live in rural areas, and their main socio-professional activity is agriculture. As a result of strong demographic growth, urbanisation, and the loss of fertile land, these populations are always on the lookout for new, increasingly fertile cropland, leading them to violate protected areas, as they no longer have any space to cut on their land, to satisfy their food requirement and for incomes. In West Africa, agriculture has been recognised as the first factor in the degradation and deforestation of protected areas (Thiombiano & Kampmann, 2010). More than 50% of the people interviewed showed that agriculture is the main factor causing the degradation and deforestation of Bontioli, a protected area in the Sudanian climatic zone in Burkina Faso (Savadogo, 2021). The dependence of rural and urban households on firewood and charcoal as a major source of energy could explain the felling of trees and the presence of charcoal production sites for the benefit of neighboring rural populations and urban towns such as Bobo-dioulasso located near these forests. More than 97% of household energy needs in Burkina Faso are met by woody forest resources (Mundler et *al*., 2010). Dinderesso and Peni classified forests are not fenced and have no physical barriers to prevent the entry of animals, including cattle and sheep, which, by grazing and trampling, contribute to the destruction of the natural regeneration of the trees; in addition, trees are mutilated by shepherds to provide fodder to animals. The contribution of overgrazing to protected areas degradation and deforestation in the Sudanian climatic zone in Burkina Faso has been claimed by many authors (Dimobe et *al*., 2015; Savadogo, 2021; Thiollay, 2006). As a result of poverty and the scarcity of non-timber forest products, people, especially those living in rural areas, are harvesting unripe fruits, roots, bark, and flowers, contributing to the degradation and deforestation of protected areas. Many studies have warned that the pressure on woody species that provide non-timber forest products contributes to the extinction of these species (Gaisberger et *al*., 2017; Savadogo, 2021). Many reasons, such as fauna hunting, looking for fresh grass for breeding, and pushing humans to cause bushfires, contribute to the degradation and deforestation of protected areas, as mentioned by Tankoano et *al*., (2015) who work in the Tiogo classified forest in Burkina Faso. Land shortages increasing due to urbanisation and population growth are also relevant factors, even if they are considered non-direct factors that could provide more details to understand the human contribution to Dinderesso and Peni classified forest degradation and deforestation within climate change and climate variability context.

# CONCLUSION

This study significantly contributes to bridging the knowledge gap concerning the LULC dynamics of the Dinderesso and Peni classified forests, as well as the anthropogenic factors driving these changes between 1986 and 2022. Utilising a robust and reliable methodology that combines Landsat image classification with a Random Forest classifier model, field trip visits, a literature review, and meetings with forest managers, the study yielded important insights that can enable forest managers and the government to take appropriate actions.

The study firstly demonstrated a high accuracy and reliability of the Random Forest model for Landsat image classification, achieving an accuracy and F1-score exceeding 0.90. Secondly, the analysis of LULC dynamics revealed a trend toward degradation and deforestation in the Dinderesso and Peni classified forests. This trend is marked by the conversion of clear forests and wooded savannahs/tree savannahs, into shrub savannahs and agroforestry parklands. In the Dinderesso forest, shrub savannah and agroforestry parklands have been expanding at annual rates of 3.86% and 3.09%, respectively. In the Peni forest, the annual growth rates for these categories are even more dramatic, at 358.54% and 0.95%, respectively. Furthermore, the study identified key anthropogenic drivers, such as excessive wood cutting, agriculture, overexploitation, charcoal production, overgrazing, and bushfires, which contribute to the degradation and deforestation of these forests. The research also highlights systemic management deficiencies in both the Dinderesso and Peni forests, which are reflective of broader challenges faced by classified forests across the country, undermining efforts toward sustainable biodiversity conservation and the preservation of local communities' livelihoods. The findings of this study are consistent with previous research that has raised alarms about the degradation and deforestation of protected forests, underscoring the need for the development of effective management systems for these areas and their neighboring communities.

# CHAPTER 4: THE PERCEPTION OF DINDERESSO AND PENI CLASSIFIED FORESTS NEIGHBORING COMMUNITIES ON DEGRADATION AND DEFORESTATION DRIVERS

## Abstract

Numerous classified forests in Burkina Faso are experiencing degradation and deforestation as a result of human activities and climate change, which impacts their sustainable management, conservation of biodiversity, and the livelihoods of neighboring communities. Having key information about protected forest degradation and deforestation at the local level is essential for improving management and preserving the livelihoods of neighboring communities. Unfortunately, there is a gap in knowledge concerning various hidden factors contributing to forest degradation and deforestation, which makes sustainable management challenging. To address the knowledge gap regarding protected area degradation and the drivers of deforestation, a survey has been conducted in the neighboring Dinderesso and Peni classified forest communities in Burkina Faso. This study aims to identify and analyse the drivers of forest degradation and deforestation in the Dinderesso and Peni regions, as well as the relationships between these drivers and neighboring communities. To conduct this study, a semi-structured questionnaire survey was administered to 850 household heads in eight neighboring communities of the Dinderesso and Peni classified forest. The results showed that anthropogenic drivers account for over 90% of the classified forest degradation and deforestation in Dinderesso and Peni, including excessive wood cutting, demographic pressure, poor management, agriculture, overexploitation, overgrazing and poverty. The study findings highlighted the existence of a significant relationship between the classified forests and their neighboring communities ($p$-value = 1.810766e-31 $\leq$ 0.05). This relationship also revealed a difference in how neighboring communities perceive the factors of forest degradation and deforestation. This study provided consistent and reliable findings relevant to improving classified forest management systems by policymakers and forest managers for biodiversity conservation and the preservation of neighboring communities' livelihoods.

**Keywords:** Anthropogenic drivers, Burkina Faso, Degradation and deforestation, Protected areas, neighboring community

# INTRODUCTION

It is widely acknowledged that the degradation of protected areas and deforestation pose significant threats to biodiversity conservation and the livelihoods of many people globally (FAO, 2020a; Fritz et *al*., 2022; Jayathilake et *al*., 2021; Thiombiano & Kampmann, 2010). From 2010 to 2020, the world has lost an average of 4.7 million hectares of forest area each year (FAO, 2020a). The research by Jayathilake et *al*., (2021) on 28 tropical forest landscapes concluded that 93% of tropical forests are threatened by degradation. According to Gaisberger et *al*., (2017), sixteen food tree species in Burkina Faso face numerous threats within their distribution area. These threats may rise due to climate change and human activities. After conducting an inventory study on tree species that provide goods to the population Savadogo et *al*., (2019) highlighted the absence of certain medicinal trees, such as *Securidaca longipedunculata* Fresen, with medium and large diameters within the study area due to overexploitation.

In Burkina Faso, protected areas cover 14% of the country's territory, while forests account for the majority at 84.42% (MECV, 2007c). These protected areas contribute to the economic development of the nation and the livelihoods of the rural population, particularly those living along their borders. Timber forest products are the leading providers of forestry sub-products in terms of employment and income for the country, contributing 5.66% to the gross domestic product (MEEVCC, 2020b). Yelkouni (2004) research revealed that fuelwood accounts for 89% of the energy needs of households neighboring the Tiogo forest, and that nontimber forest products such as shea fruit, honey, and fauna are sold primarily for income. According to Savadogo (2021), communities living on the border of Bontioli, a protected area in the south-west of Burkina Faso, benefit from provisioning ecosystem services, including wood, fodder, water, fruits, medicines, honey, and fauna, as well as regulatory ecosystem services related to air quality, rainfall, and wind protection. Many drivers, including human activities and climate change, are causing degradation and deforestation in all country-protected areas, jeopardising biodiversity conservation and the livelihoods of local communities. To address the degradation of protected areas and deforestation, many studies utilise GIS and remote sensing (Bene & Fournier, 2014; Tankoano et *al*., 2015; Tankoano et *al*., 2016; Belem et *al*., 2019; Savadogo, 2021), contribute to the sustainable management of protected areas by providing information on some drivers of degradation and deforestation. This approach of using GIS and remote sensing to identify the causes of protected areas has faced criticism from Ken et *al*., (2020), who explain that this approach can give only global information, which can be insufficient and distant from local communities' knowledge of protected areas degradation and deforestation which is more precise and detailed. Some authors advocate for the importance of conducting surveys among communities residing at the borders of protected areas due to the significant and valuable knowledge they possess regarding the degradation of these areas and the factors contributing to deforestation, which can enhance sustainable management practices (Mbayngone & Thiombiano, 2011; Ouattara et *al*., 2022; Sanou, 2023). Dinderesso and Peni classified forests in the Sudanian region of Burkina Faso are experiencing degradation and deforestation. This study aims to enhance the sustainable management of Dinderesso and Peni classified forests by increasing understanding of the drivers of degradation and deforestation. The study specifically aims to (i) identify the drivers of degradation and deforestation in the classified forests of Dinderesso and Peni, and to (ii) analyze the relationship between these drivers and neighboring communities.

## 4.1 Methods

The approach used in this study evolved from gathering data to analysing it.

### 4.1.1 Household Heads Sampling

A survey was conducted in eight neighboring communities of Dinderesso and Peni, classified forests, to identify the drivers of forest degradation and deforestation. These neighboring communities were selected based on each classified forest management plan, which previously identified them according to their distance and interaction with designated classified forests. The survey participants were primarily the heads of households in the neighboring communities. The number of households included in this study has been determined using the following equation (Shete et *al*., 2020):

$$N = z^2 * p * (1 - p)/\alpha^2 \qquad \text{Equation (14)}$$

where $N$ is the sampling size, $z$ is the confidence level at 95%, $z$ is equal to 1.96, $p$ is the proportion of the population is 0.5, and $\alpha$ is the error equal to 5%.

Given that the four neighboring communities of Dinderesso and Peni classified forests have different populations, the equation was applied based on the household proportion of each community as determined by the fifth national census of communities in Burkina Faso (INSD, 2022b). A total of 850 heads of households from eight neighboring communities were interviewed (Table 8).

Table 8: Number of household heads surveyed in each community

| Forest | Community | Household Heads Number |
|---|---|---|
| **Dinderesso** | Banakeledaga | 136 |
| | Dinderesso | 41 |
| | Nasso | 113 |
| | Ouolonkoto | 133 |
| **Total 1** | | **423** |
| **Peni** | Peni | 190 |
| | Sokouranie | 30 |
| | Taga | 37 |
| | Gnafongo | 170 |
| **Total 2** | | **427** |
| **Total (1+2)** | | **850** |

### 4.1.2 Dinderesso and Peni classified forest neighboring household heads perception on forest degradation, deforestation drivers data collection

The data were gathered using the Kobocollect tool. A semi-structured questionnaire (Appendix 8) was administered in individual interviews with randomly selected household heads (Photo 1) from each community, focusing on age, sex, and residential status as outlined in the Houet province household statistics (INSD, 2022a). The decision to direct the questionnaire to household heads is linked to the social structure in the study area, where the head is the most knowledgeable about all aspects of the household and has the authority to represent it. Before each interview, the interviewee approval form was completed and signed. A local guide was utilised in data collection to minimise bias associated with local language adaptation. The interviews were conducted in Dioula, a local language widely spoken in the study area.

Photo 1: Head of household interviewed in Peni rural commune

### 4.1.3 Data processing

The data obtained from the previous step was cleaned by removing empty data lines and correcting some recorded misspellings. After the data-cleaning process, 454 responses, representing 53.4% of the initial sample size, were analysed using an Excel spreadsheet to identify the anthropogenic drivers of Dinderesso and Peni classified forests and their relationship with neighboring communities. The high amount of misinformation recorded is primarily due to the experiences of some respondents who are migrants because of the ongoing war, leading them to claim that they are unaware of any factors driving protected forest degradation or deforestation. Some respondents, whether migrants or indigenous, mentioned that they were unaware of protected forest degradation and deforestation drivers because they do not have any connection to it. The descriptive analysis of proportions was conducted using an Excel spreadsheet. The software RStudio, version 4.4.1, has been used for multivariate analysis, including Correspondence Factor Analysis. Before conducting the Correspondence Factor Analysis, a chi-square test was carried out to evaluate the significance of the relationship between communities and classified forest degradation and deforestation drivers.

## 4.2 Results

### 4.2.1 Household Heads Profile

The details regarding the profiles of household heads are highlighted in Table 9. The majority of interviewed heads of households were men, accounting for 84.58%. The average age of the household head is 46.89 ± 14.77, ranging from 20 to 90 years old. Most heads of households are natives, representing 75.11%. Household heads represent 20 ethnic groups, with the Bobo being the most prevalent at 59.03%, while the Karaboro, Gouin, and Gourounsi are the least represented at 0.22%. Concerning their education level, 40.31% of surveyed household heads reported not having received any education, while 1.54% indicated they had attained a university level education. Household heads engage in various professional occupations to enhance their income. Considering the primary professional occupation, most household heads surveyed are farmers, accounting for 76.21% of the sample, while students are the least represented occupation at 0.44%.

Table 9: Profiles of interviewed household heads

| Variables | Modalities | Number | Proportion (%) |
|---|---|---|---|
| **Community** | Banakeledaga | 87 | 19.16 |
| | Dinderesso | 30 | 6.61 |
| | Nasso | 69 | 15.20 |
| | Ouolonkoto | 92 | 20.26 |
| | Gnafongo | 57 | 12.56 |
| | Peni | 84 | 18.50 |
| | Sokouranie | 26 | 5.73 |
| | Taga | 9 | 1.98 |
| **Age** | [20-29] | 65 | 14.32 |
| | [30-39] | 94 | 20.70 |
| | [40-49] | 91 | 20.04 |
| | [50-59] | 88 | 19.38 |
| | [60-69] | 88 | 19.38 |
| | [70-79] | 21 | 4.63 |
| | [80-90] | 7 | 1.54 |
| **Sex** | Female | 70 | 15.42 |
| | Male | 384 | 84.58 |
| **Marital status** | Married | 397 | 87.44 |
| | Single | 29 | 6.39 |
| | Widow/Widowed | 28 | 6.17 |
| **Education** | Literacy | 25 | 5.51 |
| | Nothing | 183 | 40.31 |
| | Primary | 120 | 26.43 |
| | Religious education | 58 | 12.78 |

| | | | |
|---|---|---|---|
| | Secondary | 61 | 13.44 |
| | University | 7 | 1.54 |
| **Religion** | Animist | 105 | 23.13 |
| | Catholic | 76 | 16.74 |
| | Muslim | 257 | 56.61 |
| | Protestant | 16 | 3.52 |
| **Residence status** | Indigenous | 341 | 75.11 |
| | Migrant | 113 | 24.89 |
| **Professional occupation** | Artisan | 37 | 8.15 |
| | Breeder | 9 | 1.98 |
| | Employee | 15 | 3.30 |
| | Farmer | 346 | 76.21 |
| | Householdkeeper | 6 | 1.32 |
| | Retired | 5 | 1.10 |
| | Student | 2 | 0.44 |
| | Trader | 34 | 7.49 |
| **Ethnic group** | Bissa | 2 | 0.44 |
| | Bobo | 268 | 59.03 |
| | Bwaba | 6 | 1.32 |
| | Dafing | 6 | 1.32 |
| | Dagara | 2 | 0.44 |
| | Dioula | 6 | 1.32 |
| | Gouin | 1 | 0.22 |
| | Gourounsi | 1 | 0.22 |
| | Karaboro | 1 | 0.22 |
| | Lobi | 2 | 0.44 |
| | Mossi | 29 | 6.39 |
| | Peulh | 20 | 4.41 |
| | Sambla | 8 | 1.76 |
| | Samo | 5 | 1.10 |
| | Senoufo | 3 | 0.66 |
| | Siamou | 2 | 0.44 |
| | Tiefo | 63 | 13.88 |
| | Toussian | 24 | 5.29 |
| | Turka | 3 | 0.66 |
| | Wankan | 2 | 0.44 |

### 4.2.2 Dinderesso and Peni Classified Forests Neighboring Communities' Perception of Degradation and Deforestation Drivers

Neighboring Dinderesso classified forest communities identified sixteen drivers of forest degradation and deforestation. The proportion of drivers for forest degradation and deforestation related to the Dinderesso and Peni classified forests is shown (Figure 32). The primary drivers of forest degradation and deforestation are associated with human activities. The drivers discussed are related to wood cutting abuse (WC), which accounts for 34.48%; demographic pressure (DP) at 18.68%; poverty (PV), accounting for 11.49%; bad management (BM) at 8.05%; bushfires (BF) at 6.61%; overexploitation (OE) at 6.32%; overgrazing (OG) at 3.74%; agriculture (AG) at 2.87%; rainfall scarcity (RF) at 2.30%; natural death (ND) at 1.44%; silting (ST) at 1.15%; wind (WD) at 0.86%; 0.57% each for poaching (BC), drought (DR), and soil fertility (FS); and 0.29% for pollution (PL).

The results of Peni classified forest degradation and deforestation drivers, as perceived by neighboring communities, are globally similar to those identified in the classified forest of Dinderesso. Peni classified forest neighboring communities mentioned at least fifteen forest degradation deforestation drivers. Similar to the Dinderesso classified forest, most drivers are related to human activities. The drivers of forest degradation and deforestation include wood cutting abuse (WC) at 33.49%; demographic pressure (DP) at 11.93%; agriculture (AG) at 9.17%; bad management (BM) and elephants (EP) each at 8.72%; charcoal production (CC) at 7.34%; poverty (PV) at 6.88%; rainfall scarcity (RF) and bushfires (BF) each at 3.67%; overexploitation (OE) at 1.83%; natural death (ND) at 1.38%; overgrazing (OG), drought (DR), and diseases (DS) each at 0.92%; and soil fertility (FS) at 0.46%.

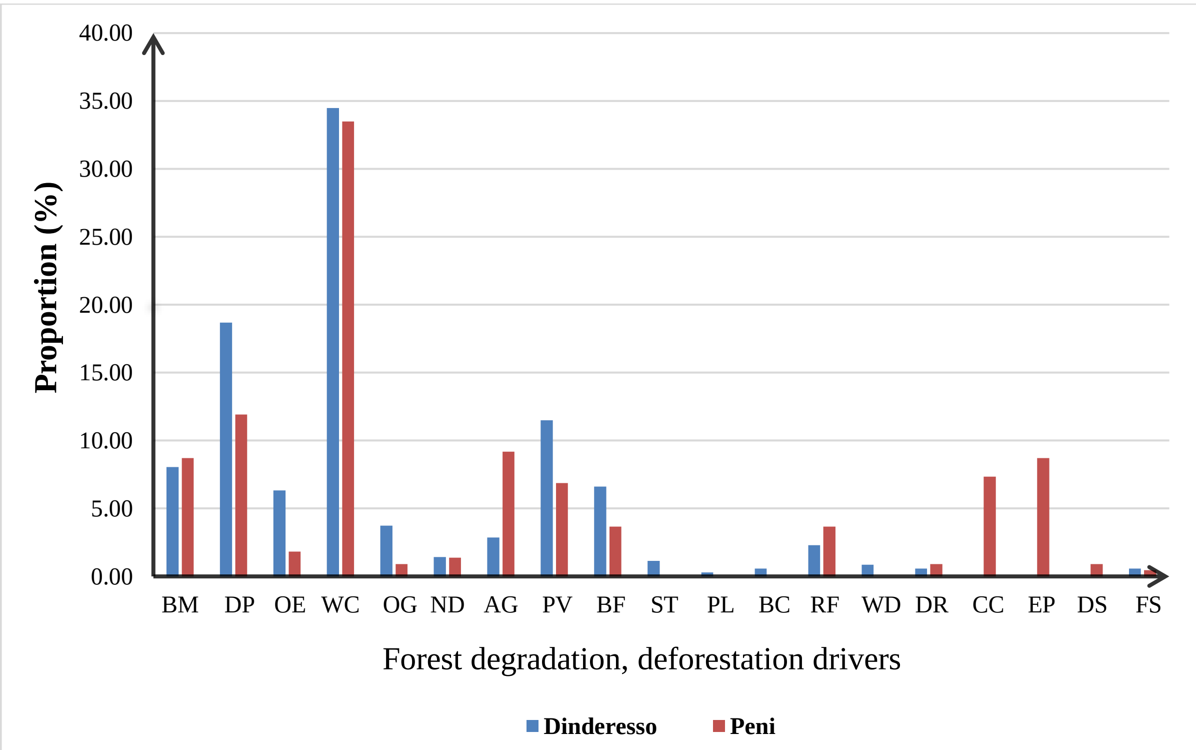


Figure 31: Dinderesso and Peni classified forest degradation and deforestation drivers

***Note**: BM (Bad Management), DP (Demographic Pressure), OE (Overexploitation), WC (Wood Cutting abuse), ND (Natural Death), AG (Agriculture), PV (Poverty), BF (Bushfire), ST (Silting), PL (Pollution), BC (Poaching), RF (Rainfall scarcity), WD (Wind), DR (Drought), CC (Charcoal production), EP (Elephant), DS (Diseases), FS (Soil Fertility).*

### 4.2.3 Relation between protected forest neighboring communities and forest degradation, deforestation drivers

The chi-square result obtained prior to the corresponding factorial analysis revealed a p-value of 1.810766e-31 $\leq$ 0.05, confirming the relationships among communities and the classified forest degradation and deforestation drivers. The eigenvalue assessment revealed that component 1 accounts for 37.132% of information variability, while component 2 accounts for 23.58% of variability. The total information provided by components 1 and 2 equals 60.71%, which is greater than 50% and significant for describing the relationships between neighboring communities and the drivers of classified forest degradation and deforestation. The chi-square test of independence P-value and the components' dimension eigenvalues are shown in Appendix 9.

