ASSESSING CITIES RESPONSE TO CLIMATE CHANGE IN THE SUDAN SAVANNA REGION OF WEST AFRICA THROUGH RENEWABLE ENERGY

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FEDERAL UNIVERSITY OF TECHNOLOGY MINNA

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A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (PhD) IN CLIMATE CHANGE AND HUMAN HABITAT

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DECLARATION

I hereby declare that this thesis titled: **"Assessing Cities Response to Climate Change in the Sudan Savanna Region of West Africa Through Renewable Energy"** is a collection of my original research work and it has not been presented for any other qualification anywhere. Information from other sources (published or unpublished) has been duly acknowledged.

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Federal University of Technology Minna, Nigeria

CERTIFICATION

This thesis, titled**: "Assessing Cities Response to Climate Change in the Sudan Savanna Region of West Africa Through Renewable Energy"** by DICKO Kagou (Ph.D./SPS/FT/2021/13004) meets the regulations governing the awards of the degree of PhD of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

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ABSTRACT

Climate change stands as a stark testament to the dramatic consequences of human actions on the planet. To better counter and mitigate its impact, several studies have been conducted worldwide. However, the contribution of such efforts is neither less nor more and is continuing to be made regardless of their results, as climate change is a matter of past, present, and future. This study is one of a number of such studies exploring how West African cities could respond to the effects of climate change by relying on renewable energy sources, using Kano and Bamako as case studies. For this purpose, it was necessary to account for the impact that climate change wrought on the two cities through the degree days method, using three decades of daily meteorological data. The findings revealed different trends, with Kano experiencing a positive variation in cooling degree days (Sen's slope = 2.308) and an increasing trend of 1.73 °C-day yr^{-1}, whilst in Bamako, a significant decreasing trend (p = 0.05) of -3.80 °C-day yr^{-1} was observed. Furthermore, Landsat data were used with Random Forest machine learning to evaluate spatiotemporal evolution in Kano and Bamako. The results of the land use maps showed the same pattern of rapid urban expansion, with built-up areas increasing from 66.88 to 242.53 km^2 representing 8.47% in annual growth rate in Kano and from 50.49 to 157.88 km^2 with an annual growth rate of 6.86% in Bamako. Meanwhile, other land use and land cover (LULC) classes, such as vegetation and bare land, decreased considerably over time in both cities. In the global context linking climate change and renewable energy as one of the solutions to its impacts, identifying suitable locations for solar power facilities is of paramount importance. This study has also addressed this concern by using the Analytic Hierarchy Process (AHP) in combination with Geographic Information Systems (GIS) to shed light on areas potentially suitable for the installation of solar power plants in the cities of Kano and Bamako. The findings revealed that Ungogo and Kumbotso in Kano, and Communes I and VI in Bamako, are the most suitable areas for solar energy development. An assessment of solar farm capacity revealed a notable gap between the two cities. In Kano, Bayero University (7.1 MW) and Ado Bayero Mall (1 MW) contributed to a total installed solar capacity of 8.1 MW, highlighting significant investment from both the academic and private sectors. Conversely, Bamako recorded only a single installation at the Institute of Applied Science, with a capacity of 0.1 MW, underscoring limited solar energy projects. The study also explored electricity access and cooking energy choices. The findings showed that approximately 64.8% of households in Kano are supplied with electricity by the Kano Electricity Distribution Company (KEDCO), compared to 35.2% who use solar panels. In Bamako, 91.5% of households receive electricity from Energy of Mali (EDM), while only 8.5% rely on solar panels as their source of electricity. Cooking energy choices further demonstrated disparities. In Kano, 42.9% of households used firewood and charcoal, while 31% relied on liquefied petroleum gas (LPG), 25.2% relied on electric stoves and only 0.6% used kerosene. In Bamako, biomass dominated, with 90.6% of households depending on firewood and charcoal, while only 9.2% relied on LPG. Moreover, the study explored the factors influencing renewable energy adoption through structural equation modeling and identified cost as a significant barrier to deployment. However, perceptions toward renewable energy varied by city. In Bamako, belief in its benefits promoted development, whereas in Kano, energy demand, social acceptance, and perceived advantages were the main drivers. The findings suggest the need to implement targeted policies to reduce costs, promote clean cooking energy solutions, and improve public awareness. Simultaneously, efforts should prioritise the development of solar energy infrastructure in areas identified as most suitable to enhance energy access and climate resilience in both cities.

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LIST OF ABBREVIATIONS AND ACRONYMS

AGW	Anthropogenic Global Warming
AHP	Analytic Hierarchical Process
AMADER	Agency for the Development of Domestic Energy and Rural Electrification
CDD	Cooling Degree Days
CFA	Confirmatory Factor Analysis
CO2	Carbon Dioxide
ECN	Energy Commission of Nigeria
ECOWAS	Economic Community of West African States
EDM SA	Energy of Mali
FA	Factor Analysis
GHG	Greenhouse Gas
GHI	Global Horizontal Irradiation
GIS	Geographic Information System
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
HI	Heat index
ICCC	Inter-Ministerial Committee on Climate Change
ICRC	International Committee of the Red Cross
IPCC	Intergovernmental Panel on Climate Change
IT	Information Technology
KEDCO	Kano Electricity Distribution Company
LGA	Local Government Area
LULC	Land Use and Land Cover
MCDM	Multiple-Criteria Decision-Making
Mtoe	Millions of tonnes of oil equivalent