The corresponding factorial analysis results (Appendix 10) revealed that the Gnafongo community made a significant contribution to component 1 and is highly positively correlated with it, exhibiting a correlation coefficient of 0.996. Examining component 2, the results indicated that the Peni, Banakeledaga, and Nasso communities made significant contributions to this component building. However, the Peni community is strongly negatively correlated with component 2, shown by a correlation coefficient of -0.766. In contrast, the Banakeledaga and Nasso communities show a positive but weak correlation to component 2, with corresponding coefficient correlations of 0.355 and 0.367.

The results of the factorial analysis (Appendix 11) indicated that the drivers of classified forest degradation and deforestation, such as elephant activities and drought, significantly contributed to the formation of component 1. These drivers showed a strong positive correlation with this component, with correlation coefficients ranging from 0.988 to 0.818 (Appendix 12). The results of the factorial analysis also highlighted that agriculture, charcoal production, tree diseases, bushfires, and demographic pressure strongly contributed to building component 2. Agriculture shows a weak negative correlation to component 2, with a correlation coefficient of 0.485 (Appendix 12). Charcoal production and tree diseases are strongly and negatively correlated with component 2, with respective correlation coefficients ranging from 0.753 to 0.610 (Appendix 12). On the other side of component 2, bushfires have a weak positive correlation with component 2, reflected by a correlation coefficient of 0.235 (Appendix 12). At the same time, demographic pressure has a strong positive correlation with component 2, indicated by a correlation coefficient of 0.640 (Appendix 12).

Examining the communities affected by classified forest degradation and deforestation drivers, the results (Figure 33) of the corresponding factorial analysis revealed that the neighboring communities of Dinderesso and Peni classified forests have differing perceptions regarding these issues. Indeed, the Gnafongo community explains Peni classified forest degradation, deforestation by elephants (EP), and drought (DR). The Peni community accuses agriculture (AG), charcoal production (CC), and tree diseases (DS) of being the primary causes of degradation and deforestation in the Peni classified forest. Regarding Dinderesso's classified forest degradation and deforestation, the communities of Banakeledaga and Nasso identified bushfires (BF) and demographic pressure (DP) as the primary causes.

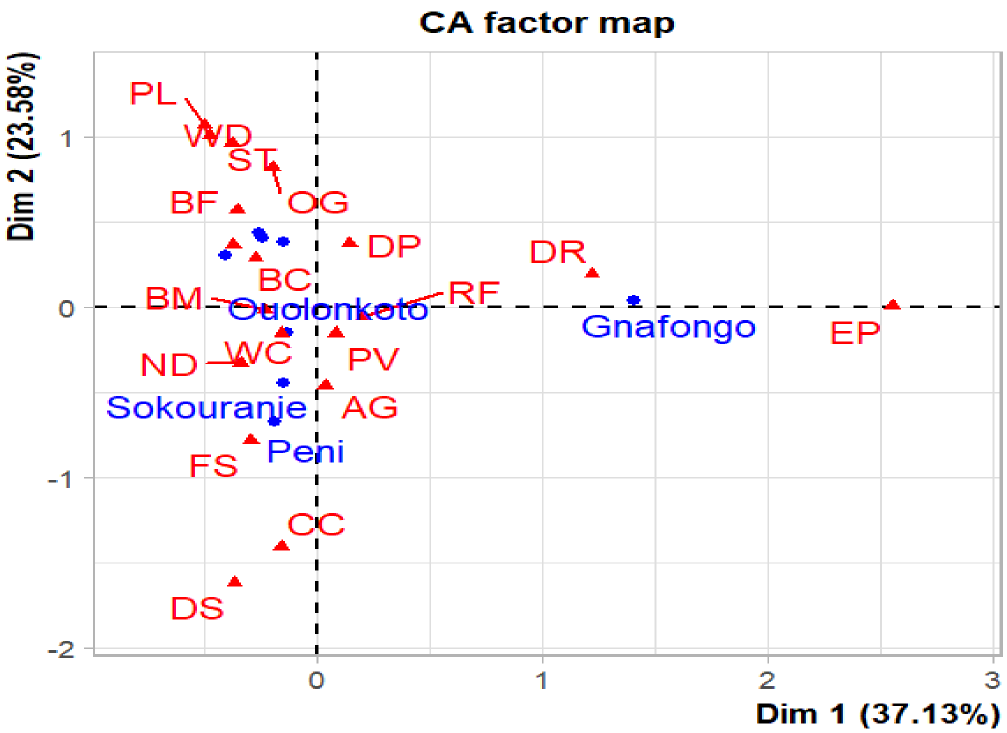


Figure 32: Neighboring Dinderesso and Peni classified forest communities perceptions of forest degradation and deforestation drivers

***Note****: Bad management (BM); Demographic pressure (DP); Overexploitation (OE); Wood abusive cutting (WC); Overgrazing (OG); Natural death (ND); Agriculture (AG); Poverty (PV); Bushfires (BF); Silting (ST); Pollution (PL); Poaching (BC); Rainfall scarcity (RF); Wind (WD); Drought (DR); Charcoal production (CC); Elephant (EP); Diseases (DS); Soil fertility (FS).*

## 4.3 Discussion

### 4.3.1 Anthropogenic Drivers of Land Use Land Cover Degradation

The findings highlighted that the drivers of forest degradation and deforestation in Dinderesso and Peni are mainly related to human activities. These findings align with numerous research studies (Thiombiano & Kampmann, 2010; Djiguemde et *al*., 2023). The anthropogenic drivers of deforestation in both Dinderesso and Peni classified forests include wood cutting abuse, demographic pressure, poor management, charcoal production, agriculture, poverty, overgrazing, overexploitation, bushfires, and poaching. The interviewed household heads indicated that they cut trees for various purposes, including energy needs, house construction, mortar production, and charcoal production. Fuelwood is the primary source of energy in Burkina Faso (Kabore et *al*., 2009). According to Mundler et *al*., (2010), over 97% of household energy needs in Burkina Faso are met by woody forest resources. The proximity of both the Dinderesso and Peni classified forests to Bobo-Dioulasso, the second largest urban area in the country, increases pressure on forest resources due to the population density. The research by Tankoano et *al*., (2016) highlighted that the proximity of the Tiogo classified forest to Ouagadougou and Koudougou increases fuelwood exploitation, which negatively affects forest resources. The demographic pressure also adversely impacts neighboring communities' access to agricultural land. The current study revealed that 76.21% of surveyed household heads engage in farming as their primary occupation. Due to the shortage of agricultural land, some individuals, with little regard for classified forest regulations, set up their farms within the forest. Phiri et *al*., (2023) highlighted similar results in Zambia and Burkina Faso (Sama et *al*., 2023; Belem et *al*., 2019). Since Dinderesso and Peni classified forests are unfenced, they have become an open source of fodder and water for livestock during both the dry and rainy seasons. This unchecked and unlawful practice by breeders contributes to the degradation of both forest resources. Many authors reported the negative impacts of livestock on forest resources (Crovo et *al*., 2021; Papoutsa et *al*., 2016). The management systems of both forests have been deemed inadequate, as noted by neighboring communities who claim they are not considered in forest management and that foresters lack the necessary resources to effectively monitor and control the entire forest. Classified forest management in Burkina Faso restricts community access to forest resources, creating conflicts between neighboring communities and forest managers. To ensure the sustainable management of protected areas and support local livelihoods, numerous authors have proposed enhancing the management system in Burkina Faso (Sama et *al*., 2023; MEEVCC, 2020). According to the surveyed household heads, poverty drives people to overexploit non-timber forest products for income. Previous studies have emphasised the overuse of non-timber forest products (Savadogo et *al*., 2019; Ministery of Environment, 2019). In addition to the surveyed anthropogenic drivers of forest degradation and deforestation, Dinderesso and Peni classified forest land cover change as also being related to rainfall scarcity, drought, and wind. This information aligns with other studies conducted in the Sudanian region, emphasizing the negative impact of climate change variability on forest land cover (Savadogo, 2021; Tankoano et *al*., 2016). Forest degradation and deforestation increase greenhouse gas emissions in the atmosphere, leading to consequences such as rainfall variability, drought, heat waves, and rising temperatures. Some studies highlighted that climate change may adversely affect the natural distribution area of many tree species and forest land cover in Burkina Faso (Millogo et *al*., 2019; Gaisberger et *al*., 2017). The findings regarding Dinderesso and Peni classified forests were consistent with previous studies, highlighting that human activities were primarily responsible for forest LULC change in the study area. These findings reflect the current condition of the country's protected forests, characterised by degradation and deforestation driven by human activities. Given this situation, enhancing the relationship between protected areas and humans is essential for the dual benefit of biodiversity conservation and improving livelihoods.

### 4. 3. 2 Relation between neighboring communities and forest degradation and deforestation drivers

The factorial analysis revealed variability in perception among the same neighboring community and two neighboring communities. These findings align with studies that concluded that the variability observed among neighboring communities may be linked to their relationships with forest resources (Ratsimbazafy, 2012). According to Faye et *al*., (2022), the variability observed among communities regarding forest degradation and the perceived drivers of deforestation could be influenced by the primary economic activity within each community. Given the illegal nature of this primary economic activity, communities are likely to reference other factors rather than the one associated with their main economic activity. Indeed, while neighboring communities do not perceive charcoal production in the Dinderesso classified forest, some field visits have allowed for the identification of charcoal production sites both within the forest and in some neighboring communities, including the Ouolonkoto community.

# CONCLUSION

The survey conducted on neighboring Dinderesso and Peni, which classified forest communities' perceptions of forest degradation and deforestation drivers, revealed interesting findings. The study results emphasised several factors contributing to forest degradation and deforestation, including human activities and climate. Among human activities and climate drivers, elephant disturbances related to the Peni classified forest have been identified as factors contributing to forest degradation and deforestation. This study demonstrated that human activities continue to be the primary cause of forest degradation and deforestation in Dinderesso and Peni. Additionally, the study results highlighted variability in the perceived drivers of forest degradation and deforestation among neighboring communities, stemming from their dependence on forest resources, location, and the influence of the main economic activity within each community. These original findings offer relevant insights that will enhance the sustainable management of Dinderesso and Peni classified forests by promoting biodiversity conservation and preserving the livelihoods of neighboring communities. These results offer reliable insights into forest degradation and deforestation, assisting managers in developing effective forest management plans, projects, and programs. Considering the unlawful nature of forest degradation, the human-related causes of deforestation in both protected forests underscore the urgent need for effective management strategies for these areas.

# CHAPTER 5: VULNERABILITY TO CLIMATE VARIABILITY AND ANTHROPOGENIC ACTIONS IN BURKINA FASO: A CASE STUDY OF THE NEIGHBORING COMMUNITIES OF DINDERESSO AND PENI CLASSIFIED FOREST


## Abstract

Protected areas' vulnerability assessments of neighboring communities do not adequately consider the relationship between climate, protected areas, and human activities, which makes managing biodiversity sustainably and preserving the livelihoods of neighboring communities challenging. This study aims to assess the vulnerability of eight neighboring communities of the Dinderesso and Peni classified forest to climate change and human activities through a simplified and consistent framework. Eight focus groups were conducted using a semi-structured questionnaire directed at resource persons from eight neighboring communities. They evaluated their vulnerability using a participatory research method. The categorical qualitative data collected were normalised and analysed using an arithmetic method in an Excel spreadsheet before being mapped with the software QGIS 3.18. The statistical analysis highlighted that there is no significant difference among the Dinderesso-classified forest neighboring communities (p-value $\geq 0.05$) regarding their exposure, sensitivity, and adaptive capacity. Regarding the Peni classified forest, the statistical analysis highlighted a significant difference among neighboring communities in terms of exposure (p-value = 0.01493), with the Peni community's exposure differing from that of Sokouranie and Taga (p-value = 0.04398433). Beyond the statistical analyses, the study results revealed variability in the vulnerability of Dinderesso and Peni classified forest neighboring communities to climate and human activities, which ranges from low to moderate. This variability is due to factors such as climate, socioeconomic conditions, geographical location, topography, altitude, and the management policies of the protected areas. These findings emphasise the importance of recognising the vulnerability of neighboring communities to climate change and human activities in the management plans and investments for protected areas by policymakers, forest managers, and stakeholders. This is vital for promoting biodiversity conservation and ensuring the well-being of local communities.



**Keywords:** Burkina Faso, Dinderesso and Peni, Neighboring communities, Protected areas, Vulnerability

# INTRODUCTION

The effects of forest degradation and deforestation are numerous and severe, affecting various areas. These result from the impacts of biodiversity loss and climate change, potentially leading to the desertification of specific areas, each presenting a significant threat to the sustainability of our livelihoods (Mugadza, 2022). The index, which specialised in assessing forest biodiversity, revealed a global biodiversity loss of 1.7 percent per year attributed to deforestation and forest degradation (FAO, 2020a). Deforestation and forest degradation contribute to climate change in many countries worldwide, which experience climate change-induced warming and extreme events such as droughts and flooding (Li et *al*., 2022). Climate change warming is also recognised as a result of biophysical process effects on forest structure changes (Lawrence et *al*., 2022).

Many studies indicate that human activities are the primary drivers of deforestation and forest degradation, contributing to sustainable forest management (FAO, 2020a; Sanou, 2023; Tankoano et *al*., 2015; Thiombiano & Kampmann, 2010). Examining the local perception of vegetation dynamics drivers, Faye et *al*., (2022) highlighted that charcoal production, bushfires, and excessive cattle grazing were the primary factors contributing to deforestation and forest degradation in Missirah, Senegal. According to Savadogo et *al*., (2019), poor practices in the exploitation of medicinal tree species contribute to the absence of adult trees. All these impacts are connected to deforestation and forest degradation, which affect human livelihoods (Asamoah et *al*., 2024; FAO, 2020; Li, 2023). According to Banerjee & Madhurima (2013), Forest degradation will impact communities that rely on the forest for food, livestock fodder, house construction, and fencing. In Burkina Faso, the forest situation is marked by deforestation and forest degradation.

In just 22 years, from 1992 to 2014, the forest area lost in the country was estimated to be nearly half of all the country's forest areas (SE/CCNUCC, 2020a). The country loses 247,145 hectares of forest area annually (MEEEA, 2022). In Analysing the dynamics of protected areas, many authors have emphasised the issues related to deforestation and forest degradation (Dimobe et *al*., 2015; Savadogo, 2021; Tankoano et *al*., 2016; Tankoano et *al*., 2015). The research on the Toessin forest dynamics revealed that human activities such as traditional agricultural practices and illegal wood exploitation are the key drivers of deforestation and forest degradation (Belem et *al*., 2019). According to Tindano et *al*., (2024) research findings indicate that gold mining has contributed to the scarcity of plant species in the Kari classified forest in western Burkina Faso due to tree cutting and soil excavation. The loss of forest areas has led to several studies in the past (Bilouktime et *al*., 2021; Ouattara et *al*., 2021; Yaovi et *al*., 2021) that offered comprehensive and significant information on the depletion of forest resources.

Deforestation and forest degradation result primarily from the interaction between forests and human activities (MEEEA, 2022; Savadogo, 2021), paradoxically, this impacts neighboring communities that have a strong relationship with forests. Many authors agree that deforestation and forest degradation negatively affect the livelihoods of populations (Simonsson, 2005; Belem et *al*., 2019; FAO, 2020a). Examining the contribution of medicinal plants to communities near the forest, Banerjee & Madhurima (2013) stated that deforestation and forest degradation could lead to health issues in the population.

In Burkina Faso, vulnerability studies concerning forests have centered on forest species. (Ouédraogo et *al*., 2017; Diawara et *al*., 2022; Yaovi et *al*., 2021). Some studies examined the adaptation capacities and resilience of neighboring communities to deforestation and forest degradation (Kabore, 2009; Yaovi et *al*., 2021). Few pieces of knowledge have focused on the vulnerability of protected forest neighboring communities to climate and human activities. The current study aims to enhance the understanding of the relationships among climate, forests, and humans to improve disaster risk management. More specifically, this study aims to assess the vulnerability of the classified forest neighboring communities of Dinderesso and Peni and to identify factors that explain this vulnerability.

## 5.1 Methods

### 5.1.1 Vulnerability assessment framework

The current study on community vulnerability assessment has been developed using a conceptual framework adapted from the vulnerability assessment framework created by GIZ (2017). The vulnerability is evaluated within this conceptual framework by utilising components of exposure, sensitivity, and adaptive capacity (Figure 34). The exposition component refers to the exposure of forest provisioning ecosystem services to climate variability factors, including drought, rainfall, and temperature. The sensitivity in this study is primarily observed in the interactions between communities and forest provisioning ecosystem services, along with natural environmental effects. The potential impact includes both direct and indirect effects on forest provisioning ecosystem services due to degradation and loss. The capacity for adaptation encompasses all the resources available within communities to address or lessen potential impacts.

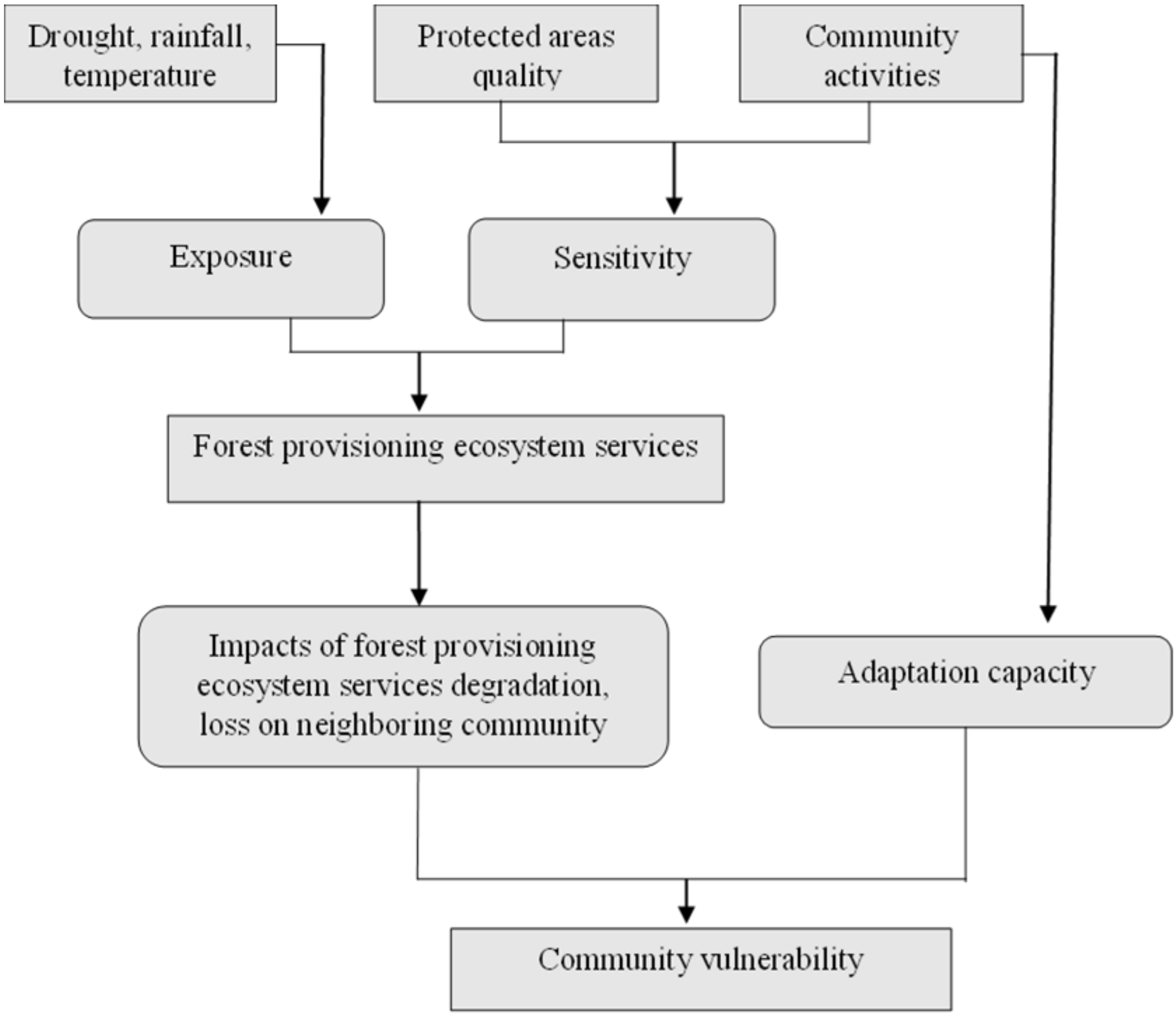


Figure 33: Vulnerability assessment framework of protected areas neighboring communities (Source: adapted from GIZ, 2017)

### 5.1.2 Simplified vulnerability assessment chain impacts

The impact chain in vulnerability assessment is crucial for identifying vulnerability variables. The literature review indicates that evidence shows forest degradation and deforestation are mainly linked to human activities (Dimobe et *al*., 2015; MEEEA, 2022; Tankoano et *al*., 2016; Thiombiano & Kampmann, 2010) and that forest provisioning ecosystem services play a crucial role in the interactions between humans and forests (Ali et *al*., 2023; Ministery of Environment, 2019; Ouattara et *al*., 2021; Savadogo, 2021). Considering these factors, the chain impact has been structured to identify the direct and indirect effects of climate variability and human activities on forest provisioning ecosystem services and the community. The simplified impact chain used to assess communities' vulnerability is shown in Figure 35.