NASA	National Aeronautics and Space Administration
NASA-POWER	National Aeronautics and Space Administration Prediction of Worldwide Energy Resources
NCCS	Malian National Climate Change Strategy
NDC	Nationally Determined Contributions
NEPA	National Electric Power Authority
NESCO	Nigerian Electricity Supply Company
NIMBY	Not In My Back Yard
NiMet	Nigeria Metrological Office
NREEEP	Nigerian National Renewable Energy and Energy Efficiency Policy
PANER	National Renewable Energy Action Plan
PHCN	Power Holding Company of Nigeria
REAN	Renewable Energy Association of Nigeria
REIPPPP	Renewable Energy Independent Power Producer Procurement Programme
SDG	Sustainable Development Goal
SE4ALL	Sustainable Energy for All Action Plan
SREP	Renewable Energy in Low Income Countries Program
SRTM	Shuttle Radar Topography Mission
SSE	Surface meteorology and Solar Energy
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TPB	Theory of Planned Behaviour
UNFCCC	United Nations Framework Convention on Climate Change
UNPD	United Nations Development Programme
USAID	United States Agency for International Development
VAR	Vector Auto Regression

WAEMU	West African Economic and Monetary Union
WHO	World Health Organization

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Climate change is no longer a distant threat but a present reality, reshaping lives, economies, and environments across the globe. As global temperatures continue to rise and extreme weather events occur more frequently, cities are on the front line of this crisis, particularly in vulnerable regions. The dependence on traditional energy systems has been pointed out as the main drivers of climate change, underlining the urgent necessity for sustainable solutions to mitigate greenhouse gas emissions. At the core of this challenge lies the paramount role of renewable energy, which provides a pathway to mitigate climate impacts while simultaneously fostering urban resilience.

Urban responses to climate change involve diverse strategies aimed at mitigating its effects and adapting to its challenges. These responses range from infrastructural adaptations to policy reforms and energy transitions aimed at enhancing urban resilience. In contrast to fossil fuels, which contribute to climate change through increased emissions of greenhouse gases (GHG), renewable energy adoption can make a significant impact on how cities address climate change.

Over the last few years, there has been a considerable body of literature on cities taking proactive measures addressing climate change through the adoption of renewable energy resources. Global efforts to address climate change have been led by cities such as Copenhagen and Singapore, which have developed comprehensive strategies involving the development of renewable energy projects, green infrastructure, and the planning of urban resilience. The city of Copenhagen has implemented nature-based solutions to address climate-induced hazards, integrating green infrastructure to manage stormwater and reduce urban heat islands (Jørgensen *et al.*, 2022). Meanwhile, Singapore is proactively addressing climate change by implementing policies to mitigate greenhouse gas emissions and adapt to its effects, supported by robust governance structures but challenged by the reliance on untested technologies (McGreevy and Chia, 2024). Following Germany's long journey dedication to climate action, the federal government's "Energiewende" policy represents a comprehensive strategy for shifting to a low-carbon, renewables-based energy future. A key goal of such policies is to enhance urban climate resilience through adoption of renewable energy (Chen, 2024). However, the success stories of the global North often starkly contrast with the realities of cities in the global South, where financial, technical, and institutional barriers impede progress.

In Africa, although it remains the most vulnerable continent to the climate challenges, and notwithstanding the continent's immense potential for renewable energy, its contribution to the energy transition is lagging far behind, due to a lack of adequate infrastructures. However, progress is evident in countries like South Africa, where initiatives such as the Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) has been a significant driver of renewable energy adoption in the country (Müller and Claar, 2021).

In West Africa, countries like Ghana have made significant progress in deploying solar energy, but persistent challenges include policy implementation issues, limited public awareness, and inadequate infrastructure development. A further significant implementation gap exists in several countries for emission reduction policies, according to the IPCC (2023), which could result in higher global greenhouse gas (GHG) emissions by 2030 compared to the levels targeted in Nationally Determined Contributions (NDCs).

The lack of integrated approaches that link renewable energy to broader climate adaptation and mitigation goals is more evident locally in the cities of Kano and Bamako. Kano, Nigeria's second largest city, is confronted with frequent power cuts from day to day and relies heavily on diesel generators, contributing to air pollution and high energy costs. On the other hand, charcoal and kerosene were reportedly the energy sources most used by households in Kano (Kiyawa *et al.*, 2017). This reliance on fossil fuels and traditional energy sources highlights a critical gap in the city's energy infrastructure and underscores the urgent need for cleaner, more sustainable alternatives.

Similar environmental concerns have been observed in Bamako, the capital of Mali, exacerbated by rapid urbanisation and limited infrastructure. The city's growing population has led to increased energy demand, much of which is met through unsustainable means such as charcoal and firewood. This not only contributes to deforestation and carbon emissions but also places a heavy burden on vulnerable communities, particularly women and children, who are often responsible for collecting fuelwood. Moreover, the absence of reliable electricity and the high cost of energy hinder households and businesses' transition to cleaner energy option.

These challenges underscore the need for targeted research to explore how renewable energy can be effectively leveraged to enhance urban climate resilience. The purpose of this study is to investigate the role of renewable energy in strengthening cities' response to climate change, with a focus on Kano and Bamako. The study aims to contribute to an understanding assessment of climate change impacts, the development of evidence-based strategies for renewable energy adoption, effective responses to urban climate responses in Kano and Bamako.

1.2 Statement of the Research Problem

The Sudan Savanna region, home to at least 80 tree species, remains of paramount importance in West Africa due to its large amounts of carbon, thus promoting exchanges between ecosystems and atmosphere (Ahlström *et al.*, 2015; Aubréville, 1938; Elberling *et al.*, 2003; Scholes and Hall, 1996), and develop livelihood support of people and biodiversity. Furthermore, the agricultural potential of the Sudan Savanna has been widely acknowledged over the years because of its favourable climatic conditions particularly for annual grain crops (Callo-Concha *et al.*, 2013; Franquin and Cocheme, 1967). Additionally, its limited tsetse fly presence enhances its importance as a pastoral region, which undoubtedly plays an essential role for the livelihoods of the local people (Kassam *et al.*, 1976).