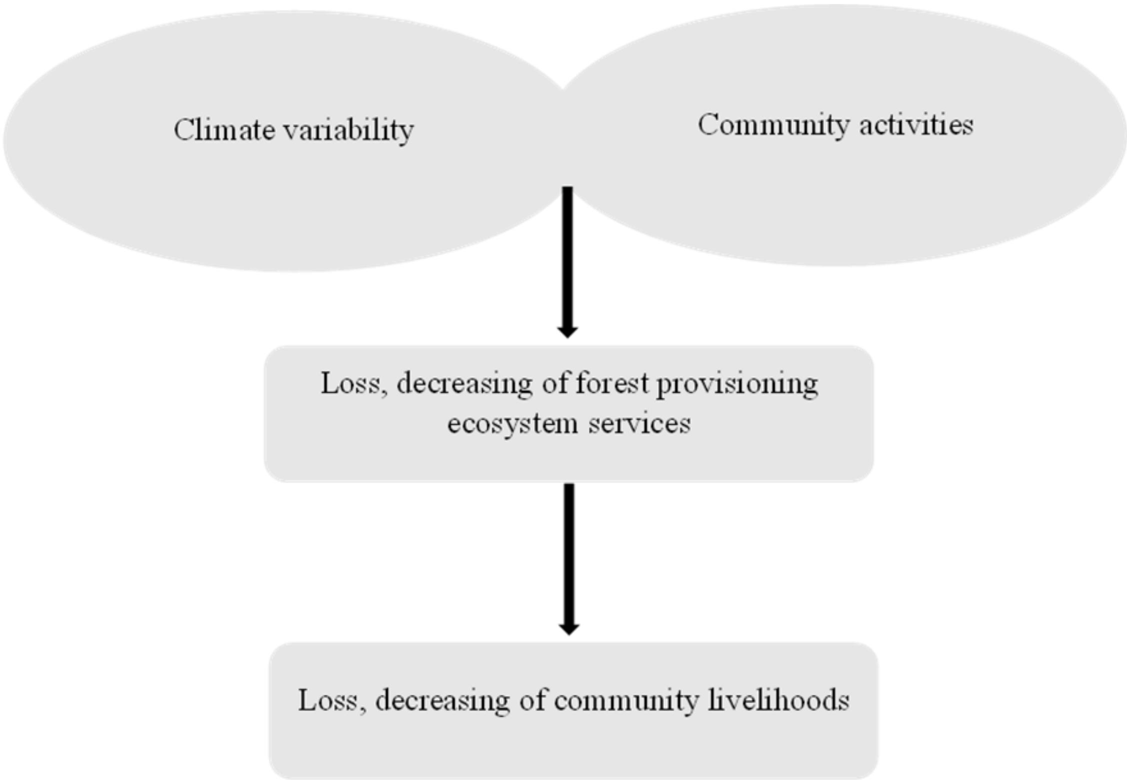


Figure 34: Simplified impacts of protected areas neighboring social vulnerability assessment (Source: adapted from GIZ, 2017)

### 5.1.3 Components and variables of communities' vulnerability assessment

Considering the vulnerability impact chain, along with the literature review and discussions with resource persons engaged in Dinderesso and Peni classified forest management, 36 qualitative categorical variables have been identified to assess the components of exposure, sensitivity, and adaptation capacity. Details of the components and variables used for the communities' vulnerability assessment are shown (Table 10).

Table 10: Components variables contribution to vulnerability (Source: adapted from GIZ, 2017)

| **Component** | **Factor** | **Variable** | **Variable contribution to vulnerability** |
|---|---|---|---|
| Exposure | Drought | The frequency of drought events in the village last ten years | The high frequency of drought events increases vulnerability |
| | | Drought duration events last ten years | High drought duration events increase vulnerability |
| | | Drought severity events last ten years | High drought severity events increase vulnerability |
| | | Drought spatial coverage | High drought spatial coverage increases vulnerability |
| | Rainfall | Rainfall evolution last ten years | Decreasing rainfall evolution increases the vulnerability |
| | | Rainfall spatial coverage last ten years | Less rainfall spatial coverage increases vulnerability |

| | | | |
|---|---|---|---|
| | Temperature | Temperature evolution last ten years | Increasing temperature evolution increases vulnerability |
| Sensitivity | Protected area quality | Forest degradation level | High forest degradation levels increase vulnerability |
| | Community activities | Population density level | High population density increases vulnerability |
| | | Level of forest exploitation for population food needs | High forest exploitation for population food needs increases vulnerability |
| | | Level of forest exploitation for firewood | High forest exploitation for firewood increases vulnerability |
| | | Level of forest exploitation for medicinal needs | High forest exploitation for medicinal needs increases the vulnerability |
| | | Level of forest exploitation for incomes | High forest exploitation for income increases the vulnerability |
| | | Level of forest exploitation for breeding | High forest exploitation for breeding increases the vulnerability |
| | | The growth rate of agricultural land | The high growth rate of agricultural land increases vulnerability |
| | | Frequency of bushfires over the last ten years | The high frequency of bushfires increases the vulnerability |
| | | Bushfires spatial coverage | High bushfire spatial coverage increases vulnerability |
| | | The practical intensity of real estate activity | The high practical intensity of real estate activity increases vulnerability |
| | | Intensity of gold mining | High intensity of panning for gold increases vulnerability |
| | | Spatial coverage of gold panning | High spatial coverage of gold panning increases vulnerability |
| Adaptation capacity | Knowledge | Level of population education/literacy | Low levels of population education/literacy increase vulnerability |
| | | Level of population awareness of forest degradation | A low level of population awareness of forest degradation increases the vulnerability |
| | | Level of population awareness of climate change | A low level of population awareness of climate change increases vulnerability |
| | | Level of population awareness of drought impact management | A low level of population awareness of drought impact management increases vulnerability |

| | | | |
|---|---|---|---|
| | | Level of population awareness of forest management | A low level of population awareness of forest management increases vulnerability |
| | | Level of population participation in forest management | Low levels of population participation in forest management increase the vulnerability |
| | Technology | Level of population access to weather forecasts | A low level of population access to weather forecasts increases the vulnerability |
| | | Level of population access to energy sources other than firewood | Low-level access of the population to energy sources other than firewood increases vulnerability |
| | Institutions | Level of awareness of the existence of customary forest management regulations among the population | Low level of awareness of the existence of customary forest management regulations among the population increased vulnerability |
| | | Level of awareness among the population of the existence of public forest management regulations | Low level of awareness among the population of the existence of public forest management regulations increase vulnerability |
| | | Level of respect for customary forest management regulations by the local population | Low level of respect for customary forest management regulations by the local population increased vulnerability |
| | | Level of respect for public forest management regulations by the local population | Low level of respect for public forest management regulations by the local population increased vulnerability |
| | | Level of efficiency of private forest management organisations | The low-level efficiency of private forest management organisations increases vulnerability |
| | | Level of efficiency of public forest management organisation | The low level of efficiency of public forest management organisations increases vulnerability |
| | Economy | Level of population access to health services | Low levels of population access to health services increase vulnerability |
| | | Level of household income in the village | Low levels of household income in the village increase the vulnerability |

### 5.1.4 Resource person identification

The choice of participants is a key point in vulnerability assessment. To ensure a consistent choice among these participants, ten consulting meetings have been held with the public of each studied community, customary administration authorities, and those in charge of managing the classified forests of Dinderesso and Peni (Photo 2, 3, 4). These meetings facilitated the identification of resource persons from each community as participants in the vulnerability assessment. These resource persons engage various socio-professional groups within each community, including traditional medicine practitioners, farmers, livestock keepers, fishermen, artisans, local public and customary authorities, and the Ministries of Forest, Agriculture, and Livestock in Houet province.

The number of resource persons varies from 13 to 20 for Nasso and Ouolonkoto, respectively. The majority of resource persons were male, with percentages ranging from 76.92% to 94.12% for Nasso and Dinderesso, respectively. The percentage of females varies from 5.88% in Dinderesso to 23.08% in Nasso. The minimum percentage of resource persons aged between 18 and 35 is 7.69% for Peni, while the maximum is 38.46% for Nasso. The minimum percentage of resource persons aged 36 years and older is 61.54% for Nasso, while the maximum is 92.31% for Peni. Table 11 presents the details of the resource persons.

Photo 2: Meeting with the Technical Director of Dinderesso forest Management

Photo 3: Meeting with Peni municipality authority

Photo 4: Meeting with Houet Province Director of Environment in charge of Dinderesso and Peni classified forest

Table 11: Characteristics of resource persons participating in communities' vulnerability assessment (Source: Millogo, 2024)

| Neighboring community | Classified forest | Resource persons | Sex (%) | | Age range (%) | |
|---|---|---|---|---|---|---|
| | | | Male | Female | [18-35] | [36 and + [ |
| **Dinderesso** | Dinderesso | 17 | 94.12 | 5.88 | 23.53 | 76.47 |
| **Nasso** | | 13 | 76.92 | 23.08 | 38.46 | 61.54 |
| **Ouolonkoto** | | 20 | 90 | 10 | 10 | 90 |
| **Banakeledaga** | | 16 | 93.75 | 6.25 | 12.5 | 87.5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Taga** | Peni | 15 | 93.33 | 6.67 | 13.33 | 86.67 |
| **Peni** | | 13 | 92.31 | 7.69 | 7.69 | 92.31 |
| **Gnafongo** | | 15 | 93.33 | 6.67 | 13.33 | 86.67 |
| **Sokouranie** | | 14 | 92.86 | 7.14 | 28.57 | 71.43 |
| **Min** | | **13** | **76.92** | **5.88** | **7.69** | **61.54** |
| **Max** | | **20** | **94.12** | **23.08** | **38.46** | **92.31** |

### 5.1.5 Variables validation and assessment

Every resource person from neighboring communities engaged in a separate focus group to validate and evaluate vulnerability variables. Eight focus group sessions (Photos 5 and 6) were conducted for the eight neighboring communities involved in the study. Each validation and assessment session lasted between 4 and 5 hours. The Active Participatory Research Method (APRM) was utilised in the validation and assessment process of vulnerability variables. The APRM is a flexible and interactive method that allows each community resource person to validate and assess vulnerability variables in their village through discussions among themselves, resulting in a unique consensus answer. Following the validation of the variable, each community resource person assessed the vulnerability component variables on a scale from 1 to 5, where 1 indicates a favorable situation (very low risk of vulnerability) and 5 indicates a situation needing improvement (very high risk of vulnerability). A semi-structured questionnaire regarding exposure, sensitivity, and adaptive capacity was utilised to evaluate each component of vulnerability.

Photo 5: Vulnerability assessment session with Ouolonkoto community (Zerbo G. C)

Photo 6: Vulnerability assessment session with Gnafongo community (Zerbo G.C)

### 5.1.6 Neighboring communities' exposure, sensitivity and adaptation capacities statistical analysis assessment

Given the nature of the data (qualitative ordinal) collected to evaluate the exposure, sensitivity, and adaptation capacities of neighboring communities, the Kruskal-Wallis test was used to assess the significance of variability in these vulnerability components among the neighboring communities of both studied forests. The Dunn's test with Bonferroni correction has been applied as a post-hoc test in the event of a significant difference observed.

### 5.1.7 Variables normalisation

All categorical variables assessed by each village participant have been normalised to convert them into a new score scale ranging from 0 to 1. This process aims to enhance the understanding of variable values concerning vulnerability for mapping purposes. Using Table 12, the scores of the categorical variables have been converted into metric values ranging from 0 to 1 to achieve this normalisation.

Table 12: Categorical variables normalisation table scores (Source : GIZ, 2017)

| Categorical variable class | Normalisation range score from 0 to 1 | Normalised score from 0 to 1 | Description |
|---|---|---|---|
| **1** | 0-0.2 | 0.1 | No situation improvement needs |
| **2** | > 0.2-0.4 | 0.3 | Positive situation |
| **3** | > 0.4-0.6 | 0.5 | Neutral situation |
| **4** | > 0.6-0.8 | 0.7 | Negative situation to improve |
| **5** | > 0.8-1 | 0.9 | Criticise situation to be improved |

### 5.1.8 Components variables indicators weighting

Given the large number of variables (36) in the vulnerability assessment of neighboring communities, the current assessment assigns equal weight to all variable indicators. All variables are considered to have equal weight.

### 5.1.9 Component indicators and vulnerability assessment

The vulnerability component indicators were calculated using the arithmetic method (GIZ, 2017). The arithmetic method is easy to understand, reducing bias when merging vulnerability component variables for calculating composite indicators. The following equations were used to calculate the vulnerability of neighboring communities in the Excel spreadsheet:

$$EI = \frac{(I_1+I_2+I_3+\cdots I_n)}{n}$$ Equation (15)

$$SI = \frac{(I_1+I_2+I_3+\cdots I_n)}{n}$$ Equation (16)

$$PII = \frac{(EI+SI)}{2}$$ Equation (17)

$$ACI = \frac{(I_1+I_2+I_3+\cdots I_n)}{n}$$ Equation (18)

$$CVI = \frac{(PII+ACI)}{2}$$ Equation (19)

Note: EI= corresponding to Exposure indicator component, SI = Sensitivity indicator component, PII= Potential impact indicator, ACI = Adaptation capacity indicator component, n = number of component variable indicator, and CVI = Community vulnerability indicator; I1, I2, I3, In the component individual variable indicator.

After assessing vulnerability indicators on a scale from 1 to 5, we assigned class values and colours to illustrate exposure, sensitivity, adaptation capacity, and community vulnerability levels using QGIS software version 3.18 for mapping outputs.

## 5.2 Results

### 5.2.1 Communities' vulnerability components indicators

The vulnerability component indicators of both Dinderesso and Peni classified forest neighboring communities' exposure, sensitivity, adaptation capacity, and vulnerability (Table 13) indicated the existence of different variabilities. The exposure indicator values ranged from 0.4 for the neighboring communities of Banakeledaga, Nasso, Ouolonkoto, and Sokouranie to 0.7 for the neighboring communities of Taga and Peni. The sensitivity variables indicator values ranged from 0.5 for the neighboring communities of Gnafongo and Sokouranie to 0.7 for the neighboring communities of Nasso, Ouolonkoto, and Peni. The adaptation capacity indicator values ranged from 0.3 for the Nasso community to 0.5 for the neighboring communities of Ouolonkoto, Gnafongo, and Peni. Vulnerability indicator values varied from 0.4 for the Banakeledaga, Nasso, and Sokouranie neighboring communities to 0.6 for the Peni community.

Table 13: Exposure, Sensitivity, Adaptation capacity and vulnerability indicators (Source: Millogo, 2024)

| Community | Classified forest | EI | SI | ACI | CVI |
|---|---|---|---|---|---|
| **Banakeledaga** | Dinderesso | 0.4 | 0.6 | 0.4 | 0.4 |
| **Dinderesso** | | 0.5 | 0.6 | 0.4 | 0.5 |
| **Nasso** | | 0.4 | 0.7 | 0.3 | 0.4 |
| **Ouolonkoto** | | 0.4 | 0.7 | 0.5 | 0.5 |
| **Mean** | | **0.43** | **0.65** | **0.4** | **0.45** |
| **Standard deviation** | | **0.05** | **0.06** | **0.08** | **0.06** |
| **Ganfongo** | Peni | 0.6 | 0.5 | 0.5 | 0.5 |
| **Peni** | | 0.7 | 0.7 | 0.5 | 0.6 |
| **Sokouranie** | | 0.4 | 0.5 | 0.4 | 0.4 |
| **Taga** | | 0.4 | 0.6 | 0.4 | 0.5 |
| **Mean** | | **0.53** | **0.58** | **0.45** | **0.5** |
| **Standard deviation** | | **0.15** | **0.1** | **0.06** | **0.08** |

*Legend: EI= Exposure indicator component; SI= Sensitivity indicator component; ACI= Adaptation capacity indicator component; CVI= Community vulnerability indicator*

### 5.2.2 Neighboring communities' exposure to drought, rainfall, and temperature variability

The Kruskal-Wallis test results indicated that there is no significant difference (p-value = 0.8735) in the exposure to drought, rainfall, and temperature among the neighboring communities of Dinderesso (Table 14). Regarding the exposure of Peni's neighboring communities, the Kruskal-Wallis test indicated a significant difference (p-value = 0.01493) among these communities (Table 14). The Dunn's test with Bonferroni correction for Peni neighboring multiple comparisons revealed significant differences between Peni and Sokouranie neighboring communities (adjusted p-value = 0.04398433), as well as between Peni and Taga neighboring communities (adjusted p-value = 0.04398433) (Table 15). The exposure box plots for both Dinderesso and Peni's neighboring communities are illustrated in Figures 36 and 37, respectively.

Despite the extensive statistical analysis, the results of the neighboring Dinderesso and Peni classified forest communities' exposure to drought, rainfall, and temperature changes demonstrated that the communities experience varying levels of exposure to these factors (Figure 38). Neighboring Dinderesso classified forest communities experience different levels of exposure, ranging from low for the Banakeledaga, Nasso, and Ouolonkoto communities to moderate for the Dinderesso community. Concerning the neighboring communities of Peni classified forest, they experienced low exposure in Sokouranie and Taga, moderate exposure in Gnafongo, and high exposure in Peni.

Table 14: Dinderesso and Peni neighboring communities exposure Kruskal-Wallis test

| Location | Chi-squared | df | p-value |
|---|---|---|---|
| Dinderesso forest neighboring communities | 0.69881 | 3 | 0.8735 |
| Peni forest neighboring communities | 10.475 | 3 | 0.01493 |

Table 15: Peni neighboring communities multiple comparisons Dunn's test with Bonferroni correction

| Communities-comparison | Z-score | P-value unadjusted | P-value adjusted |
|---|---|---|---|
| Gnafongo - Peni | -1.018266 | 0.308551395 | 1 |
| Gnafongo - Sokouranie | 1.663168 | 0.096278737 | 0.57767242 |
| Peni - Sokouranie | 2.681435 | 0.007330722 | 0.04398433 |
| Gnafongo - Taga | 1.663168 | 0.096278737 | 0.57767242 |
| Peni - Taga | 2.681435 | 0.007330722 | 0.04398433 |
| Sokouranie - Taga | 0 | 1 | 1 |

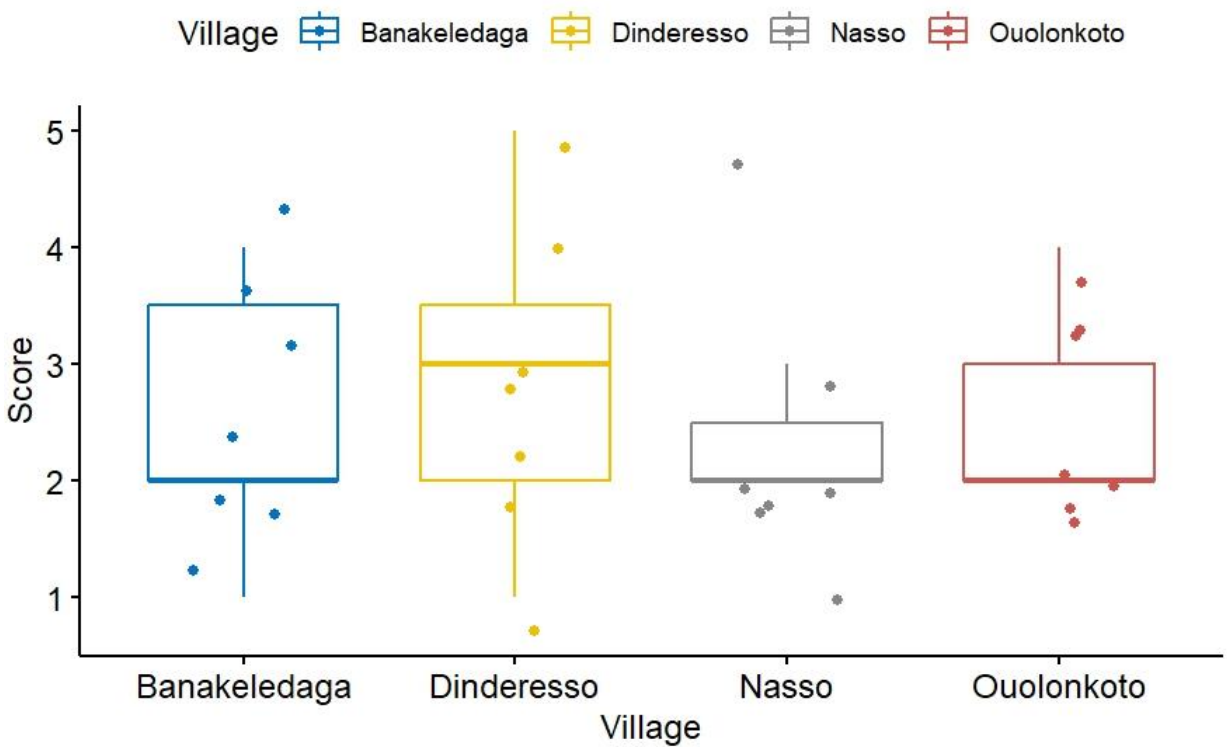


Figure 35: Dinderesso neighboring communities' exposure boxplots variability

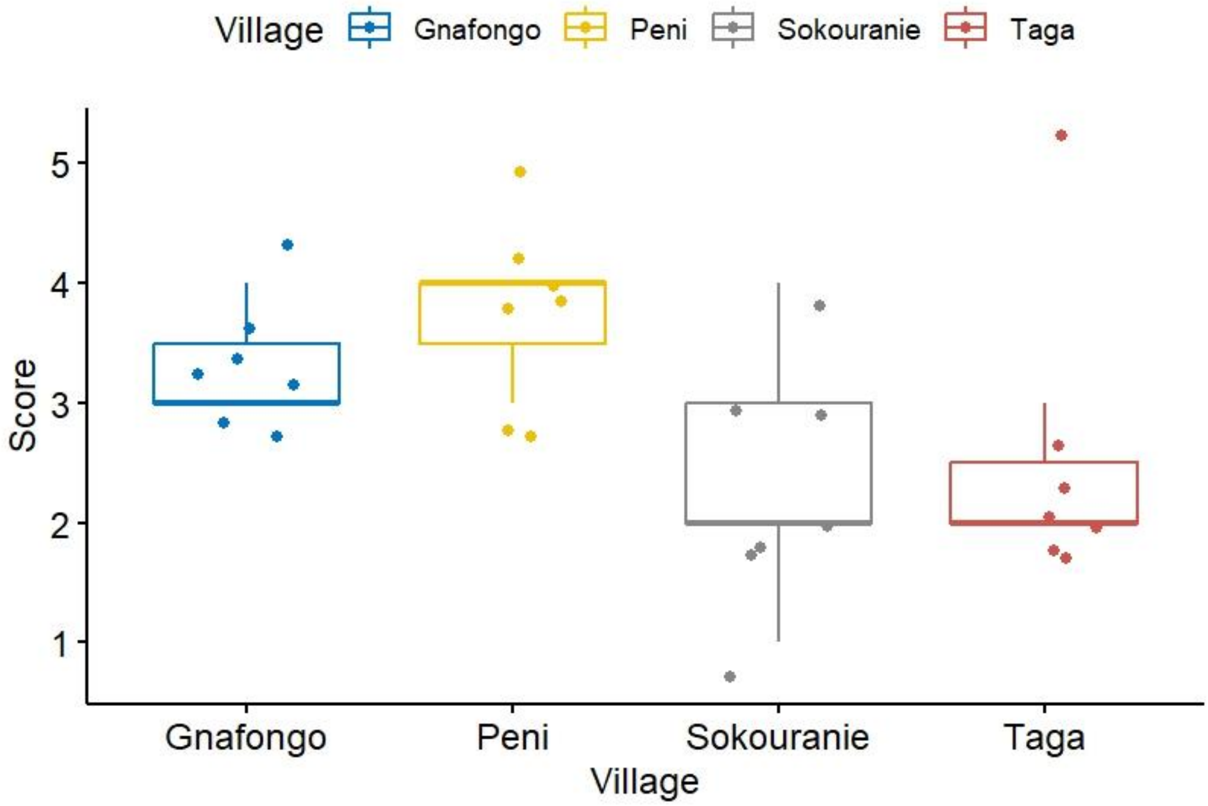


Figure 36: Peni neighboring communities' exposure boxplots variability

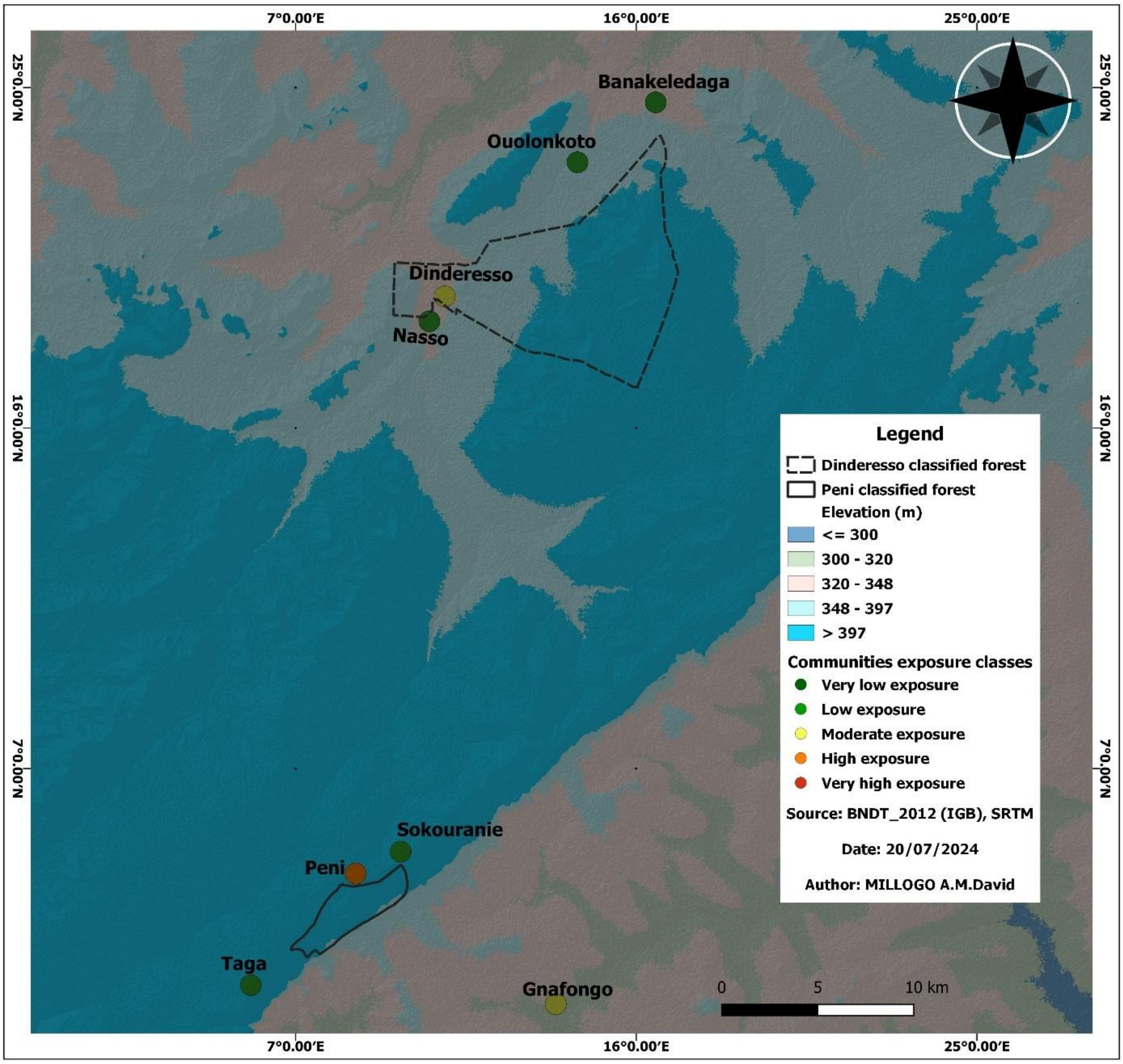


Figure 37: Dinderesso and Peni classified forest neighboring communities' exposure to drought, rainfall and temperature variability (Source: Millogo, 2024)

### 5.2.3 Neighboring communities' sensitivity to forest provisioning ecosystem services degradation, losses

The Kruskal-Wallis test results indicated that there are no significant differences in sensitivity between the neighboring communities of Dinderesso and Peni (p-values = 0.3928 and 0.2467, respectively; Table 16). The sensitivity boxplots for both Dinderesso and Peni's neighboring communities are highlighted in Figures 39 and 40, respectively.

Despite the lack of a statistically significant difference in sensitivity among neighboring communities, as highlighted by the Kruskal-Wallis test, the results from the neighboring Dinderesso and Peni classified forest communities show a variation in sensitivity levels to human activities affecting forest provisioning ecosystem services (Figure 41). The sensitivity levels among communities neighboring the Dinderesso classified forest range from moderate in the Banakeledaga and Dinderesso communities to high in the Nasso and Ouolonkoto communities. The sensitivity results of neighboring Peni classified forest communities range from moderate for Gnafongo, Sokouranie, and Taga to high for the Peni community.

Table 16: Dinderesso and Peni neighboring communities sensitivity Kruskal-Wallis test

| Location | Chi-squared | df | p-value |
|---|---|---|---|
| Dinderesso forest neighboring communities | 2.9926 | 3 | 0.3928 |
| Peni forest neighboring communities | 4.1402 | 3 | 0.2467 |

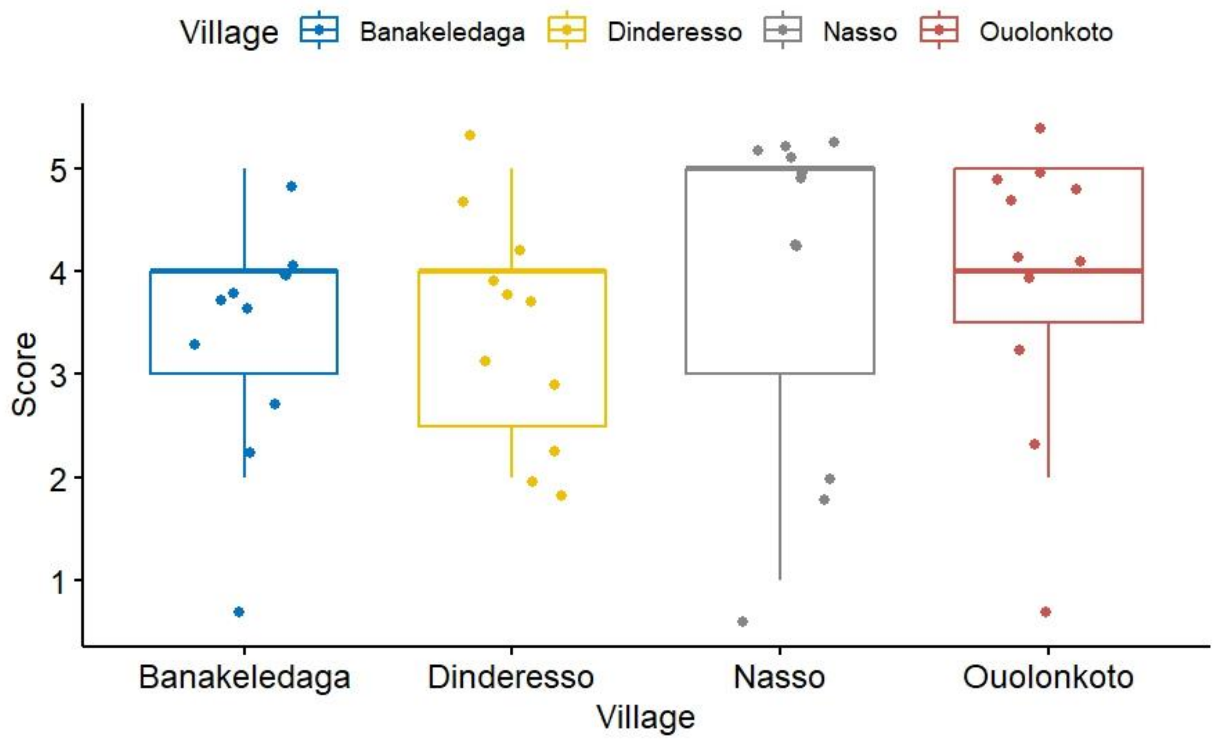


Figure 38: Dinderesso neighboring communities' sensitivity boxplots variability

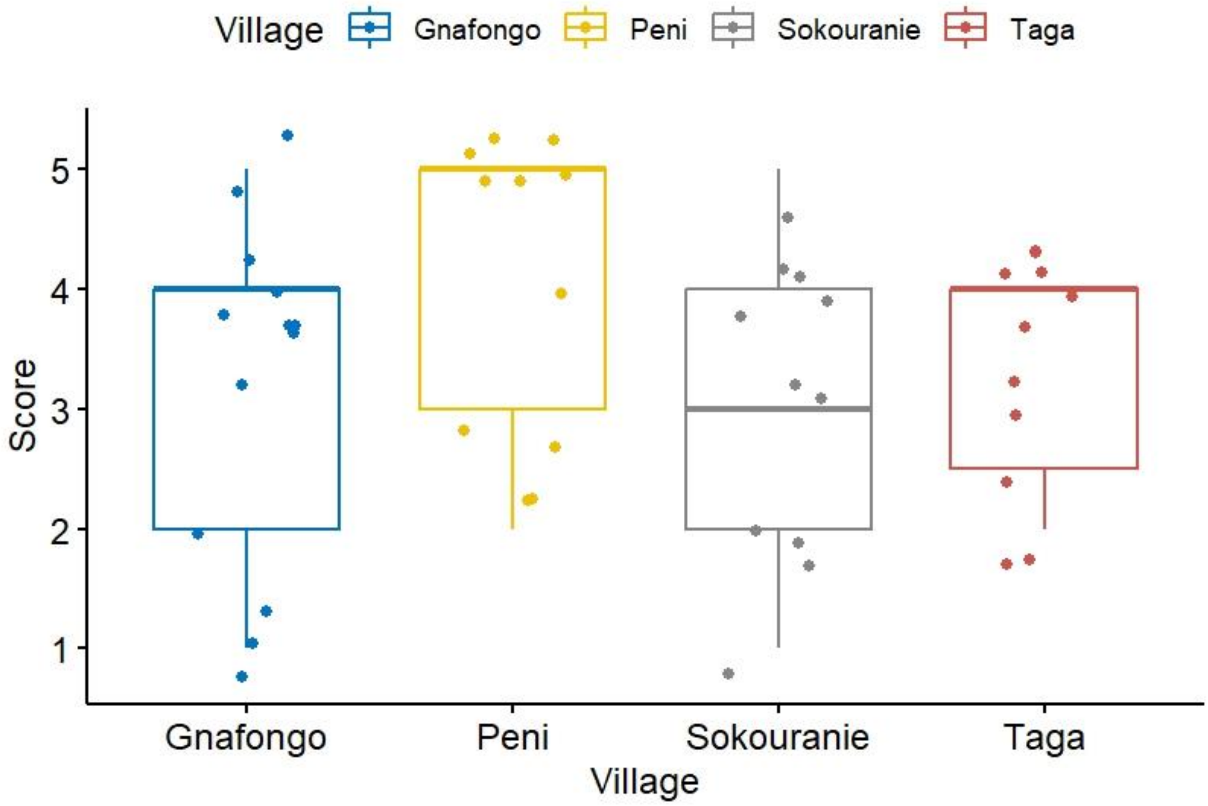


Figure 40: Peni neighboring communities' sensitivity boxplots variability

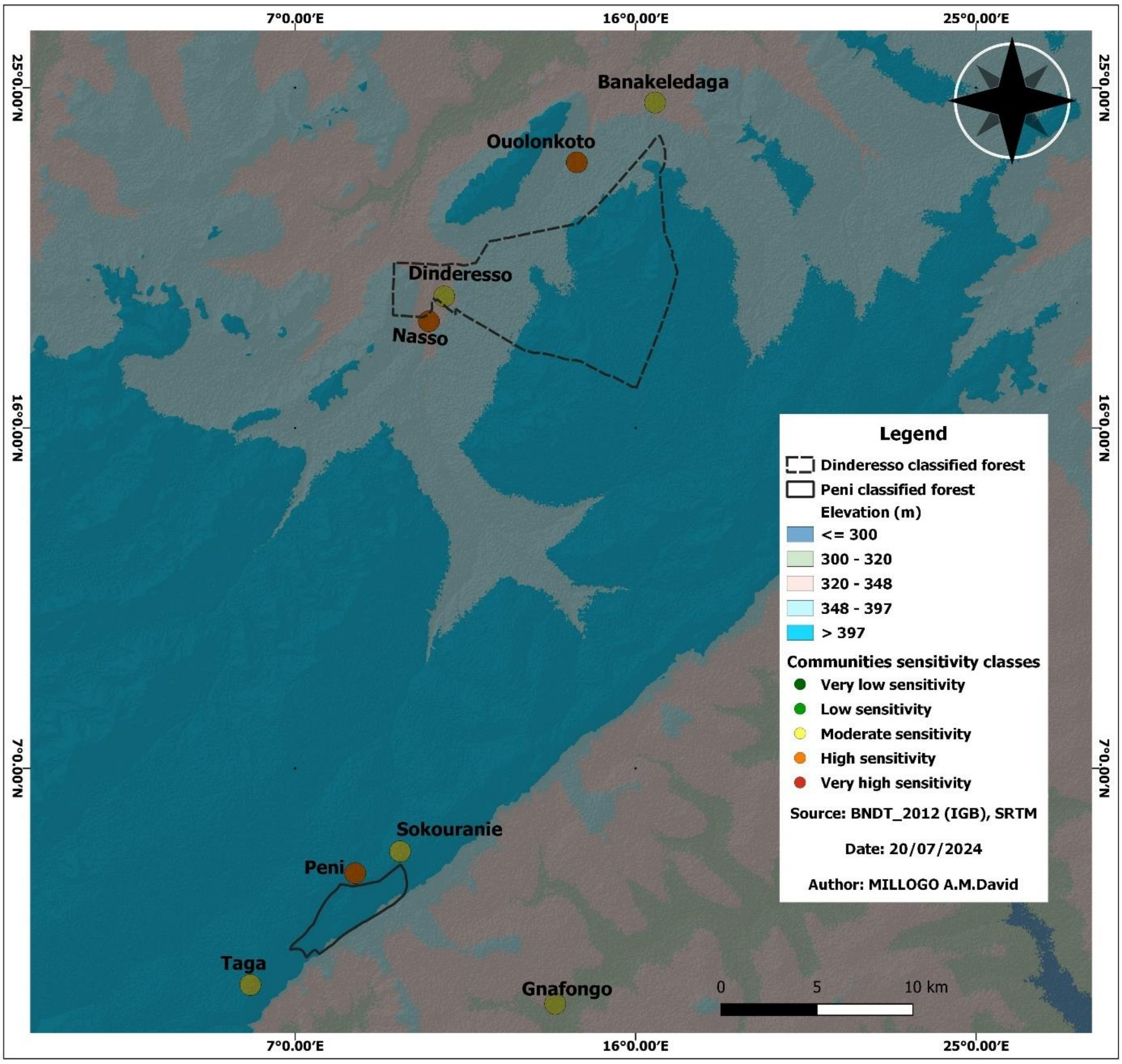


Figure 39: Dinderesso and Peni classified forest neighboring communities' sensitivity to forest provisionning ecosystem services degradation and loss (Source: Millogo, 2024)

### 5.2.4 Neighboring communities' adaptation capacity to provisioning ecosystem services degradation, loss

The Kruskal-Wallis test result indicated that there is no significant difference in adaptation capacities among the Dinderesso (p-value = 0.1948) and Peni (p-value = 0.8745) neighboring communities (Table 17). Both Dinderesso and Peni's neighboring communities' adaptation capacities boxplots are highlighted in Figure 42 and Figure 43, respectively.