However, the region of West Africa is significantly affected by climate change, with the cities of Kano and Bamako being particularly affected. Although national governments have implemented various strategies to adapt to and mitigate the impacts of climate change, progress has been slow. Meanwhile, it has been widely recognised that the energy sector is potentially an important sector to mitigate greenhouse gas emissions by implementing energy policy that encourage the usage of renewable energy which plays a critical role for climate change mitigation, improve air quality, wealth and development. For example, Mali committed to reduce GHG emissions in the energy sector by developing renewable energy technologies such as hydropower, solar energy, and wind (NDCMali, 2021), but it does not seem to work because firewood is the most used energy in households in the country including Bamako, the capital city (Coulibaly *et al.*, 2021; Gazull *et al.*, 2019). Similar aspects have been observed in the metropolis of Kano with wood fuel, kerosene and charcoal (Kiyawa *et al.*, 2017). Several authors claimed that there is no effective climate policy without joined up collaborative approaches that involve all levels of government (Kern and Gotelind Alber, 2008).

For many years, it has been acknowledged that the emphasis on addressing climate change globally has largely been on nation-states, which have often struggled to negotiate extensive agreements or implement successful actions (Rosenzweig *et al.*, 2010). As far as Kano and Bamako are concerned, there are few initiatives in the renewable energy sector aimed at climate change adaptation and mitigation at the national level in either country (Dioha and Emodi, 2018; Druet *et al.*, 2021; Elum and Momodu, 2017). Besides, it makes more sense to concentrate these efforts at the city scale in order to build stronger barriers against climate change. However, despite the implementation of renewable energy policies to facilitate their deployment, it still seems to be stalled and the dependence on unsustainable energies such as firewood, charcoal which have already been linked to deforestation thereby contributing to the disruption of our climate which is still very persistent. More importantly, in order to know how far the expansion of renewable energies can be taken, it is essential to assess the current renewable energy potentials, which are not immune from the prevailing weather conditions.

In light of cities responding to climate change impacts, dozens of studies have addressed the importance of renewable energy in an era of climate change in West Africa (Elum and Momodu, 2017; Epule *et al.*, 2021; Gazull *et al.*, 2019; Lwasa *et al.*, 2018; Maiga *et al.*, 2008; Nygaard *et al.*, 2010; Oyedepo *et al.*, 2019; Shaaban and Petinrin, 2013) using different methods. For example, Nygaard *et al.* (2010) used satellite images to map renewable energy and the potential zones for the whole Mali, without mentioning their means of deployment. Similarly, Gazull *et al.* (2019) made a survey analysis of energy use in Bamako, however relied solely on the social aspect. Furthermore, Oyedepo *et al.* (2019) have also worked on the centralisation of power generation in Nigeria without addressing the policies options. Despite these contributions, there remains a significant gap in comprehensive studies that examine the current status of renewable energy adoption, identify barriers to its development.

1.3 Research Questions

This study is guided by the following research questions:

i. How has climate change affected the cities of Kano and Bamako?
ii. How have the cities of Kano and Bamako expanded in the last 30 years?
iii. What is the actual potential of renewable energy that could support climate change adaptation and mitigation?

iv. What is the current status of renewable energy adoption in Kano and Bamako, and what factors influence the deployment of renewable energy in these cities?

1.4 Aim and Objectives

This research aims to assess two selected cities' response to climate change in the Sudan Savanna of West Africa through renewable energy.

1.4.1 Specific objectives

This study aims to achieve the following objectives:

i. Analyse the trends of cooling degree days and heat index between 1992 and 2022

ii. Evaluate the LULC change of the study area over the period 1992-2022

iii. Identify suitable locations for installing solar powerplants

iv. Examine the current status of renewable energy adoption and potential barriers for renewable energy development

1.5 Research Hypotheses

Ho1: There is no significant trend in cooling degree days (CDD) between 1992 and 2022.

Ho2: There is no significant trend in the heat index (HI) between 1992 and 2022.

Ho3: There is no significant change in land use and land cover (LULC) in the study area between 1992 and 2022.

Ho4: There are no significant spatial variations in the suitability of locations for solar power plant development in the study area.

Ho5: Increased energy demand positively influences the adoption of renewable energy.

Ho6: Environmental knowledge is expected to positively affect the implementation of renewable energy.

Ho7: Public acceptance positively contributes to the deployment of renewable energy.

Ho8: Positive beliefs regarding the benefits of renewable energy are likely to enhance its deployment.

Ho9: Perceptions of renewable energy costs negatively impact its adoption.

1.6 Justification for the Study

Unlike in previous decades, cities are now recognised as critical arenas for climate change mitigation and adaptation efforts. This study provides a comprehensive analysis of the current impacts of climate change on the cities of Kano and Bamako, as well as strategies for adaptation and mitigation centered on renewable energy. The research also aligns with the 7th and 13th Sustainable Development Goals (SDGs), which focus on ensuring access to affordable and clean energy and taking urgent action to combat climate change. By addressing these goals, the study contributes to the global effort to promote sustainable development.

This study provides the foundation for shaping policies that mitigate trends, aligning with the National Action Plan for Renewable Energy (PANER), which seeks to install 1.42 gigawatts of renewable energy in Mali and across the West African Economic and Monetary Union (WAEMU), of which Mali is a member. Furthermore, it contributes to the advancement of renewable energy technologies under Nigeria's National Renewable Energy and Energy Efficiency Policy (NREEEP) and supports Mali's National Climate Change Strategy (NCCS).

The findings of this study are relevant for national and international organisations such as the Renewable Energy in Low Income Countries Programme (SREP), Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), International Committee of the Red Cross (ICRC), United Nations Development Programme (UNDP), and United States Agency for International Development (USAID). These organisations can apply the results to improve operational performance in renewable energy deployment, disaster risk reduction, and climate adaptation strategies. Specifically, it highlights priority areas for solar power installations, enabling improved resource allocation and project execution.

Furthermore, this research stimulates further studies by providing a framework for assessing the intersection of climate change and renewable energy adoption in urban settings. The methodologies employed, such as the use of Cooling Degree Days (CDD) for trend analysis and Geographic Information Systems (GIS) with the Analytic Hierarchy Process (AHP) for identifying suitable locations for solar power plants, can be replicated or expanded upon in other regions. Researchers can explore additional renewable energy technologies, comparative studies across similar climates, and socio-economic impacts of renewable energy adoption. By addressing these gaps, future studies can deepen the understanding of renewable energy as a solution to climate challenges.

Finally, this study contributes significantly to advancing the frontiers of knowledge in climate adaptation and renewable energy development. It provides decision-makers, climatologists, engineers, and entrepreneurs with critical insights into the potential and practicality of renewable energy technologies. The findings enrich ongoing discourse on urban climate resilience, renewable energy policy, and sustainable development, serving as a resource for revising, refining, and extending theoretical and practical approaches in the field.

1.7 Scope and Limitation of the Study

1.7.1 Scope of the study

The temporal scope of this study spans from 1992 to 2022, covering a 30-year period. This duration aligns with the standard climatological baseline recommended by the World Meteorological Organization (WMO) for assessing long-term climate change (IPCC, 2007). The chosen period ensures that both historical shifts and more recent trends in environmental and energy-related patterns are adequately captured.

This study focuses on two urban centres, Kano in Nigeria and Bamako in Mali. Both cities being situated within the Sudan Savanna zone of West Africa, a region known for its ecological sensitivity and vulnerability to climate change impacts (Aleman *et al.*, 2016). These cities were selected due to their high population densities, substantial solar energy potential, and increasing energy demand, making them ideal case studies for examining urban responses to climate change through the adoption of renewable energy.

The scope of the study encompasses the analysis of urban climate impacts, land use and land cover transformations, solar energy site suitability, and societal perceptions of renewable energy, with a specific focus on photovoltaic solar systems. Furthermore, the study does not cover agricultural or industrial energy systems; instead, it concentrates on the urban household and infrastructure scale, where energy demand and exposure to climate stress are most pronounced.

1.7.2 Limitation of the study

While this research provides a multidimensional understanding of climate-driven energy needs in urban West Africa, it is subject to several limitations. The selection of only two cities, though methodologically justified for comparative insights, limits the generalisability of findings across other cities in the region that may exhibit different climatic, infrastructural, and governance dynamics. The exclusive focus on solar energy, while reflecting current national energy priorities and feasibility constraints, does not account for the potential roles of complementary renewable technologies, which could offer diversified solutions under varying environmental and socio-economic contexts. Another limitation is the absence of future climate projections, such as downscaled climate scenarios from regional models, which could have enriched the long-term strategic planning dimension of the research.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Conceptual Framework

To better grasp the phenomenon of climate change, several experts have set out to define the term "climate change". So, what is climate change? According to (IPCC, 2007) "climate change refers to a change in the state of the climate that can be identified (for example, using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer". Furthermore, in its Third Assessment Report, the IPCC further affirmed that the Earth's climate is changing due to human activities, particularly energy use, and that further changes are inevitable. On the other hand, the United Nations Framework Convention on Climate Change (UNFCCC) defines climate change as "a change in climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable periods of time" (UNFCC, 1992).

While climate change unfolds over an extended period, the magnitude of its deviation from normal conditions and the resulting environmental impacts are profoundly significant. Indeed, climate change has become evident in several regions of West Africa. According to Mohammed *et al.* (2019), Kano metropolis has experienced upward changes in temperature of about 2°C was recorded in 2018 (27.7°C) compared to 25.9°C in the 1980s. These changes have been accompanied by the emergence of urban heat islands and increased rainfall variability, largely driven by anthropogenic activities such as land use changes, vegetation loss, and land degradation. Similarly, several authors, including (Touré Halimatou *et al.*, 2017), Diallo and Bao (2010) and Fofana *et al.* (2022) have shown the evidence of climate change in the city of Bamako with extreme rainfall events, increasing temperature, flash flood among others. As reported by Dodman (2008), the floods of the year 2002 have left 4,000 houses in ruins in Bamako, and the city is experiencing extreme difficulties in accessing water.

Furthermore, available evidence suggests that climate change is likely to increase the vulnerability of all agro-ecological zones in Mali through rising temperatures and inconsistent rainfall, dramatically affecting food security and economic growth (Butt *et al.*, 2006; Dell *et al.*, 2012), and sea level rise is expected to intensify the impacts of flooding in large rivers, especially the Niger River, potentially resulting in serious implications for Mali (Magadza, 2000). Additionally, it is anticipated that the country is expected experience a rise in average temperatures of 1 to 2.75°C by 2030, followed by an increase of 2 to 4°C prior to 2060 (Butt *et al.*, 2005, 2006; Konate, 2010). Findings have shown that Nigeria is already facing various environmental challenges, which have been directly linked to current climate change (Ayuba *et al.*, 2007; Chindo and Nyelong, 2004; Mshelia, 2005; Odjugo and Isi, 2004). Meanwhile, recurrent events such as unpredictable rainfall and rising temperatures are also considered manifestations of climate change. These trends are expected to intensify, particularly in the northern and southern regions of Nigeria, worsening existing challenges such as droughts, flooding, and the submersion of coastal areas (Ayanlade *et al.*, 2017; Nebedum *et al.*, 2016; Odjugo, 2006; Odjugo, 2001; Oladipo, 2010; Ololube *et al.*, 2015).