Although there is no statistically significant difference between the Dinderesso and Peni neighboring communities, some variations in adaptation capacity levels remain. The results indicate that the Ouolonkoto community has a moderate adaptation capacity, while Banakeledaga, Dinderesso, and Nasso exhibit a high adaptation capacity (Figure 44). The results showed that Peni classified forest communities such as Gnafongo and Peni have a moderate adaptation capacity; Sokouranie and Taga's communities have a high adaptation capacity (Figure 44).

Table 17: Dinderesso and Peni neighboring communities adaptation capacities Kruskal-Wallis test

| Location | Chi-squared | df | p-value |
|---|---|---|---|
| Dinderesso forest neighboring communities | 4.7042 | 3 | 0.1948 |
| Peni forest neighboring communities | 0.6946 | 3 | 0.8745 |

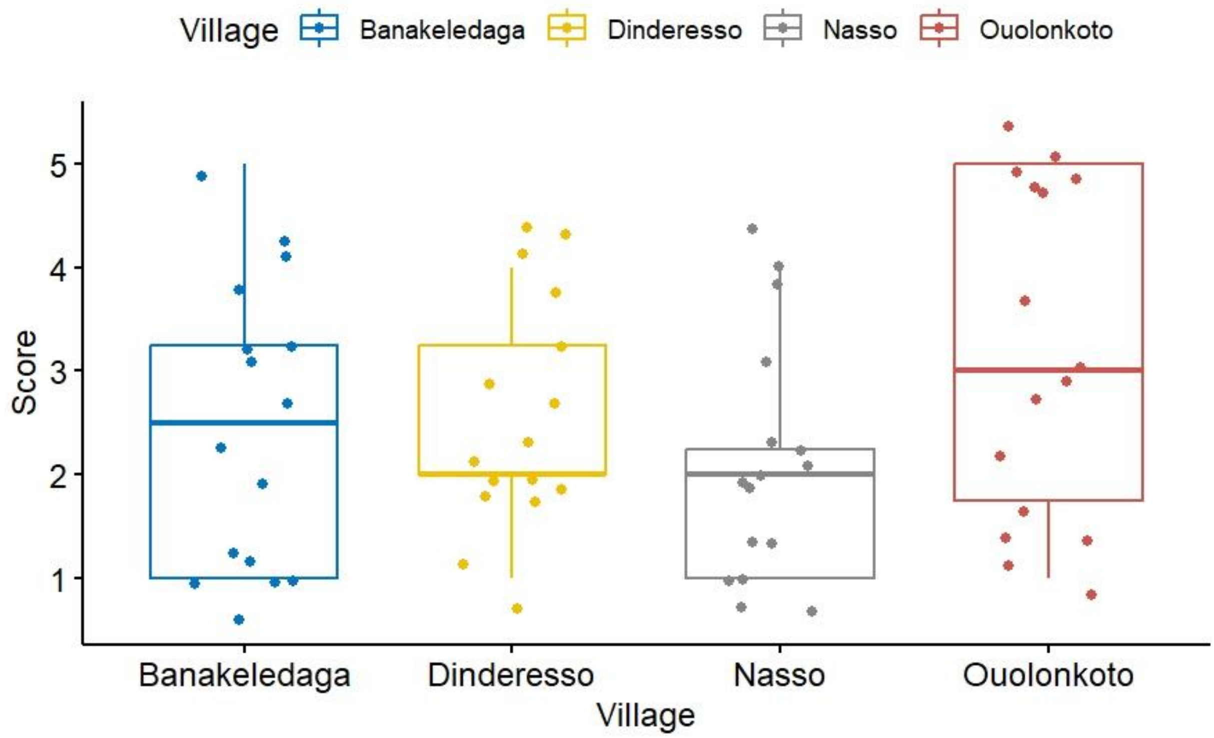


Figure 40: Dinderesso neighboring communities' adaptation capacities boxplots variability

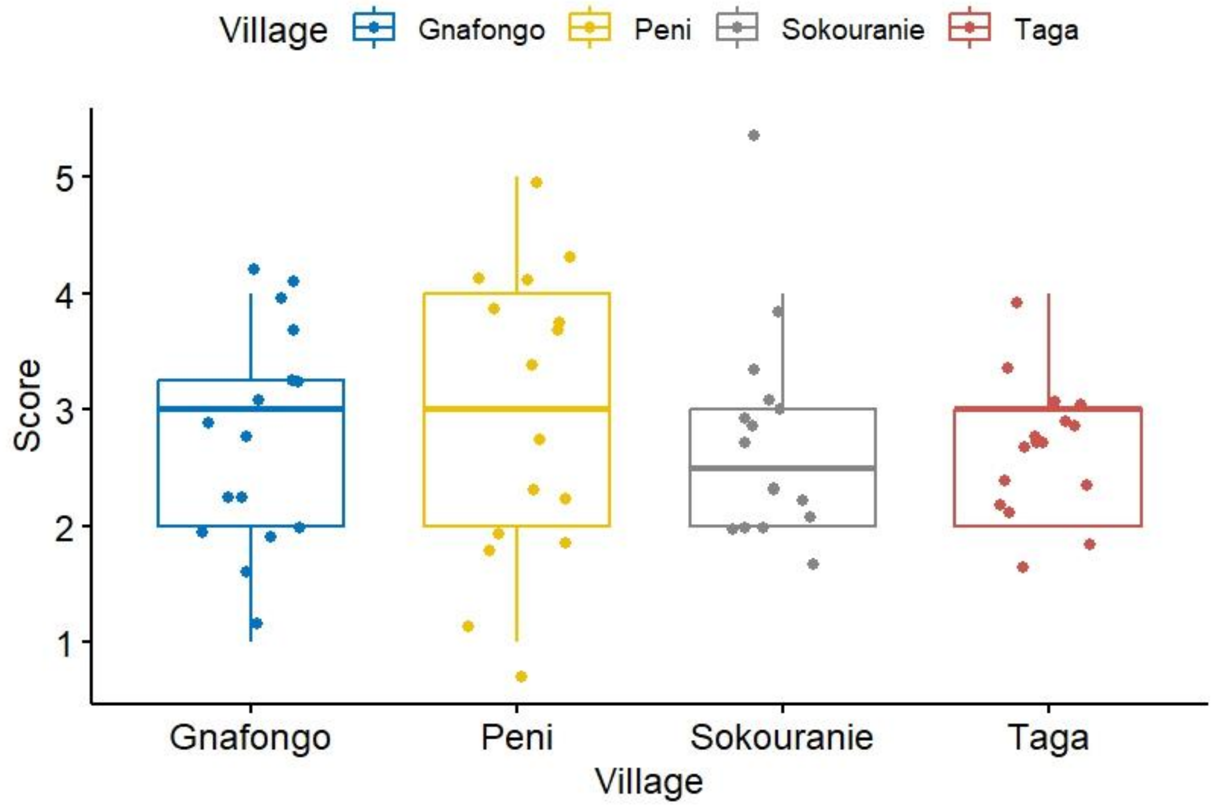


Figure 41: Peni neighboring communities' adaptation capacities boxplots variability

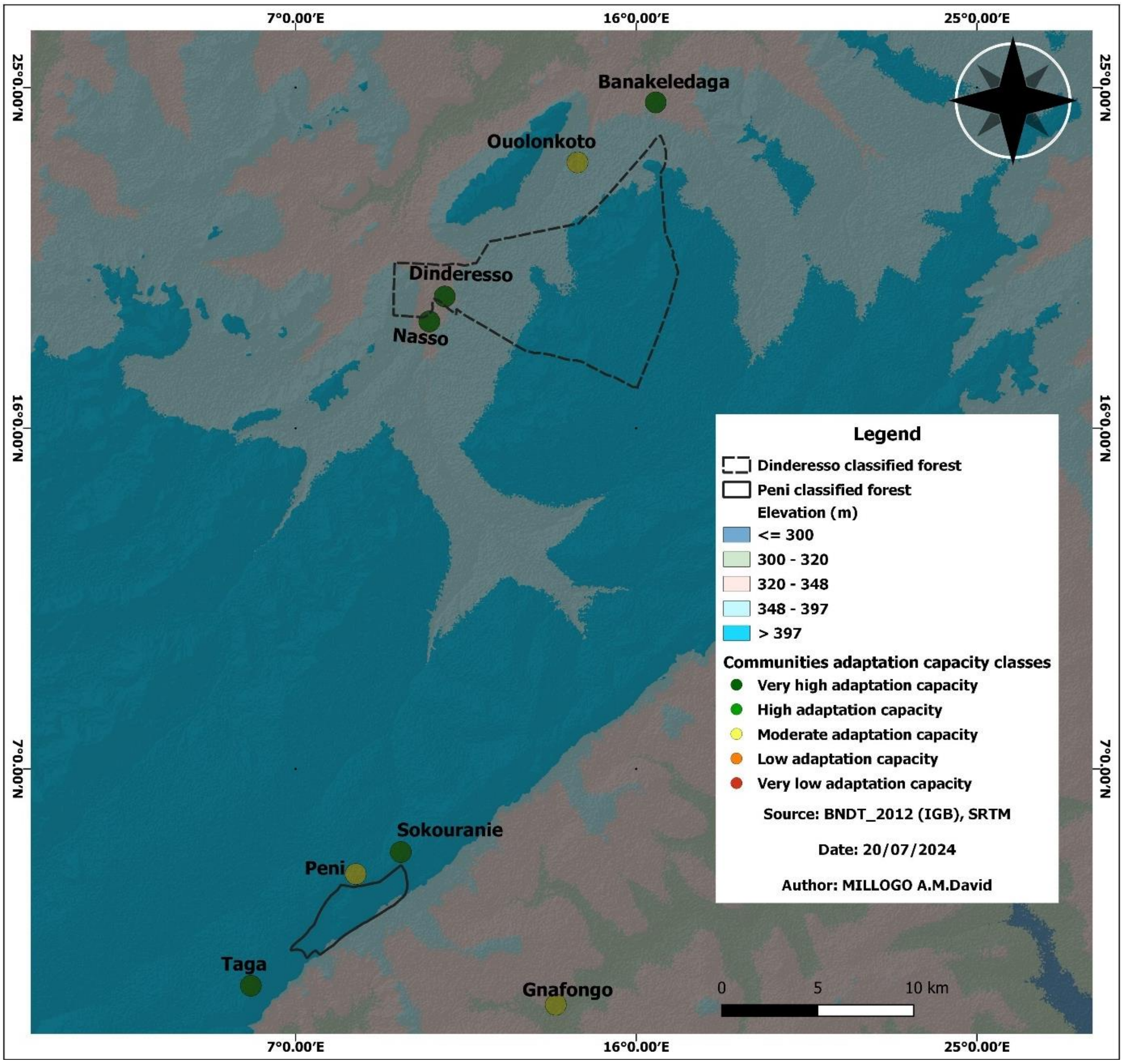


Figure 42: Dinderesso and Peni classified forest neighboring communities' adaptation capacities to forest provisionning ecosystem services degradation and loss (Source : Millogo, 2024)

### 5.2.5 Neighboring communities' vulnerability

The vulnerability results of the neighboring Dinderesso and Peni classified forest communities to climate variability and human activities reveal different levels of vulnerability among these communities (Figure 45). The neighboring Dinderesso classified forest communities, which include Dinderesso and Ouolonkoto, displayed moderate levels of vulnerability, whereas Banakeledaga and Nasso showed low levels of vulnerability. Regarding the Peni classified forest communities, the results highlighted that Gnafongo, Peni, and Taga exhibit a moderate vulnerability level, while Sokouranie has a low vulnerability level.

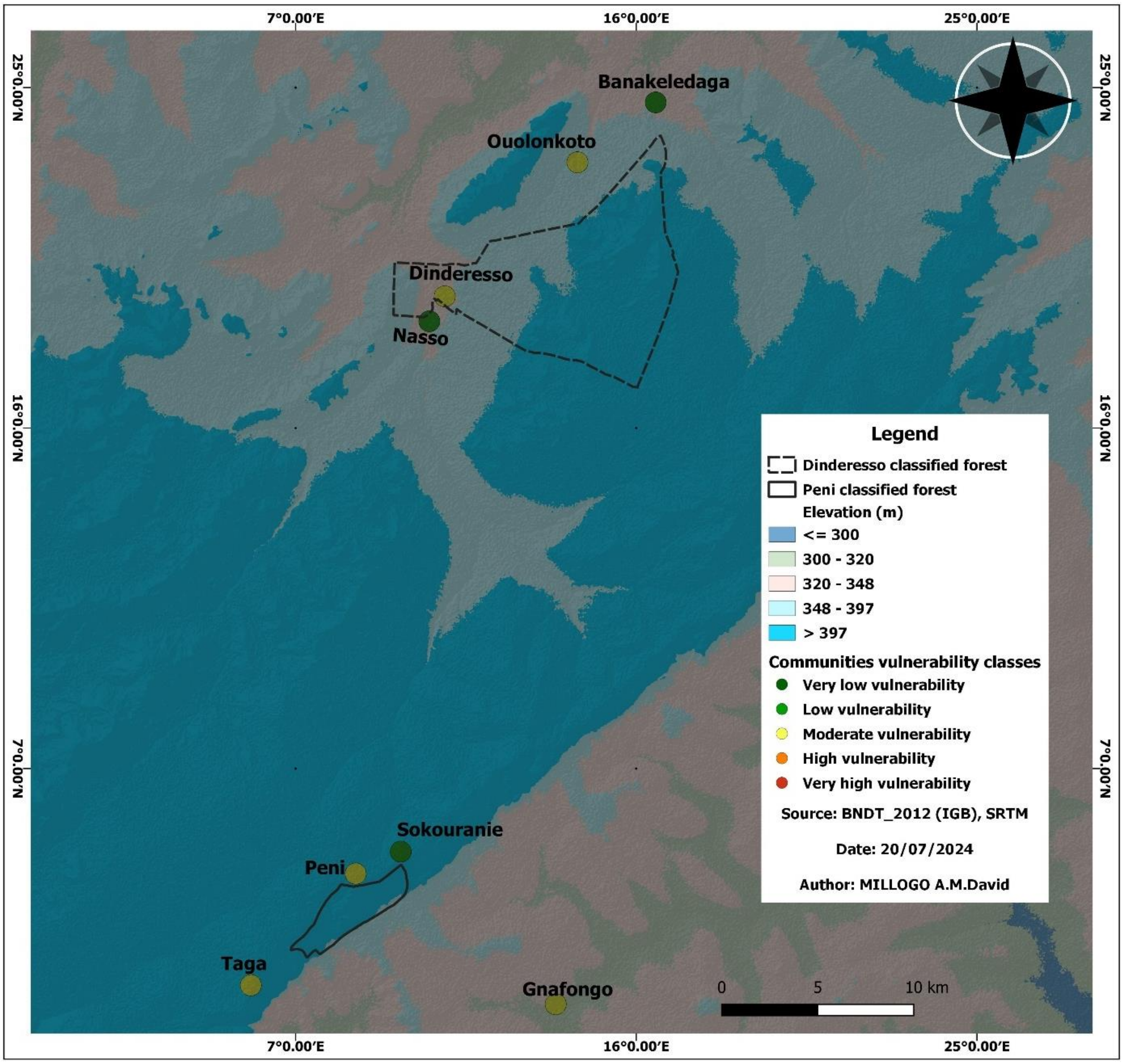


Figure 43: Dinderesso and Peni classified forest neighboring communities' vulnerability to climate and human activities (Source: Millogo, 2024)

# 5.3 Discussion

## 5.3.1 Neighboring communities' exposure to drought, rainfall, and temperature variability

The study revealed that the communities neighboring the two forests have been impacted by climate variability, including alterations in drought, rainfall, and temperature over the past decade. All neighboring communities reported experiencing at least one instance of drought during this period. They also observed changes in decreasing rainfall and increasing temperature over the last ten years. These results align with the research of Runde et *al*., (2022), which predicted increases in drought and warming within tropical areas from 30 degrees North to 30 degrees South. A spatiotemporal analysis of rainfall trends in Burkina Faso from 1961 to 2010 revealed a decrease in rainfall from North to South (Toure et *al*., 2015). Some research conducted in Bobo-Dioulasso, the province where the current study area is located, predicted an increase in temperature from 2012 to 2100 (Kabore et *al*., 2017). All the neighboring communities involved in this study are situated in the same Sudanian climatic zone, so we can anticipate a similar level of exposure experienced by the communities, considering that exposure is solely related to climate.

However, the results indicated that the exposure to drought, rainfall, and temperature varies slightly among the neighboring forest communities and between the different groups of neighboring forest communities. This suggests that community exposure to climate change variability may depend not only on geographical location but also on various criteria, including topography, community experiences with climate change and variability, significant events, well-being status, traditional knowledge, soil type, vegetation, and occupation, all of which could influence perceptions of exposure (Deléglise et *al*., 2023; Gentle et *al*., 2014; Knapp et *al*., 2015; Pandey et *al*., 2018). Indeed, all the neighboring communities studied are not homogeneous and exhibit topographical variations, as well as a diversity of ethnic groups within each community, each with distinct habits and occupations.

During the participatory assessment of the neighboring Dinderesso and Peni, the vulnerability of classified forest communities was evaluated. Some community participants, including Banakeledaga, appreciated the exposure to drought and its impacts, such as crop loss, reduced yields, tree mortality, and drying water points. This community is situated in the lowlands at an average altitude of 300 meters (Ouattara et *al*., 2018), they may not recognise some drought events with a low impact on their livelihoods because the lowlands can retain more water in the soil for a longer time than certain highlands, such as the Peni community, which has an average altitude exceeding 400 m. According to Hollunder et *al*., (2022), areas at lower altitudes may be less susceptible to drought compared to those at higher altitudes, owing to the limited availability of water and nutrients for plants. This type of neighboring community may not appreciate the effects of drought, rainfall, and temperature as much as other communities in the highlands.

Listening to other community participants, such as Peni, as well as the severity of drought events, rainfall, and temperature changes they experienced, their precise explanation of climate change and variability demonstrated the community's consistent knowledge of these issues. This strong knowledge was evident in the Peni community. Their highland location, combined with their experience of droughts, rainfall, and temperature trends, may account for their significant level of exposure. The existing knowledge within the Peni community may account for the significant differences observed when compared to the Sokouranie and Taga communities. Beyond the Peni community, the exposure of all other communities to drought, rainfall, and temperature ranges from low to moderate, which is considered non-critical in comparison to high exposure.

### 5.3.2 Neighboring communities' sensitivity

The results obtained from the participatory assessment of the neighboring communities of Dinderesso and Peni classified the sensitivity of forests related to forest provisioning ecosystem services. This assessment revealed a sensitivity variation from moderate to high, indicating that all the neighboring communities maintain relationships with these forests for provisioning ecosystem services in order to satisfy households' food needs, treat diseases, feed livestock, and build construction. Forests have long supported food security for rural communities and their crops (FAO, 2020a; Pérez-Moreno et *al*., 2021; Piya Luni et *al*., 2011). According to Eshetu & Tesfaye (2024), firewood and charcoal production generate income for rural households and fulfill their energy needs. Forest provisioning ecosystem services contribute to the livelihoods of rural communities by providing food, traditional medicine, fodder, and construction materials, as mentioned by Kalaba et *al*., (2013) and Savadogo (2021).

Participants from various neighboring communities agreed that the relationship includes the benefits they derive from forest provisioning ecosystem services. Other factors, such as traditional gold mining, agricultural activities, land and property development, firewood collection, and community population density, can negatively impact these ecosystem services and the neighboring communities themselves, both directly and indirectly. Some research highlights that populations with stronger connections to natural resources may be more affected and vulnerable if these resources are disrupted or degraded (Patrick, 2003). The overexploitation of forest provisioning ecosystem services contributes to their degradation (Boafo et *al*., 2014). By engaging in extensive agriculture, humans negatively impact the degradation and loss of forest provisioning ecosystem services (FAO, 2020a; MEEEA, 2022; Thiombiano & Kampmann, 2010).