In contrast to the IPCC definition of climate change, the one from the UNFCCC establishes a distinction between changes caused by human activities that affect atmospheric composition and natural climate variability. This distinction is significant for this study, especially insofar as it refers to changes in atmospheric composition largely driven by greenhouse gas emissions. This is further corroborated by Dodman (2009) and Hegerl and Cubasch (1996), who assert that climate change is largely driven by the levels of greenhouse gases in the atmosphere that trap solar heat within the Earth’s lower atmosphere.

According to the AAAS (2019), addressing the challenges posed by climate change necessitates two primary approaches: adapting to changes that are currently happening or anticipated in the future (adaptation), and limiting the extent of these changes by reducing or eliminating greenhouse gas emissions (mitigation). Verheyen (2005), suggests that adaptation focuses on preventing direct damage, whereas mitigation aims at indirect damage prevention. However, some scholars have noted that failures often stem from a lack of integration between adaptation and mitigation strategies (for example, Landauer *et al.*, 2015). In contrast, other researchers, such as Ulsrud *et al.* (2008), Winkler and Marquand (2009), have characterized responses as mechanisms to advance sustainable development pathways, which include transitions to low-carbon economies, biofarming, horticulture, agroforestry, ecological sanitation, water harvesting, solar-powered water purification, innovative transportation systems, decentralised energy solutions, recycling, and participatory crop breeding.

Nevertheless, in both cases, it is a matter of taking action to confront the serious repercussions of climate change on global production, human livelihoods and the environment, whether by adapting to or mitigating its effects at national or local scales. However, as anthropogenic activities have allegedly caused climate change and are continuing to do so, especially with the increasing of urban population, global efforts have concentrated predominantly on mitigation measures.

Among various methods regarding mitigating climate change, reducing GHG emissions through renewable energy technologies is among the most widely embraced. Referring to IPCC (2011) report, renewable energy is defined as “any form of energy from solar, geophysical or biological sources that are replenished by natural processes at a rate that equals or exceeds its rate of use”. For many years, there has been a rising interest on urban responses to climate change, along with a considerable emphasis on their critical role in addressing the challenge.

Consequently, to ensure that any city response to climate change aftermath is not in vain, efforts must be directed towards sustainable solutions that minimise long-term adaptation costs.

The conceptual approach of this study (Figure 2.1), is based on the two variables discussed so far, climate change and how to respond to its impact at city scale using renewable energy. These variables are deeply interlinked, with renewable energy serving as a vital tool in tackling climate change, contributing to both mitigation efforts and adaptation strategies. Therefore, in this study, a response is defined “as any action taken by a region, city, nation, community, or individual to cope with or address climate change impact, either in anticipation of such change or after it has occurred including all factors that enable and constrain that action”.