Investigating forest degradation and deforestation in Ghana, Kyere-Boateng & Marek (2021) mentioned population growth, land tenure, and illegal mining as drivers. The results of the current study revealed that communities adjacent to the two forests are affected differently by forest provisioning ecosystem services due to human influence. The differences in sensitivity levels observed among neighboring communities may be attributed to the strength of the relationship each community has with the forest, the quality of forest resources, the level of community education, community wealth status, and the forest's sustainable management system. The Ouolonkoto community recognises that its relationship with the Dinderesso forest is important, as many women in the community, for example, are involved in charcoal production.

This activity provides them with income to support their household needs. Some community participants, such as Dinderesso and Taga, believe that the forest is degraded, causing them to struggle to find many forest products as they did in the past. This perception of forest degradation, along with the scarcity or loss of various forest products, such as certain fauna species and medicinal plants, diminishes the strength of their connection to the forest. Even if they are aware that their activities contribute to forest provisioning ecosystem services, neighboring communities of Dinderesso and Peni classified forests said that because of the forest protection statute, they hide from forest managers to cut fresh trees for income and their households' energy needs for making charcoal. Some communities stated that the training, advice, and support from public and private organisations enabled them to recognise the importance of preserving biodiversity and transformed their relationship with forest provisioning ecosystem services.

Other communities asserted that they no longer had sufficient farmland for their children. To fulfill their needs, they cut down some unprotected trees in the forest to create new farms and houses for their children, as well as to replace their old, unproductive farms. Other communities, like Gnafongo, noted that they are distant from the forest, which diminishes their ability to provide forest ecosystem services. Some studies conducted at the household level indicated that education level, availability of trees as a resource, distance to the forest, and family size can negatively or positively affect households' dependence on fuel income (Eshetu & Tesfaye, 2024).

Comparing the quantity of forest provisioning ecosystem services sold by communities, Kalaba et *al*., (2013) showed that some communities exploited and sold greater amounts of forest provisioning ecosystem services than others. According to Mcdonald et *al*., (2009), the proximity of protected areas to urban areas contributes to the degradation of forested areas. Interestingly, regarding environmental protection, Legutko-Kobus et *al*., (2023) highlighted the significance of an environmental protection framework to ensure effective management and regulation of environmental areas.

### 5.3.3 Neighboring communities' adaptation capacity

Regarding the adaptation capacities of communities, the results revealed varying levels of these capacities among the neighboring communities of the two forests. Assessing adaptation capacities based on knowledge, technology, institutions, and economic factors enabled the identification of each community's level of adaptation capacity, which ranges from moderate to high. Understanding the impacts of climate change, variability, and human activities on forest provisioning ecosystem services is crucial for disaster risk management. As a sub-factor of knowledge, education can enhance community knowledge and its adaptive capacity to prevent or cope with disaster risks, such as the degradation and loss of forest provisioning ecosystem services. According to Choden et *al*., (2020) and Wu & Lee (2015), education enhances adaptive capacity. During the participatory assessment of neighboring Dinderesso and Peni, classified forest communities reported that training and news from the media enhanced their understanding of climate change, variability, and forest sustainability management.

By comparing participants' perceptions of education levels within their community, it appears that some communities have high and moderate education levels, which affect the neighboring communities' ability to adapt to forest provisioning ecosystem services due to drought, rainfall, temperature, and human activities. Higher education levels offer improved access to information and greater capacity for adaptation (Dafiesta & Rapera, 2014; Zhang et *al*., 2019). Over many years of projects, the commitment to forest restoration, supported by environmental offices, has enhanced neighboring communities' knowledge through training in climate change, breeding fauna species, producing seedlings in nurseries, tree planting, and more. Considering the rising disaster risks globally, especially in West African nations, timely and accurate information can enhance adaptation capacities for more effective disaster risk management. For that reason, technology plays a crucial role in enhancing adaptation capacity. Numerous authors have highlighted the significant role of technology in communication during disaster risk management (Anser et *al*., 2021; Chimanga & Kanja, 2020; Eakin et *al*., 2015).

During the participatory exchange, the neighboring communities of Dinderesso and Peni classified forest agreed that they sometimes received information about climate and sustainable forest management from public and private organisations. Regarding the devices from which they obtained this information, they mentioned phones, radio, and television. Due to various socio-economic factors, communities confirmed that within the community, some individuals may lack some or all of the mentioned devices, making it difficult for them to access timely information that can enhance their adaptation capacity. This reality of access to technology among neighboring communities helps us better understand the varying levels of adaptation capacity that are observed. Indeed, while some communities enjoy high access to technology, which increases their likelihood of receiving information about climate and sustainable forest management, other communities struggle to obtain the same information due to limited access to technology.

To lessen the negative impacts of human activity on forest provisioning ecosystem services, some community participants suggested using alternative sources of firewood, such as crop residues, biogas, and more efficient cooking systems that require less firewood. Renewable energy, as an alternative to firewood, reduces carbon dioxide emissions and enhances the capacity of communities to adapt at any location level (Suman, 2021). Unfortunately, the cost of gas and biogas, along with the limited availability of crop residues, are reasons cited by some community members to explain their challenges in utilising these alternative fuel energy sources. Thus, utilising this alternative energy source is uncommon in each community and varies between them, which explains their differing adaptation capacities. In disaster risk reduction, establishing institutions with effective policies, regulations, and measures contributes to controlling and reducing human activities that can negatively impact forest provisioning ecosystem services and climate change variability.

In all the neighboring communities studied, participants confirmed the existence of environmental offices from the public government, a local organisation for forest management established by the government environmental office, and customary chieftaincy. All these institutions advocate for reducing carbon dioxide emissions through public and local regulations. Despite all these efforts, community participants expressed that some individuals do not fully respect these regulations. That situation adversely impacts the adaptation capacities of communities that have low respect for regulations, in contrast to those with high respect for them. In addition to respecting community regulations set by institutions, participants assessed the efficiency of both government and local institutions in managing forest sustainability. Their responses demonstrated varying levels of efficiency for the government and local institutions across the communities.

Participants indicated that some institutions operate with moderate efficiency, which may not benefit community adaptation capacities compared to those where institutions exhibit high efficiency. According to Anser et *al*., (2021) and Chimanga & Kanja, (2020), effective institutions are essential for enhancing adaptation capacities in disaster risk management. Regarding the economic contribution to adaptation capacity, neighboring communities indicated that most households have moderate to low income, which diminishes their adaptation capacities. Even though they acknowledge the efforts of green economy initiatives designed to enhance and diversify their incomes, particularly for the communities surrounding Dinderesso forest that have hosted numerous years of forest sustainability management projects, these communities still lack the substantial income needed to bolster their adaptation capacities.

Examining the participants representing studied communities, several socio-professional groups emerge, including farmers, breeders, fishers, hunters, tradipraticians, retailers, and government workers. Many of these groups depend on climate and forest products, which negatively affect the income and adaptive capacities of communities. To enhance communities' adaptation capacities, solutions such as income source diversification through green activities and financial credit from banking institutions have been suggested (Chepkoech et *al*., 2020).

### 5.3.4 Neighboring communities' vulnerability

The vulnerability of neighboring Dinderesso and Peni classified forest communities, under the influence of drought, rainfall, temperature variability, and human activities, revealed varying levels of vulnerability ranging from low to moderate. These findings align with numerous studies that have emphasised the differing vulnerability levels observed among communities (Abeje et *al*., 2019; Bolin et *al*., 2014a; Datta et *al*., 2024). Neighboring communities that exhibit higher vulnerability are linked to their capacity to adapt to exposure and sensitivity. The Ouolonkoto community is more vulnerable due to their strong relationships, which adversely affect forest livelihoods and ecosystem services, leaving them with a reduced capacity to adapt to sensitive issues. The Peni community is highly vulnerable due to their greater exposure and sensitivity, coupled with a lower capacity for adaptation. Communities with low vulnerability levels demonstrate lower exposure, reduced sensitivity, and enhanced adaptation capacity, such as the Banakeledaga and Sokouranie communities.

Generally, the vulnerability results of neighboring communities are non-critical due to various efforts that have improved forest sustainability management, livelihoods, and several factors related to location, socio-economic characteristics, and the existing classified forest management policy. Additionally, all stakeholders include public and private organisations, along with neighboring communities, dedicated to the sustainable management of the Dinderesso and Peni classified forests.

# CONCLUSION

This study allowed the assessment of neighboring Dinderesso and Peni classified forest communities' vulnerability. The findings indicated varying degrees of vulnerability among the neighboring communities, with Banakeledaga, Nasso, and Sokouranie showing low vulnerability, while Ouolonkoto, Dinderesso, Peni, Taga, and Gnafongo exhibited moderate vulnerability. The differing vulnerability noted between the adjacent Dinderesso and Peni classified forests can be attributed to various factors such as climate, geographical positioning, topography, altitude, socioeconomic traits, and the management policies of forest resources. The study findings emphasized the importance of considering the vulnerability of neighboring communities in classified forests management plans and investments by policymakers, forest managers and stakeholders. This is especially crucial for forest resource management plans and investments for sustainable biodiversity conservation and livelihood preservation. This approach can serve as a valuable tool in disaster risk management among climate, forest, and human relationships.

# GENERAL CONCLUSION RECOMMENDATIONS AND LIMITATIONS

## GENERAL CONCLUSION

The general objective of the current study was to enhance the understanding of how climate variability and human activities affect protected areas and their neighboring communities in the Sudanian climatic zone of Burkina Faso. Using consistent and reliable methodologies, the approaches to assess specific objectives highlighted crucial relevant information.

Firstly, the study examining the relationships between rainfall and temperature in the Sudanian climatic zone vegetation of Burkina Faso from 2001 to 2022 using TAMSAT (rainfall), ERA 5 (temperature), and MODIS NDVI data has highlighted a strong positive relationship between the SPEI6 and the NDVI. Additionally, it reveals that the Sudanian climatic zone vegetation experienced several severe and extreme drought events from 2001 to 2005 and from 2013 to 2016. These findings also revealed the ongoing occurrence of drought events in the Sudanian climatic zone, which alternate with years of wet conditions. All these results clearly showed that rainfall and temperature negatively affected vegetation cover in the Sudanian climatic zone from 2001 to 2022.

Secondly, the focus on the effects of anthropogenic drivers on vegetation through the spatiotemporal analysis of land use and land cover dynamics in Dinderesso and Peni classified forests from 1986 to 2022 based on Landsat satellite images, which highlighted the degradation and deforestation of both forests during the study period. This degradation and deforestation involve the transformation of gallery forest, clear forest, and wooded savannah/tree savannah into shrub savannah and agroforestry parklands in the examined forests. In Dinderesso's classified forest, Shrub Savannah and agroforestry parklands are expanding at annual rates of 3.86% and 3.09%, respectively. The same pattern is observed in the Peni classified forest, where the shrub savannah and the agroforestry parklands expand at annual rates of 358.54% and 0.95%, respectively. The field trip visits organised in the two studied classified forests, along with resource person meetings and the study on the perception of the neighboring communities of Dinderesso and Peni classified forests regarding degradation and deforestation drivers, revealed that humans contribute to over 90% of the degradation and deforestation in the Dinderesso and Peni classified forests. The other drivers of forest degradation and deforestation highlighted in this study are related to climate and elephant disturbances, primarily in the Peni classified forest. Additionally, this study revealed variability in the drivers of forest degradation and deforestation among neighboring communities, attributable to their dependence on forest resources, their geographic location, and the influence of the primary economic activity within the community. Thirdly, the social vulnerability of forest neighboring communities in Dinderesso and Peni to climate variability and anthropogenic drivers highlights that these communities experience varying degrees of vulnerability. Indeed, Banakeledaga, Nasso, and Sokouranie showed low vulnerability, whereas Ouolonkoto, Dinderesso, Peni, Taga, and Gnafongo displayed moderate vulnerability. The variability in vulnerability degrees observed among communities is attributed to several factors, including climate, geographical location, topography, altitude, socioeconomic characteristics, and management policies regarding forest resources.

The findings showed varying levels of vulnerability among the neighboring communities, with Banakeledaga, Nasso, and Sokouranie demonstrating low vulnerability, while Ouolonkoto, Dinderesso, Peni, Taga, and Gnafongo displayed moderate vulnerability. The differing vulnerability observed between the adjacent Dinderesso and Peni classified forests can be attributed to several factors, including climate, geographical positioning, topography, altitude, socioeconomic traits, and management policies regarding forest resources.

# RECOMMENDATIONS

These findings highlight important implications regarding the adaptation to climate variability, climate change, conservation of forest biodiversity, and the resilience of communities neighboring protected forests in the Sudanian climatic zone. These implications pertain to the environmental, socio-economic, and policy spheres. At the environmental level, it is essential to establish a climate monitoring system for the sustainable management of Sudanian climatic zone vegetation. Regarding the socio-economic aspect, the strong link between protected forest resources and adjacent communities contributes to forest degradation, deforestation, and loss of livelihoods. This situation necessitates enhancing the sustainable management plan for protected forest resources through green investments to provide neighboring communities with alternative and diversified livelihoods. The varying levels of vulnerability observed among neighboring communities suggest implementing a vulnerability monitoring system with sustainable measures to enhance their resilience to climate and human activities. Finally, these findings highlight a crucial need to establish sustainable forest resource management policies tailored to the specific context of the Sudanian climatic zone.

# LIMITATIONS

Despite the consistent and reliable findings presented in the current study, some limitations have been observed. Firstly, this study did not emphasise how different vegetation classes respond to climate variability. This response regarding vegetation classes could provide more precise and meaningful information about the vegetation classes that are more vulnerable to climate variability. Additionally, this study utilised Landsat satellite images with a spatial resolution of 30 m, indicating that certain objects cannot be detected by the Landsat satellite sensors, which may hinder the ability to highlight more details concerning the spatiotemporal dynamics of forest areas. Additionally, the study on the vulnerability of neighboring communities to climate variability and human activities was conducted entirely through a qualitative approach and focused exclusively on forest provisioning ecosystem services.

This study offers meaningful and consistent findings essential for enhancing the relationships among climate, forests, and humans. It provided essential information on the sustainable management of forest areas and the preservation of communities' livelihoods through coherent plans, strategies, and investments directed at forest management by policymakers, managers, and all stakeholders. Firstly, the upcoming research studies should examine a broader study area, encompassing the Sudan-Sahelian and Sahelian climatic zones' vegetation. The focus should be on highlighting various vegetation classes about climate variability and climate change. Secondly, it is important to address vegetation response to climate variability based on future climate conditions. Thirdly, more studies should focus on the vulnerability of neighboring communities to climate change and human activities on a large scale while combining qualitative and quantitative approaches to enhance the assessment. The final recommendation is directed at policymakers, forest managers, and financial stakeholders to include neighboring communities in vulnerability assessments for any management plans or investments related to protected forest areas.

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# APPENDIXES

## Appendix 1: MODIS NDVI downloading R script

```
library(tidyverse)

library(MODIStsp)



MODIStsp_get_prodlayers("M*D13Q1") # see bands names


# Modis Vegetation indices downloading ! Pay attention to area and/or

# period of interest. Files can be really huge.


print("---- Start Vegetation Data Downloading -----")

MODIStsp(

  gui = FALSE,

  out_folder = "VegetationData",

  out_folder_mod = "VegetationData",

  selprod = "Vegetation Indexes_16Days_250m (M*D13Q1)",

  bandsel = "NDVI", # select band of interest

  user = "User name", #eartdata username

  password = "Pass word", #earthdata password

  start_date = "2001.01.01", # start_date modify as needed

  end_date = "2022.12.31", # end_date modify as needed

  verbose = FALSE,

  spatmeth = "file",

  spafile = "VegetationData/shapefile/bfa_admbnda_adm0_igb_20200323.shp",

  out_format = "GTiff"

)


cat(

  "All files were downloaded, see *.tif files here:

  /VegetationData/bfa_admbnda_adm0_igb_20200323/VI_16Days_250m_v6/NDVI/"
```

```
)
## Moving all processed geotiff files into ndvi-tif/
if(!fs::dir_exists("ndvi-tif")) fs::dir_create("ndvi-tif")

path_to_tifs <- "~/modis-ndvi/VegetationData/bfa_admbnda_adm0_igb_20200323/VI_16Days_250m_v6/NDVI"

tif_files <- fs::dir_ls(path = path_to_tifs,glob = "*.tif")
fs::file_move(path = tif_files,new_path = "ndvi-tif/")
```

# Appendix 2: Raw Dinderesso classified forest classification accuracy for 1986, 2006, 2010, 2016, and 2022 Landsat images

| CLASSES | WB/WA | GF | CF | WS/TS | SS | AP | BA/BS | TOTAL ROW |
|---|---|---|---|---|---|---|---|---|
| **YEAR 1986** | | | | | | | | |
| **WB/WA** | 54 | 0 | 0 | 0 | 0 | 0 | 0 | 54 |
| **GF** | 0 | 64 | 3 | 0 | 0 | 0 | 0 | 67 |
| **CF** | 1 | 1 | 336 | 0 | 1 | 0 | 0 | 339 |
| **WS/TS** | 0 | 0 | 0 | 79 | 0 | 3 | 0 | 82 |
| **SS** | 0 | 0 | 0 | 0 | 103 | 0 | 0 | 103 |
| **AP** | 0 | 0 | 0 | 9 | 0 | 44 | 2 | 55 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 0 | 66 | 66 |
| **TOTAL COLUMN** | 55 | 65 | 339 | 88 | 104 | 47 | 68 | 766 |
| **PRODUCER ACCURACY (%)** | 98.18 | 98.46 | 99.12 | 89.77 | 99.04 | 93.62 | 97.06 | |
| **USER ACCURACY (%)** | 100 | 95.52 | 99.12 | 96.34 | 100 | 80 | 100 | |
| **KAPPA COEFFICIENT** | 0.92 | | | | | | | |
| **OVERALL ACCURACY (%)** | 94.06 | | | | | | | |
| **YEAR 2006** | | | | | | | | |
| **WB/WA** | 71 | 0 | 0 | 1 | 0 | 0 | 0 | 72 |
| **GF** | 0 | 79 | 0 | 0 | 0 | 0 | 0 | 79 |
| **CF** | 0 | 0 | 266 | 2 | 0 | 0 | 0 | 268 |
| **WS/TS** | 0 | 0 | 0 | 38 | 0 | 1 | 0 | 39 |
| **SS** | 0 | 0 | 0 | 0 | 107 | 0 | 0 | 107 |
| **AP** | 0 | 0 | 0 | 5 | 2 | 36 | 0 | 43 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 0 | 119 | 119 |
| **TOTAL COLUMN** | 71 | 79 | 266 | 46 | 109 | 37 | 119 | 727 |
| **PRODUCER ACCURACY (%)** | 100 | 100 | 100 | 82.61 | 98.17 | 97.3 | 100 | |
| **USER ACCURACY (%)** | 98.61 | 100 | 99.25 | 97.44 | 100 | 83.72 | 100 | |
| **KAPPA COEFFICIENT** | 0.90 | | | | | | | |
| **OVERALL ACCURACY (%)** | 92.81 | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **YEAR 2010** | | | | | | | | |
| **WB/WA** | 75 | 0 | 0 | 1 | 0 | 0 | 0 | 76 |
| **GF** | 0 | 66 | 0 | 0 | 0 | 0 | 0 | 66 |
| **CF** | 1 | 0 | 105 | 1 | 0 | 2 | 0 | 109 |
| **WS/TS** | 0 | 0 | 0 | 44 | 0 | 2 | 0 | 46 |
| **SS** | 0 | 0 | 0 | 0 | 69 | 0 | 0 | 69 |
| **AP** | 0 | 0 | 0 | 6 | 0 | 61 | 0 | 67 |
| **BA/BS** | 0 | 0 | 0 | 2 | 0 | 0 | 121 | 123 |
| **TOTAL COLUMN** | 76 | 66 | 105 | 54 | 69 | 65 | 121 | 556 |
| **PRODUCER ACCURACY (%)** | 98.68 | 100 | 100 | 81.48 | 100 | 93.85 | 100 | |
| **USER ACCURACY (%)** | 98.68 | 100 | 96.33 | 95.65 | 100 | 91.04 | 98.37 | |
| **KAPPA COEFFICIENT** | 0.92 | | | | | | | |
| **OVERALL ACCURACY (%)** | 94.32 | | | | | | | |
| **YEAR 2016** | | | | | | | | |
| **WB/WA** | 87 | 0 | 0 | 2 | 0 | 0 | 0 | 89 |
| **GF** | 0 | 75 | 2 | 0 | 0 | 0 | 0 | 77 |
| **CF** | 6 | 0 | 72 | 0 | 0 | 0 | 2 | 80 |
| **WS/TS** | 1 | 0 | 0 | 29 | 0 | 0 | 1 | 31 |
| **SS** | 0 | 0 | 0 | 0 | 100 | 6 | 0 | 106 |
| **AP** | 1 | 0 | 0 | 1 | 2 | 63 | 1 | 68 |
| **BA/BS** | 0 | 0 | 0 | 1 | 0 | 0 | 103 | 104 |
| **TOTAL COLUMN** | 95 | 75 | 74 | 33 | 102 | 69 | 107 | 555 |
| **PRODUCER ACCURACY (%)** | 91.58 | 100 | 97.3 | 87.88 | 98.04 | 91.3 | 96.26 | |
| **USER ACCURACY (%)** | 97.75 | 97.4 | 90 | 93.55 | 94.34 | 92.65 | 99.04 | |
| **KAPPA COEFFICIENT** | 0.91 | | | | | | | |
| **OVERALL ACCURACY (%)** | 93.13 | | | | | | | |
| **YEAR 2022** | | | | | | | | |
| **WB/WA** | 101 | 0 | 0 | 0 | 0 | 0 | 0 | 101 |
| **GF** | 0 | 64 | 1 | 0 | 0 | 0 | 0 | 65 |
| **CF** | 2 | 1 | 51 | 0 | 0 | 4 | 0 | 58 |
| **WS/TS** | 0 | 0 | 0 | 53 | 0 | 6 | 2 | 61 |
| **SS** | 0 | 0 | 0 | 0 | 119 | 0 | 0 | 119 |
| **AP** | 0 | 0 | 0 | 1 | 0 | 87 | 0 | 88 |
| **BA/BS** | 0 | 0 | 0 | 3 | 0 | 0 | 70 | 73 |
| **TOTAL COLUMN** | 103 | 65 | 52 | 57 | 119 | 97 | 72 | 565 |
| **PRODUCER ACCURACY (%)** | 98.06 | 98.46 | 98.08 | 92.98 | 100 | 89.69 | 97.22 | |
| **USER ACCURACY (%)** | 100 | 98.46 | 87.93 | 86.89 | 100 | 98.86 | 95.89 | |
| **KAPPA COEFFICIENT** | 0.92 | | | | | | | |
| **OVERALL ACCURACY (%)** | 94.23 | | | | | | | |