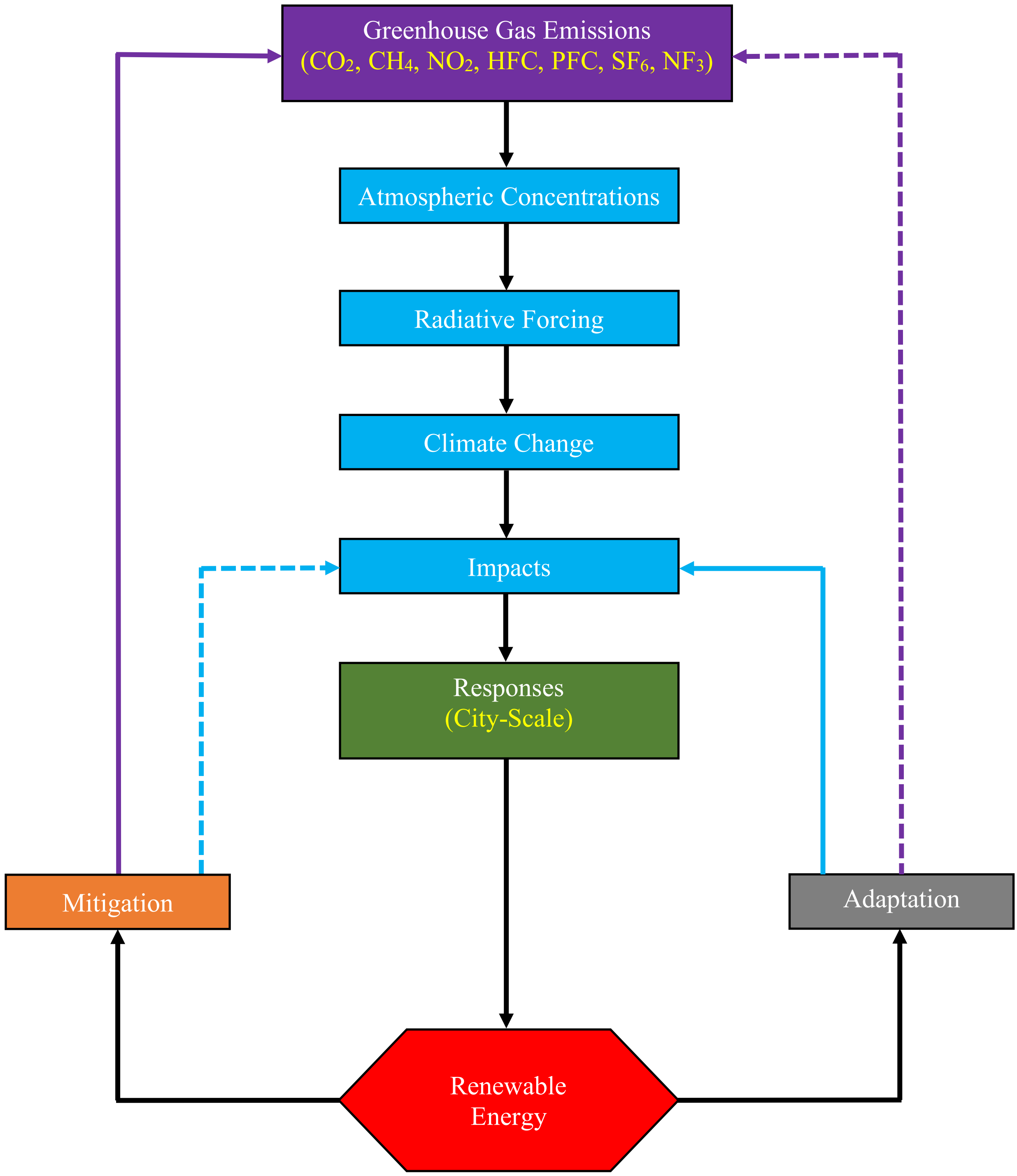


Figure 2.1 Conceptual Framework for the Study

2.2 Theoretical Framework

2.2.1 Anthropogenic global warming (AGW) theory

The theory of anthropogenic climate change posits that human activities, particularly the combustion of fossil fuels such as coal, oil, and natural gas, are the primary drivers of contemporary climate change. The scientific community overwhelmingly concurs that climate change is causing significant harm to the environment. Numerous peer-reviewed studies indicate that 97% of climate scientists agree that human actions are the principal cause of climate change.

The Intergovernmental Panel on Climate Change (IPCC), the leading authority advocating for the understanding of anthropogenic global warming concluded that Earth planet had been heating up in an accelerated pace of about 0.8° during the 20th century, and that this warming is entirely due to human activity, with natural variations of only about 0.2° at maximum (IPCC, 2007). Furthermore, supporters of the anthropogenic global warming theory human-induced CO_2 emissions are driving a range of environmental crises, including flooding, droughts, extreme weather events, crop failures, species loss, the spread of diseases, rising sea levels, and famines (Bast, 2010). In addition, Susan (2016) evaluated the consistency of AGW theory by reviewing 24,210 papers from 69,406 authors, and found that on average 99.99% of publishing scientists accept Anthropogenic Global Warming with near unanimity. Other writers such as Cook *et al.* (2013) a review of 11,944 climate abstracts from 1991 to 2011, covering the themes of “global climate change” or “global warming,” revealed that 97.2% of the studies supported the conclusion that humans are causing global warming.

First, before embarking on any climate change mitigation and adaptation measures, it is imperative to understand what is causing climate change. Therefore, as Anthropogenic Global Warming theory clearly demonstrates that climate change is largely due to human activities, thus it has become an important tool in showing where to take decisions to respond to climate change.

Actually, we know we should do something to change the climate by significantly reducing the causes of its disturbance, but we prefer to choose to do nothing. For instance, Parncutt (2019) reported that if anthropogenic emissions were to cease abruptly, half of the human-produced CO_2 could be removed within decades, depending on the health of the planet's oceans and forests, though a smaller portion can linger for millennia. However, a smaller fraction could persist for thousands of years. Only a rapid and substantial reduction in human emissions can prevent catastrophic consequences. Embracing renewable energy offers a potential solution to reducing emissions from human activities responsible for global warming.

2.2.2 Not in my back yard (NIMBY) theory

The Nimby (Not In My Backyard) theory revolves around the social resistance to the siting of necessary facilities, infrastructure, and services, despite their importance in meeting collective needs. NIMBY has been used mostly to describe and pejoratively refers to people who oppose development (Burningham, 2000; Devine-Wright, 2011). This theory has thus been used to explain the attitudes of those who oppose the development of potentially hazardous facilities (such as landfills, power plants, location, incinerators, and cell phone antennas), renewable energy technologies plants (such as solar and wind energy) as well as protests, incinerators, and cell phone antennas), and also protests against "unwanted" human services facilities (such as alcohol rehabilitation centres, prisons, and homeless shelters)

Several authors have been using NIMBY theory for one reason or another and have shown its characteristics. For example, Freudenburg and Pastor (1992), identified three distinct perspectives of NIMBY. The first perceives NIMBY as an ignorant response; hence, where the public is considered misinformed, prompting planners either to educate them or disregard their objections. The second sees NIMBY as a self-serving response, considering such opposition less important than those based on broader societal or environmental concerns. The final perspective considers NIMBY as a rational response, where local resistance reflects legitimate concerns over the effects of new projects. Similarly, Devine-Wright (2011) and O'Neil (2021). Researchers have utilised the NIMBY theory to effectively examine community acceptance of renewable energy projects. The NIMBY concept is frequently cited to explain the perceived "social gap" between widespread public support for renewable energy and the frequent local resistance to specific project proposals (Bell *et al.*, 2005).

Going beyond mere discussion and understanding of the attitudes of people who object to the acceptance of facilities to find a solution for the social group is an extraordinary thing. Ergo, the Nimby theory seems to be effective as long as this study already aims to address why renewable energy deployment is slowing down and how this problem can be solved for the public benefit by mitigating climate change.

The relationship between climate change and the strategies developed to respond to its effects is deeply interconnected. Considering that renewable energy technologies are acknowledged to be an effective solution to global warming, the Nimby theory explicitly outlines the problems and solutions faced when deploying such technologies in the community.

2.2.3 Theory of planned behaviour (TPB)

The Theory of Planned Behaviour (TPB) is a psychological theory developed by Ajzen (1985) which suggests that an individual's choice and decision to participate in a particular behaviour, such as playing or quitting a game, can be predicted by his or her intention to engage in that behaviour. As illustrated in Figure 2.2, the Theory of Planned behaviour stipulates that intention towards attitude, subject norms and perceptual behavioural control altogether determine the behavioural intentions and behaviours of an individual. It is basically an extension of the theory of reasoned action by including the concept of perceived behavioural control, defined as an individual's perception of the ease or difficulty of performing a particular behaviour (Douglas and Howard, 2015).