*Note: WB/WA = Water Body/Wetland Area, GF = Gallery Forest, WS/TS = Wooded Savannah/Tree Savannah, SS = Shrub Savannah, AP = Agroforestry Park, BA/BS = Build Area/Bare Soil*

# Appendix 3 : Raw Peni classified forest classification accuracy for 1986, 2006, 2010, 2016, and 2022 Landsat images

| CLASSES | WB/WA | GF | WS/TS | SS | AP | BA/BS | TOTAL |
|---|---|---|---|---|---|---|---|
| **YEAR 1986** | | | | | | | |
| **WB/WA** | 21 | 0 | 0 | 0 | 2 | 0 | 23 |
| **GF** | 0 | 49 | 0 | 0 | 0 | 0 | 49 |
| **WS/TS** | 0 | 0 | 67 | 0 | 1 | 0 | 68 |
| **SS** | 0 | 0 | 2 | 69 | 0 | 0 | 71 |
| **AP** | 0 | 0 | 0 | 0 | 78 | 0 | 78 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 104 | 104 |
| **TOTAL COLUMN** | 21 | 49 | 69 | 69 | 81 | 104 | 393 |
| **PRODUCER ACCURACY (%)** | 100 | 100 | 97.1 | 100 | 96.3 | 100 | |
| **USER ACCURACY (%)** | 91.3 | 100 | 98.53 | 97.18 | 100 | 100 | |
| **KAPPA COEFFICIENT** | 0.97 | | | | | | |
| **OVERALL ACCURACY (%)** | 98.13 | | | | | | |
| **YEAR 2006** | | | | | | | |
| **WB/WA** | 30 | 0 | 0 | 0 | 0 | 0 | 30 |
| **GF** | 1 | 58 | 0 | 0 | 0 | 0 | 59 |
| **WS/TS** | 1 | 0 | 63 | 0 | 0 | 0 | 64 |
| **SS** | 1 | 0 | 0 | 60 | 0 | 0 | 61 |
| **AP** | 0 | 0 | 0 | 0 | 64 | 0 | 64 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 66 | 66 |
| **TOTAL COLUMN** | 33 | 58 | 63 | 60 | 64 | 66 | 344 |
| **PRODUCER ACCURACY (%)** | 90.91 | 100 | 100 | 100 | 100 | 100 | |
| **USER ACCURACY (%)** | 100 | 98.31 | 98.44 | 98.36 | 100 | 100 | |
| **KAPPA COEFFICIENT** | 0.995 | | | | | | |
| **OVERALL ACCURACY (%)** | 99.76 | | | | | | |
| **YEAR 2010** | | | | | | | |
| **WB/WA** | 14 | 0 | 0 | 0 | 0 | 0 | 14 |
| **GF** | 0 | 52 | 2 | 0 | 0 | 0 | 54 |
| **WS/TS** | 0 | 0 | 53 | 0 | 1 | 0 | 54 |
| **SS** | 0 | 0 | 0 | 81 | 0 | 0 | 81 |
| **AP** | 0 | 0 | 0 | 1 | 80 | 6 | 87 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 57 | 57 |
| **TOTAL COLUMN** | 14 | 52 | 55 | 82 | 81 | 63 | 347 |
| **PRODUCER ACCURACY (%)** | 100 | 100 | 96.36 | 98.78 | 98.77 | 90.48 | |
| **USER ACCURACY (%)** | 100 | 96.3 | 98.15 | 100 | 91.95 | 100 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **KAPPA COEFFICIENT** | 0.92 | | | | | | |
| **OVERALL ACCURACY (%)** | 94.85 | | | | | | |
| | | | **YEAR 2016** | | | | |
| **WB/WA** | 26 | 0 | 0 | 0 | 1 | 0 | 27 |
| **GF** | 1 | 49 | 0 | 0 | 0 | 0 | 50 |
| **WS/TS** | 0 | 0 | 85 | 0 | 0 | 0 | 85 |
| **SS** | 0 | 0 | 0 | 73 | 0 | 0 | 73 |
| **AP** | 0 | 0 | 0 | 1 | 52 | 1 | 54 |
| **BA/BS** | 0 | 0 | 0 | 0 | 0 | 100 | 100 |
| **TOTAL COLUMN** | 27 | 49 | 85 | 74 | 53 | 101 | 389 |
| **PRODUCER ACCURACY (%)** | 96.3 | 100 | 100 | 98.65 | 98.11 | 99.01 | |
| **USER ACCURACY (%)** | 96.3 | 98 | 100 | 100 | 96.3 | 100 | |
| **KAPPA COEFFICIENT** | 0.97 | | | | | | |
| **OVERALL ACCURACY (%)** | 97.55 | | | | | | |
| | | | **YEAR 2022** | | | | |
| **WB/WA** | 18 | 1 | 0 | 1 | 0 | 0 | 20 |
| **GF** | 0 | 36 | 2 | 0 | 0 | 0 | 38 |
| **WS/TS** | 0 | 0 | 52 | 0 | 0 | 0 | 52 |
| **SS** | 0 | 0 | 0 | 65 | 0 | 2 | 67 |
| **AP** | 0 | 0 | 0 | 0 | 74 | 0 | 74 |
| **BA/BS** | 0 | 0 | 0 | 0 | 1 | 129 | 130 |
| **TOTAL COLUMN** | 18 | 37 | 54 | 66 | 75 | 131 | 381 |
| **PRODUCER ACCURACY (%)** | 100 | 97.3 | 96.3 | 98.48 | 98.67 | 98.47 | |
| **USER ACCURACY (%)** | 90 | 94.74 | 100 | 97.01 | 100 | 99.23 | |
| **KAPPA COEFFICIENT** | 0.96 | | | | | | |
| **OVERALL ACCURACY (%)** | 98.00 | | | | | | |

*Note: WB/WA = Water Body/Wetland Area, GF = Gallery Forest, WS/TS = Wooded Savannah/Tree Savannah, SS = Shrub Savannah, AP = Agroforestry Park, BA/BS = Build Area/Bare Soil*

# Appendix 4 : Dinderesso classified forest Card's confusion matrix with producer accuracy (PA), user accuracy (UA), and areas adjusted with a 95% confidence interval

| 1986/Dinderesso classified forest | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | WB/WA | GF | CF | WS/TS | SS | AP | BA/BS | Total | UA (%) |
| **WB/WA** | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 100.00 ± 0.00 |
| **GF** | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 95.52 ± 4.99 |
| **CF** | 0.00 | 0.00 | 0.41 | 0.00 | 0.00 | 0.00 | 0.00 | 0.42 | 99.12 ± 1.00 |
| **WS/TS** | 0.00 | 0.00 | 0.00 | 0.26 | 0.00 | 0.01 | 0.00 | 0.27 | 96.34 ± 4.09 |
| **SS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.00 | 0.00 | 0.06 | 100.00 ± 0.00 |
| **AP** | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.14 | 0.01 | 0.18 | 80.00 ± 10.67 |
| **BA/BS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 ± 0.00 |
| **Total** | 0.06 | 0.02 | 0.42 | 0.29 | 0.06 | 0.15 | 0.01 | 1.00 | |
| **PA (%)** | 97.93 ± 3.98 | 97.63 ± 13.38 | 99.82 ± 0.19 | 89.77 ± 5.55 | 97.89 ± 4.04 | 93.62 ± 6.73 | 39.75 ± 32.88 | | |
| **Adjusted area (ha)** | 524.69 ± 21 | 147.66 ± 22 | 3662.42 ± 38 | 2526.02 ± 183 | 516.86 ± 21 | 1349.64 ± 194 | 95.32 ± 79 | | |
| **OA (%)** | 95 ± 2.24 | | | | | | | | |
| **2022/Dinderesso classified forest** | | | | | | | | | |
| | WB/WA | GF | CF | WS/TS | SS | AP | BA/BS | Total | UA (%) |
| **WB/WA** | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 100.00 ± 0.00 |
| **GF** | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 98.46 ± 3.02 |
| **CF** | 0.01 | 0.01 | 0.33 | 0.00 | 0.00 | 0.03 | 0.00 | 0.38 | 87.93 ± 8.46 |
| **WS/TS** | 0.00 | 0.00 | 0.00 | 0.12 | 0.00 | 0.01 | 0.00 | 0.14 | 86.89 ± 8.54 |
| **SS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.14 | 0.00 | 0.00 | 0.14 | 100.00 ± 0.00 |
| **AP** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.28 | 0.00 | 0.29 | 98.86 ± 2.23 |
| **BA/BS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 95.89 ± 3.48 |
| **Total** | 0.04 | 0.03 | 0.33 | 0.12 | 0.14 | 0.32 | 0.01 | 1.00 | |
| **PA (%)** | 70.77 ± 28.42 | 76.07 ± 35.68 | 99.90 ± 0.19 | 97.20 ± 5.09 | 100.00 ± 0.00 | 87.73 ± 7.34 | 46.41 ± 34.20 | | |
| **Adjusted area (ha)** | 395.25 ± 159 | 241.37 ± 113 | 2949.78 ± 283 | 1078.59 ± 117 | 1234.71 ± 0.00 | 2850.09 ± 245 | 73.82 ± 54 | | |
| **OA (%)** | 93.25± 3.48 | | | | | | | | |

*Legend: = Water Body/Wetland Area (WB/WA), (WB/WA), Gallery Forest (GF), Clear Forest (CF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS).*

# Appendix 5: Peni classified forest Card's confusion matrix with producer accuracy (PA), user accuracy (UA), and areas adjusted with a 95% confidence interval

| 1986/Peni classified forest | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | WB/WA | GF | WS/TS | SS | AP | BA/BS | Total | UA (%) |
| **WB/WA** | 0.27 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.29 | 91.30 ± 11.77 |
| **GF** | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 100.00 ± 0.00 |
| **WS/TS** | 0.00 | 0.00 | 0.23 | 0.00 | 0.00 | 0.00 | 0.23 | 98.53± 2.88 |
| **SS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 97.18 ± 3.88 |
| **AP** | 0.00 | 0.00 | 0.00 | 0.00 | 0.43 | 0.00 | 0.43 | 100.00 ± 0.00 |
| **BA/BS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 100.00 ± 0.00 |
| **Total** | 0.27 | 0.03 | 0.23 | 0.00 | 0.46 | 0.01 | 1.00 | |
| **PA (%)** | 100.00 ± 0.00 | 100.00 ± 0.00 | 99.98 ± 0.02 | 100.00 ± 0.00 | 93.76 ± 7.11 | 100.00 ± 0.00 | | |
| **Adjusted area (ha)** | 294.26 ± 38 | 34.92 ± 0.00 | 252.33 ± 7 | 1.49 ± 0.00 | 509.78 ± 39 | 11.43 ±0.00 | | |
| **OA (%)** | 97.12 ± 3.50 | | | | | | | |

| 2022/Peni classified forest | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | WB/WA | GF | WS/TS | SS | AP | BA/BS | Total | UA (%) |
| **WB/WA** | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 90.00 ± 13.49 |
| **GF** | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 94.74 ± 7.20 |
| **WS/TS** | 0.00 | 0.00 | 0.13 | 0.00 | 0.00 | 0.00 | 0.13 | 100.00 ± 0.00 |
| **SS** | 0.00 | 0.00 | 0.00 | 0.17 | 0.00 | 0.01 | 0.18 | 97.01 ± 4.11 |
| **AP** | 0.00 | 0.00 | 0.00 | 0.00 | 0.62 | 0.00 | 0.62 | 100.00 ± 0.00 |
| **BA/BS** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 99.23 ± 1.51 |
| **Total** | 0.06 | 0.01 | 0.13 | 0.18 | 0.62 | 0.01 | 1.00 | |
| **PA (%)** | 100.00 ± 0.00 | 73.89 ±37.84 | 99.62 ± 0.51 | 98.21 ± 3.44 | 100.00 ± 0.00 | 14.36 ± 16.92 | | |
| **Adjusted area (ha)** | 62.37 ± 9 | 13.27 ± 7 | 144.27 ± 1 | 193.81 ± 11 | 683.65 ± 0.00 | 6.84 ± 8 | | |

| | |
|---|---|
| **OA (%)** | 98.79 ± 1.12 |

*Legend: = Water Body/Wetland Area (WB/WA), (WB/WA), Gallery Forest (GF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS).*

# Appendix 6: Dinderesso classified forest LULC adjusted area and annual growth rate

| | Area (ha) | | | | | Magnitude (ha) | | | | | Rate per annum (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1986** | **2006** | **2010** | **2016** | **2022** | **1986-2006** | **2006-2010** | **2010-2016** | **2016-2022** | **1986-2022** | **1986-2006** | **2006-2010** | **2010-2016** | **2016-2022** | **1986-2022** |
| **WB/WA** | 524.69 | 69.14 | 208.2 | 496.13 | 395.25 | 455.55 | -139.06 | -287.93 | 100.88 | 129.44 | -4.34 | 50.28 | 23.05 | -3.39 | -0.69 |
| **GF** | 147.66 | 346.05 | 188.37 | 323.04 | 241.37 | -198.39 | 157.68 | -134.67 | 81.67 | -93.71 | 6.72 | -11.39 | 11.92 | -4.21 | 1.76 |
| **CF** | 3662.42 | 4224.43 | 4030.21 | 3250.88 | 2949.78 | -562.01 | 194.22 | 779.33 | 301.1 | 712.64 | 0.77 | -1.15 | -3.22 | -1.54 | -0.54 |
| **WS/TS** | 2526.02 | 1375.86 | 871.11 | 136.32 | 1078.59 | 1150.16 | 504.75 | 734.79 | -942.27 | 1447.43 | -2.28 | -9.17 | -14.06 | 115.20 | -1.59 |
| **SS** | 516.86 | 648.48 | 821.61 | 2858.22 | 1234.71 | -131.62 | -173.13 | -2036.61 | 1623.51 | -717.85 | 1.27 | 6.67 | 41.31 | -9.47 | 3.86 |
| **AP** | 1349.64 | 2134.17 | 2689.3 | 1630.32 | 2850.09 | -784.53 | -555.13 | 1058.98 | -1219.77 | -1500.45 | 2.91 | 6.50 | -6.56 | 12.47 | 3.09 |
| **BA/BS** | 95.32 | 24.48 | 13.81 | 127.7 | 73.82 | 70.84 | 10.67 | -113.89 | 53.88 | 21.5 | -3.72 | -10.90 | 137.45 | -7.03 | -0.63 |

*Legend: = Water Body/Wetland Area (WB/WA), (WB/WA), Gallery Forest (GF), Clear Forest (CF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS).*

# Appendix 7 :Peni classified forest LULC adjusted area and annual growth rate

| | Area (ha) | | | | | Magnitude (ha) | | | | | Rate per annum (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1986 | 2006 | 2010 | 2016 | 2022 | 1986-2006 | 2006-2010 | 2010-2016 | 2016-2022 | 1986-2022 | 1986-2006 | 2006-2010 | 2010-2016 | 2016-2022 | 1986-2022 |
| **WB/WA** | 294.26 | 111.71 | 207.99 | 464.4 | 62.37 | 182.55 | -96.28 | -256.41 | 402.03 | 231.89 | -3.10 | 21.55 | 20.55 | -14.43 | -2.19 |
| **GF** | 34.92 | 15.75 | 17.77 | 10.67 | 13.27 | 19.17 | -2.02 | 7.1 | -2.6 | 21.65 | -2.74 | 3.21 | -6.66 | 4.06 | -1.72 |
| **WS/TS** | 252.33 | 123.15 | 267.8 | 203.31 | 144.27 | 129.18 | -144.65 | 64.49 | 59.04 | 108.06 | -2.56 | 29.36 | -4.01 | -4.84 | -1.19 |
| **SS** | 1.49 | 153.68 | 84.79 | 221.72 | 193.81 | -152.19 | 68.89 | -136.93 | 27.91 | -192.32 | 510.70 | -11.21 | 26.92 | -2.10 | 358.54 |
| **AP** | 509.78 | 695.52 | 488.1 | 198.21 | 683.65 | -185.74 | 207.42 | 289.89 | -485.44 | -173.87 | 1.82 | -7.46 | -9.90 | 40.82 | 0.95 |
| **BA/BS** | 11.43 | 4.41 | 37.76 | 5.9 | 6.84 | 7.02 | -33.35 | 31.86 | -0.94 | 4.59 | -3.07 | 189.06 | -14.06 | 2.66 | -1.12 |

*Legend: = Water Body/Wetland Area (WB/WA), (WB/WA), Gallery Forest (GF), Wooded Savannah/Tree Savannah (WS/TS), Shrub Savannah (SS), Agroforestry Parkland (AP), and Build Area/Bare Soil (BA/BS).*

# Appendix 8: Kobocollect semi-structure questionnaire



## Perception des communautes riveraines sur les facteurs de degradation, defeforestation des aires protegees en zone soudanienne au Burkina Faso

**INTRODUCTION**

*Bonjour/Bonsoir. Je me nomme __, je suis de nationalité Burkinabé, j'effectue actuellement des études doctorales dans le domaine du changement climatique et la gestion des risques de catastrophe au sein de la Faculté des Sciences de l'Homme et de la Société à l'Université de Lomé (Togo). Je vous remercie de me recevoir et de m'accorder votre temps et votre attention pour répondre à mes questions.*

---

**Nom de l'enqueteur**

- ○ KIENDREBEOGO Sayouba
- ○ SANON Simplice
- ○ GANDEMA Abdoul Kader
- ○ KIEMDE Rasmane

**Date**

yyyy-mm-dd hh:mm

---

**A.1 Etes vous d'accord a repondre de facon volontaire a notre questionnaire?**

*Accord de consentement Votre participation à travers vos connaissances et vos réponses au questionnaire contribueront permettront d'améliorer la gestion durable des aires protégées et la préservation des moyens d'existences des communautés riveraines. Le présent entretien est anonyme et vos réponses confidentielles seront exclusivement utilisées pour les besoins de l'étude par l'équipe de recherche, dans le respect de la conformité de vos réponses. Partageant une copropriété de la présente étude avec l'équipe de recherche, les informations et conclusion de l'étude seront mises à votre disposition de façon libre. Avant d'entamer l'entrevue, je souhaiterais savoir si vous avez des commentaires et solliciter votre accord volontaire*

- ○ Oui
- ○ Non

### SECTION I:INFORMATIONS GENERALES

**I-1 Region**

- ○ Hauts-Bassins
- ○ Centre-Ouest
- ○ Cascades

**I-2 Province**

- ◯ Houet
- ◯ Comoe
- ◯ Bale
- ◯ Ziro

**I-3 Commune/Village**

- ◯ Wolonkoto
- ◯ Banakeledaga
- ◯ Nasso
- ◯ Dinderesso
- ◯ Gnafongo
- ◯ Sokourani
- ◯ Taga
- ◯ Peni