The Theory of Planned Behaviour has received considerable attention in the literature, applied in several fields such as health, psychology, climate change, renewable energy and many others. For instance, Hrubes *et al.* (2001) applied the Theory of Planned Behaviour to give prediction and explanation of hunting presented results that strongly support the effectiveness of the theory. Moving forward, Pourmand *et al.* (2020) have also used TPB to self-care in patients with hypertension. Moreover, Liobikienė *et al.* (2021), Yee *et al.* (2022) and Read *et al.* (2013) reported on the effectiveness of the theory in the deployment and public acceptance of renewable energy technologies. According to Armitage and Conner (2001), from a database of 185 independent research studies conducted to the end of 1997, the TPB contributed 27% and 39% of the variance in behaviour and intention, respectively.

To promote sustainable development and tackle climate change, several recent research papers such as Irfan *et al.* (2021), Gamel *et al.* (2022), Daiyabu *et al.* (2022), Bhutto *et al.* (2020) have used the TPB and shown its relevance in addressing the barriers of public participation in renewable energies deployment. Therefore, as renewable energy development is part of the purpose of this study, the use of such theory is particularly necessary for the study.

The Theory of Planned Behaviour appears to be useful for this study that it provides an understanding of the behaviour and intentions of the population towards renewable energy. As a result, it promotes policy consistency and drives the adoption of renewable energy to lower greenhouse gas emissions.

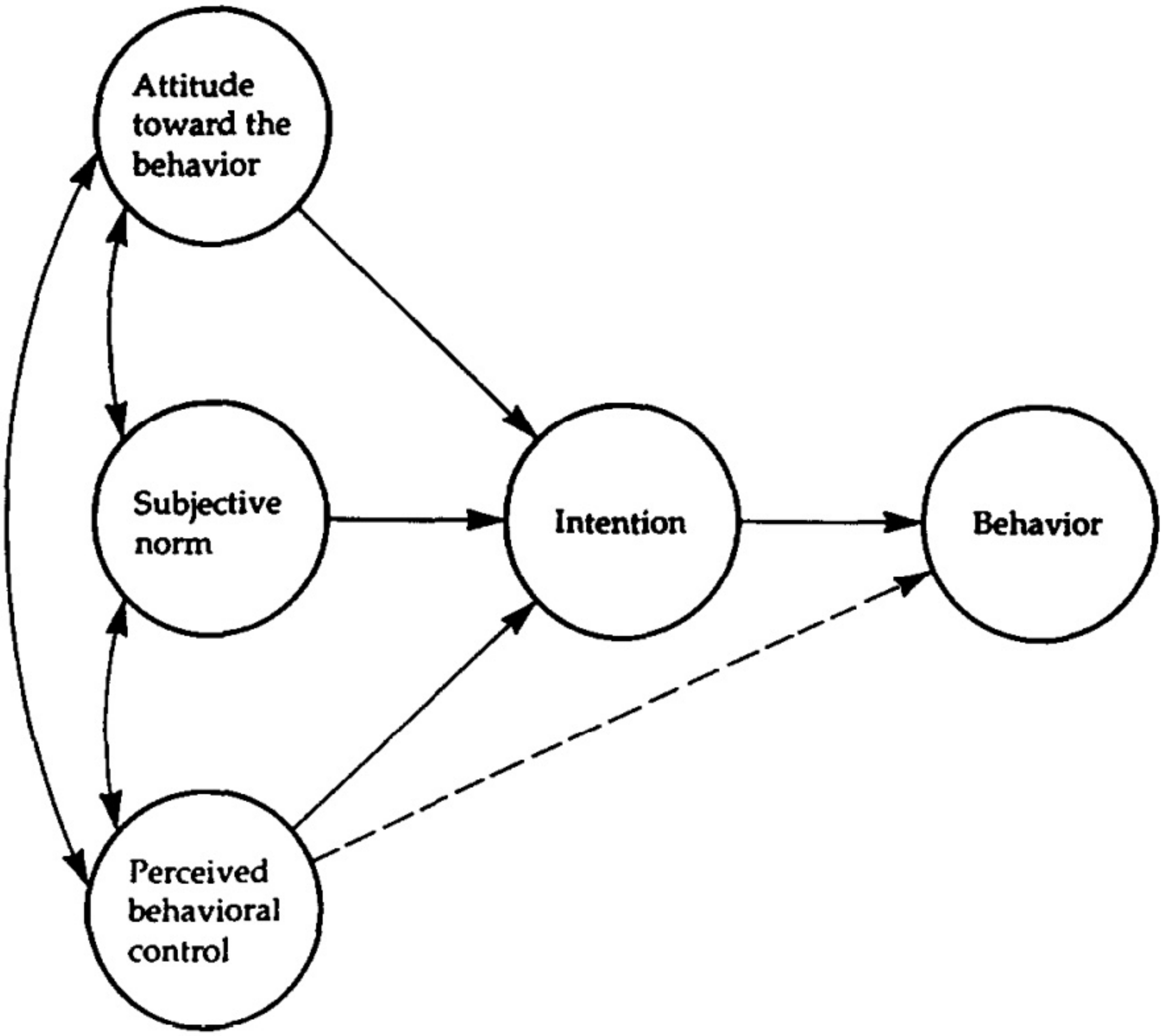


Figure 2.2 Theory of Planned Behaviour

Source: Ajzen (1985)

2.2.4 Prospect theory

Over a decade of laboratory experiences have revealed that people consistently break the principles of subjective expected utility theory (Kahneman *et al.*, 1982). These results enabled two psychologists Daniel Kahneman and Amos Tversky, to develop Prospect theory and to present it as a leading alternative approach for explaining individuals' choices under conditions of risk. Prospect theory postulates that losses and benefits are valuated in different manners, therefore individuals make decisions on the basis of perceived benefits rather than perceived losses. The theory argues that the interpretation of choices, as gains or losses, influences the level of risk taken. Bringing it in the climate change arena, losses can be seen as all damages due to changes in the climate and benefits as the policy climate implemented to reduce these losses.