**I-4 Secteur/Quartier**

*Texte*

______________________________

**I-5 Sexe**

- ◯ Feminin
- ◯ Masculin

**I-6 Quel est votre age?**

*Il s'agit de l'age de la personne enquetee en annee*

______________________________

**I-7 Nationalite**

- ◯ Burkina Faso
- ◯ Mali
- ◯ Niger
- ◯ Cote d'Ivoire
- ◯ Ghana
- ◯ Togo
- ◯ Autre



K

**I-7.1 Si autre nationalite, preciser**

*Saisir le nom du pays*

**I-8 Groupe ethnique**

- ◯ Bobo
- ◯ Dioula
- ◯ Bwaba
- ◯ Mossi
- ◯ Peulh
- ◯ Tiefo
- ◯ Toussian
- ◯ Turka
- ◯ Senoufo
- ◯ Sambla
- ◯ Dagara
- ◯ Samo
- ◯ Autre

**I-8.1 Si autre groupe ethnique, preciser**

**I-9 Niveau d'education**

- ◯ Aucun
- ◯ Primaire
- ◯ Secondaire
- ◯ Universitaire
- ◯ Education religieuse
- ◯ Alphabetisation

**I-10 Situation matrimoniale**

- ◯ Celibataire
- ◯ Marie (e)
- ◯ Veuf/Veuve



L

**I-11 Religion**

- ○ Animiste
- ○ Musulman
- ○ Catholique
- ○ Protestant
- ○ Autre

**I-12 Si autre religion (preciser)**

---

**I-13 Statut de residence**

- ○ Autochtone
- ○ Migrant
- ○ Deplacee interne

**I-14 Taille du menage**

---

**I-15 Quelle est votre occupation socio-professionnelle principale?**

- ○ Agriculture
- ○ Elevage
- ○ Commerce
- ○ Artisan
- ○ Fonctionnaire
- ○ Autre

**I-16 Autre occupation socio-professionnelle**

*a preciser*

---



M

**I-17 Depuis combien de temps residez-vous dans le village?**

- < 1 an
- 1 an
- 2 ans
- 3 ans
- 4 ans
- 5 ans
- 6 ans
- 7 ans
- 8 ans
- 9 ans
- 10 ans
- 11 ans
- 12 ans
- 14 ans
- 15 ans
- 16 ans
- 17 ans
- 18 ans
- 19 ans
- 20 ans
- 21 ans
- 22 ans
- 23 ans
- 24 ans
- 25 ans
- 26 ans
- 27 ans
- 28 ans
- 29 ans
- 30 ans
- > 30 ans



N

## » SECTION II:PERCEPTION DES COMMUNAUTES RIVERAINES SUR L'EXISTENCE ET LES LIMITES DE LA FORET CLASSEEE

**II-1 Etes-vous au courant de l'existence de la foret classee?**

- Oui
- Non

**II-2 Si oui, Quel est votre niveau de connaissance des limites de la foret classee?**

- Aucune connaissance
- Faible Connaissance
- Assez-bonne connaissance
- Bonne connaissance
- Tres bonne connaissance

## » SECTION III: USAGE DES BIENS ET SERVICES ECOSYSTEMIQUES PAR LES COMMUNAUTES RIVERAINES

**III-1 Beneficiez-vous des biens et services de la foret classee?**

- Oui
- Non

**III-2 Quels sont les biens et services de la foret classee dont vous beneficiez?**

*Cette question fait reference a tout avantage direct ou indirect dont la personne tire profit de la foret classee*

**III-3 Utilisez-vous des biens et services de la foret classee pour vos soins?**

- Oui
- Non

**III-3.1 Quels sont les biens et services de la foret classee dont vous avez recours pour vos soins?**

**III-4 Utilisez-vous des biens et services de la foret classee pour votre alimentation?**

- Oui
- Non

**III-4.1 Quels sont les biens et services de la foret classee que vous utilisez pour votre alimentation?**

**III-5 Utilisez-vous des biens et services de la foret classee comme fourrage pour le betail?**

- Oui
- Non



O

III-5.1 Quelles sont les especes fourrageres que vous exploitez dans la foret classee pour l'alimentation du betail?

III-6 Utilisez-vous les ressources en eau de la foret classee?

- Oui
- Non

III-6.1 A quel fins utilisez-vous les ressources en eau de la foret classee?

III-7 Utilisez-vous le bois de la foret classee comme bois d'energie?

- Oui
- Non

III-7.1 Quelles sont les especes utilisees pour le bois d'energie?

**III-7.2 Utilisez-vous d'autres sources d'energie autre que le bois d'energie?**

- Oui
- Non

**III-7.3 Quelles sont les autres sources d'energie utilisees autres que le bois d'energie?**

- [ ] Gaz butane
- [ ] Bio-gaz
- [ ] Residus de recoltes
- [ ] Biochar
- [ ] Autre

III-7.3.1 Preciser autres sources d'energie

III-8 Utilisez-vous le bois de la foret classee comme bois de service?

- Oui
- Non

III-8.1 Quelles sont les especes utilisees comme bois de service?



P

**III-9 Utilisez-vous les biens et services de la foret classee comme source de revenus?**

- ◯ Oui
- ◯ Non

**III-10 Quels sont les biens et services de la foret classee que vous utilisez comme source de revenus?**

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**III-11 Pourquoi vous ne beneficiez pas des biens et services de la foret classee?**

---

**III-12 Quelle est la part de contribution des biens et services de la foret classee dans l'alimentation de votre menage?**

- ◯ Nulle
- ◯ Peu important
- ◯ Assez-important
- ◯ Important
- ◯ Tres important
- ◯ Aucune idee

**III-13 Quelle est la part de contribution des biens et services de la foret classee dans le traitement des maladies dans votre menage?**

- ◯ Nulle
- ◯ Peu important
- ◯ Assez-important
- ◯ Important
- ◯ Tres important
- ◯ Aucune idee

**III-14 Quelle est la part de contribution des biens et services de la foret classee dans le revenu de votre menage?**

- ◯ Nulle
- ◯ Peu imortant
- ◯ Assez-important
- ◯ Important
- ◯ Tres important
- ◯ Aucune idee



Q

**III-15 Quel est de facon global selon vous la part de contribution des biens et services de la foret classee a la vie de votre menage?**

- ○ Nulle
- ○ Peu important
- ○ Assez-important
- ○ Important
- ○ Tres important
- ○ Aucune idee

## SECTION IV: FACTEURS DE DEGRADATION ET DE DEFORESTATION DE LA FORET CLASSEE

**IV-1 Avez-vous remarque des changements sur l'etat des ressources naturelles dans votre village ces 20 dernieres annees?**

- ○ Oui
- ○ Non

**IV-2 Quels sont les changements que vous avez observes ces 20 dernieres annees sur les ressources naturelles dans votre village?**

---

**IV-3 Quelle appreciation faites-vous de la dynamique des ressources naturelles dans votre village depuis ces 20 dernieres annees?**

- ○ Stable
- ○ Dimunition
- ○ Augmentation
- ○ Aucune idee

**IV-4 Quelles sont les causes de la dimunition des ressources naturelles dans votre village?**

---

**IV- 5 Quelles sont les causes de l'augmentation des ressources forestieres dans votre village?**

---

**IV-6 Avez-vous remarque des changements sur l'etat des ressources de la foret classee ces 20 dernieres annees?**

- ○ Oui
- ○ Non

**IV-7 Quels sont les changements que vous avez observes ces 20 dernieres annees sur les ressources de la foret classee?**

---



R

**IV-8 Quelle appreciation faites-vous de la dynamique des ressources de la foret classee ces 20 dernieres annees?**

- Stable
- Dimunition
- Augmentation

**IV-9 Quelles sont les causes de la dimunition des ressources de la foret classee?**

**IV-9 Quelles sont les causes de l'augmentation des ressources de la foret classee ?**

## SECTION V: MODALITES DE GOUVERNANCE DES RESSOURCES FORESTIERES DE LA FORET CLASSEE

**V-1 Existe t'il dans votre village une reglementation (traditionnelle/coutumiere) qui encadre la gestion des ressources forestieres?**

- Oui
- Non

**V-2 Qui est le garant de la reglementation traditionnelle/coutumiere dans votre village?**

**V-3 Quelle appreciation faites-vous du niveau de connaissance de cette reglementation traditionnelle/coutumiere par la population?**

- Aucune idee
- Pas connue
- Peu connue
- Assez-bien connue
- Bien connue
- Tres bien connue

**V-4 Quelle appreciation faites-vous du niveau de respect de la reglementation (traditionnelle/coutumiere) par la population?**

- Aucune idee
- Pas respectee
- Peu respectee
- Assez-bien respectee
- Bien respectee
- Tres bien respectee

**V-5 Existe t'il dans votre village une reglementation de l'administration publique qui encadre la gestion des ressources forestieres?**

- Oui
- Non

**V-6 Quelle appreciation faites-vous du niveau de connaissance de la reglementation de l'administration publique par la population?**

- Aucune idee
- Pas connue
- Peu connue
- Assez bien connue
- Bien connue
- Tres bien connue

**V-7 Quelle appreciation faites-vous du niveau de respect de la reglementation publique par la population?**

- Aucune idee
- Pas respectee
- Peu respectee
- Assez-bien respectee
- Bien respectee
- Tres bien respectee

## SECTION VI: CONTRIBUTION DES POPULATIONS A LA GOUVERNANCE DES RESSOURCES FORESTIERES DANS LA FORET CLASSEE

**VI-1 Avez-vous des actions et ou des pratiques que vous mettez en oeuvre pour une gestion durable des ressources de la foret classee?**

- Oui
- Non

**VI-2 Quelles sont les actions et ou pratiques que vous mettez en oeuvre pour la gestion durable des ressources de la foret classee?**

______________________________

**VI-3 Rencontrez-vous des difficultes qui entravent votre contribution a la gestion durable de la foret classee?**

- Oui
- Non



T

**VI-4 Quelles sont les difficultes que vous rencontrez qui entravent votre contribution a la gestion durable de la foret classee?**

______________________________

**VI-5 Avez-vous des besoins pour ameliorer votre contribution a la gestion durable de la foret classee?**

- ○ Oui
- ○ Non

**VI-6 Quels sont vos besoins pour ameliorer votre contribution a la gestion durable de la foret classee?**

______________________________

## SECTION VII: PHOTOS

**VII-1 Photo 1**

Click here to upload file. (< 10MB)

**VII-2 Photo 2**

Click here to upload file. (< 10MB)

**VIII-Coordonnees GPS**

______________________________

latitude (x.y °)

______________

longitude (x.y °)

______________

altitude (m)

______________

accuracy (m)

______________

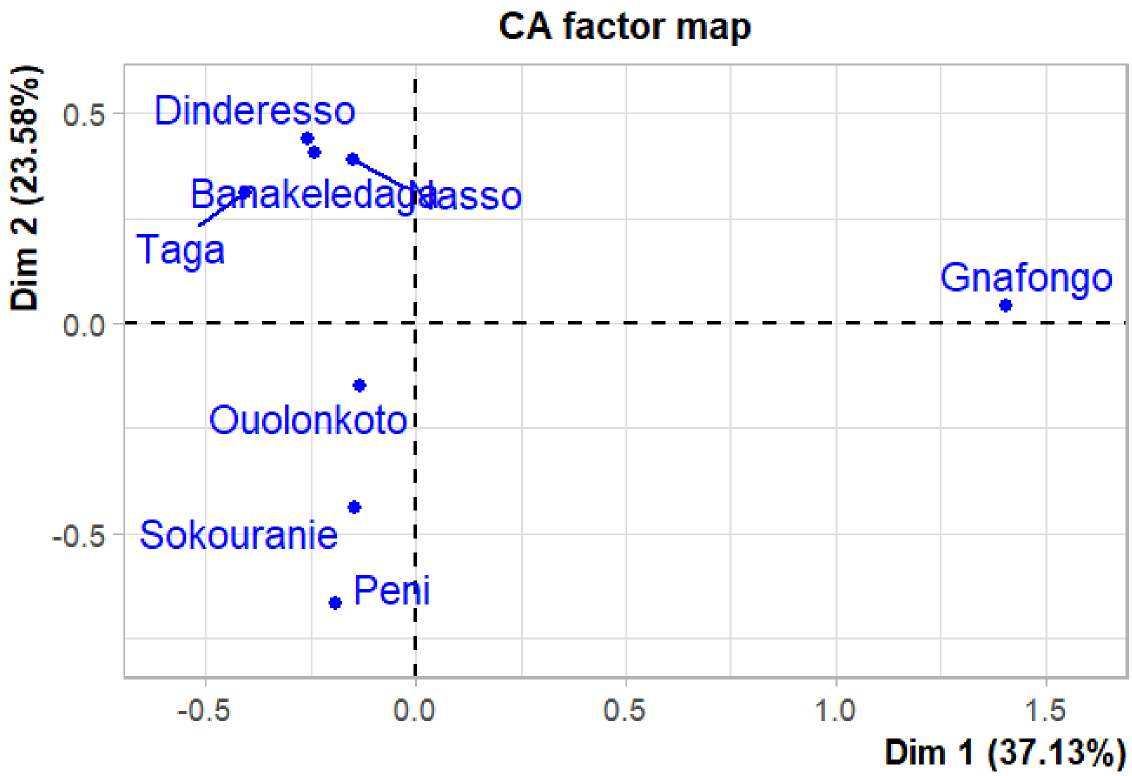


U

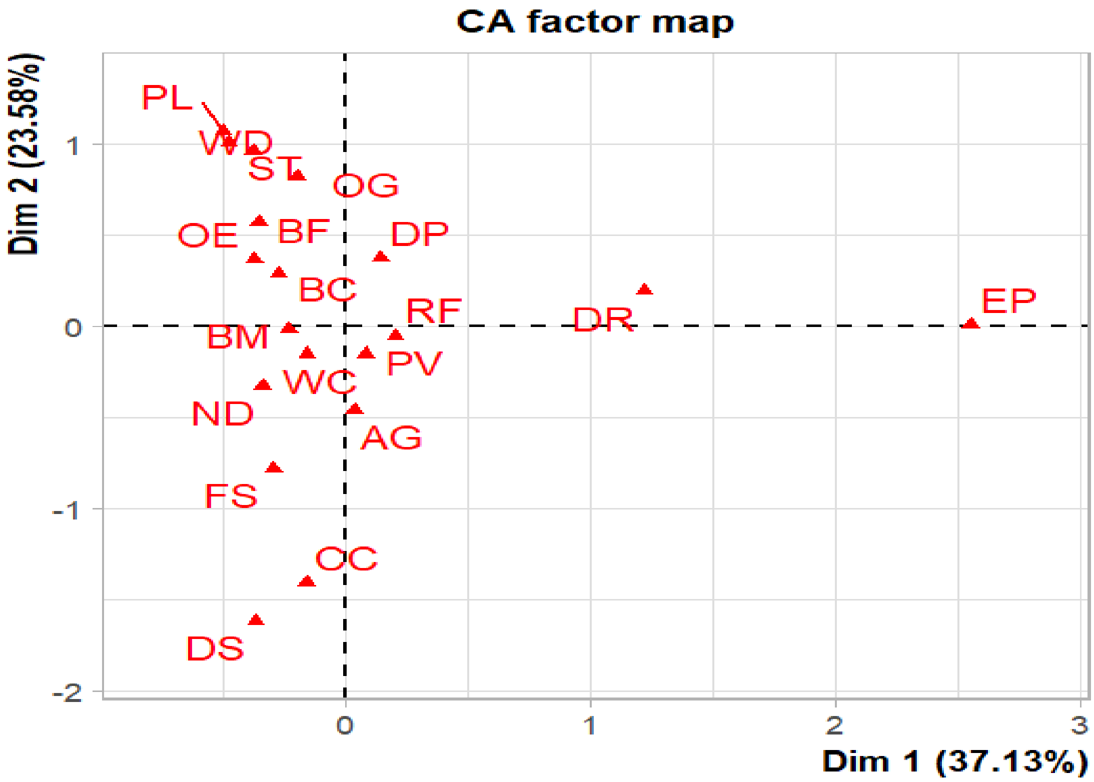
## Appendix 9: Corresponding Factorial Analysis chi-square test P-value and eigenvalues

| Chi-square test P-value | $1.810766e-31 \leq 0.05$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | Eigenvalues | | | | |
| **Component dimension** | Dim1 | Dim2 | Dim3 | Dim4 | Dim5 | Dim6 | Dim7 |
| **Variance** | 0.268 | 0.17 | 0.137 | 0.081 | 0.041 | 0.015 | 0.008 |
| **% of variance** | 37.132 | 23.583 | 19.032 | 11.224 | 5.738 | 2.117 | 1.174 |
| **Cumulative % of variance** | 37.132 | 60.715 | 79.747 | 90.971 | 96.709 | 98.826 | 100 |

## Appendix 10 : Neighboring communities' representation in components 1 and 2



## Appendix 11: Dinderesso and Peni classified forest degradation and deforestation drivers displayed in components 1 and 2




***Note***: *Bad management (BM); Demographic pressure (DP); Overexploitation (OE); Wood abusive cutting (WC); Overgrazing (OG); Natural death (ND); Agriculture (AG); Poverty (PV); Bushfires (BF); Silting (ST); Pollution (PL); Poaching (BC); Rainfall scarcity (RF); Wind (WD); Drought (DR); Charcoal production (CC); Elephant (EP); Diseases (DS); Soil fertility (FS).*

# Appendix 12: Corresponding factorial analysis rows and columns eigenvalues

```
Rows
                Iner*1000     Dim.1     ctr    cos2     Dim.2     ct
r
Banakeledaga |     87.340 |  -0.239   4.041   0.124 |   0.405  18.24
8
Dinderesso   |     60.105 |  -0.259   1.732   0.077 |   0.441   7.88
6
Gnafongo     |    234.373 |   1.405  87.243   0.996 |   0.041   0.11
4
Nasso        |     65.469 |  -0.151   1.357   0.055 |   0.389  14.12
3
Ouolonkoto   |    108.313 |  -0.133   1.309   0.032 |  -0.147   2.53
2
Peni         |    109.707 |  -0.190   2.563   0.063 |  -0.667  49.43
8
Sokouranie   |     25.481 |  -0.144   0.440   0.046 |  -0.441   6.45
6
Taga         |     30.075 |  -0.408   1.316   0.117 |   0.311   1.20
3
                 cos2     Dim.3     ctr    cos2
Banakeledaga    0.355 |   0.316  13.787   0.217 |
Dinderesso      0.223 |  -0.008   0.003   0.000 |
Gnafongo        0.001 |   0.061   0.324   0.002 |
Nasso           0.367 |  -0.042   0.209   0.004 |
Ouolonkoto      0.040 |  -0.693  69.296   0.878 |
Peni            0.766 |   0.289  11.480   0.144 |
Sokouranie      0.431 |   0.296   3.621   0.195 |
Taga            0.068 |   0.288   1.281   0.058 |

Columns (the 10 first)
                Iner*1000     Dim.1     ctr    cos2     Dim.2     ct
r
AG           |     22.842 |   0.038   0.028   0.003 |  -0.457   6.51
9
BC           |      6.486 |  -0.275   0.100   0.041 |   0.292   0.17
8
BF           |     75.646 |  -0.354   2.571   0.091 |   0.570  10.45
9
BM           |     27.982 |  -0.232   1.672   0.160 |  -0.011   0.00
6
CC           |     74.355 |  -0.159   0.266   0.010 |  -1.407  32.92
3
DP           |     35.243 |   0.144   1.243   0.094 |   0.374  13.25
8
DR           |     12.868 |   1.220   3.930   0.818 |   0.195   0.15
9
DS           |     15.158 |  -0.368   0.179   0.032 |  -1.617   5.43
6
EP           |    221.440 |   2.553  81.710   0.988 |   0.008   0.00
1
FS           |      9.720 |  -0.294   0.171   0.047 |  -0.777   1.88
5
                 cos2     Dim.3     ctr    cos2
AG              0.485 |   0.388   5.819   0.349 |
BC              0.047 |  -0.993   2.539   0.537 |
BF              0.235 |   0.605  14.635   0.265 |
BM              0.000 |   0.360   7.829   0.384 |
CC              0.753 |   0.745  11.431   0.211 |
DP              0.640 |   0.042   0.204   0.008 |
DR              0.021 |  -0.414   0.882   0.094 |
DS              0.610 |   0.779   1.564   0.142 |
EP              0.000 |   0.198   0.956   0.006 |
FS              0.330 |  -0.988   3.770   0.532 |
```