Prospect theory has received much attention, involving several scientific researches as a powerful theory of behaviour even though its use appears to be more widespread in economics where the theory's creators have won a Nobel Prize in economics. Although measures to respond to the impacts of climate change include an economics input. Getting back to what we are interested in, for example, climate change, Osberghaus (2017) has explored in a comprehensive way the relevance of Prospect theory in the concept of adaptation and mitigation of climate change. Some authors such as Häckel *et al.* (2017) have also proved its efficiency by testing it to explain the energy efficiency gap. In a similar way Cheng *et al.* (2020) have also applied Prospect theory to a study of low-carbon lifestyle promotion across policies leading to a recommendation for its applicability in the context of addressing climate change issues.

However, it is important to note that Prospect theory addresses an individual decision. Admittedly, many climate decisions are made collectively, including policy makers and other stakeholders. Once, these are established, though, decisions may directly involve one individual to another. For example, making the decision not to drive a car, or not to use fossil fuels in the house, or deciding to use renewable energy, or any other decision aimed at protecting the environment, most often requires individual decisions. Therefore, considering that collective decisions when formulating policies require individual decisions from their formulation to their implementation, Prospect theory can show its usefulness for this study in this sense of understanding.

Although the environmental justifications for renewable energy technologies are convincing, there is still a gap in their use by society. Prospect theory emphasises the value of decisions taken today to deal with a current crisis rather than those taken to address future events. In fact, it shows how important immediate decisions are important in reducing damages on people and their environment. Aside from that, what evidence exists that decisions are made tomorrow, or that someone else makes decisions when no longer part of this world?

Under these uncertain conditions that mankind is constantly experiencing, it actually could be better to act and focus on the benefits that the world could have in accepting renewable energy sources than to concentrate on the future losses. With that in mind, Prospect theory serves as a powerful tool and introduces a novel element to this study, encapsulated in six simple words: act wisely now to reap future benefits.

2.2.5 Multi-criteria decision-making (MCDM) theory

The Multiple-Criteria Decision-Making (MCDM) theory involves using information technology approaches to evaluate and select the most suitable option from several alternatives, integrating multiple criteria and ranking preferences to achieve the desired outcome. By employing computational and mathematical tools to support subjective assessments of performance criteria, MCDM has been widely recognised as a powerful theory and technique for decision-making. It serves as an umbrella term for various methods that aid individuals in making decisions based on their preferences, particularly when faced with multiple conflicting criteria (Ho, 2008).

The most of GIS-based site suitability studies utilise Multiple-Criteria Decision-Making (MCDM) to analyse and synthesise complex problems involving multiple variables (Lewis *et al.*, 2015). The Analytic Hierarchical Process developed by Saaty (1980), is one such approach for multi-criteria decision-making and the most popular and reliable based on the reviewed literature. AHP has seen an incredible amount of use over the last several decades in identifying suitable areas for renewable energy technologies installation. Several scholars have been used the AHP to identify suitable areas for renewable energy technologies implementations. For example, Al Garni and Awasthi (2017) have used the AHP to identify a suitable site for solar power plants in Saudi Arabia. Similarly, Anwarzai and Nagasaka (2017) have conducted wind and solar energy implementation in Afghanistan using the GIS-AHP tool. Moreover, Bagheri *et al.* (2021) have also employed the AHP to assess climate change vulnerability and hazards index of the city of Terengganu in Malaysia. Besides, many other authors (for example, Colak *et al.*, 2020; Doljak and Stanojević, 2017; Doorga *et al.*, 2019; Effat, 2013; Giamalaki and Tsoutsos, 2019; Majumdar and Pasqualetti, 2019; Merrouni *et al.*, 2016; Noorollahi *et al.*, 2016; Ruiz *et al.*, 2020; Shorabeh *et al.*, 2019; Tahri *et al.*, 2015; Uyan, 2013; Watson and Hudson, 2015; Yousefi *et al.*, 2018; Zoghi *et al.*, 2017) have applied the APH method combined with GIS to achieve excellent results.

The Analytic Hierarchical Process has been successfully used extensively in renewable energy sector to identify suitable sites that can receive renewable energy technologies plants. This method is therefore highly applicable for identifying suitable locations for the installation of renewable energy technologies and assessing the vulnerability of the study area to future climate change.

Mitigation of climate change requires a successful implementation of renewable energy in order to reduce GHG emissions in cities. As such, the Multiple-Criteria Decision-Making (MCDM) theory presents a useful tool in large part to facilitate the identification of suitable locations for renewable technologies but also to assess the vulnerability of cities to climate change.

2.3 Review of Related Studies

2.3.1 Cities and climate change

For the first time, urban areas represent roughly half of the world population, and this proportion is projected to rise over time, reaching 60% by 2030, and 70% by 2050 (WHO, 2018). Cities consume about 60 to 80% of energy worldwide and contribute about the same amount to global CO_2 emissions, thus to climate change (OECD, 2010). Consequently, cities are confronting various effects of climate change, including extreme heat events, sea-level rise, floods, urban heat islands, air and water contamination, and the spread of diseases.

So far, many research studies have been conducted regarding the challenges of climate change in cities around the world and explored solutions to this problem. For example, an empirical study by Scott *et al.* (2001) has shown the impact of climate change in human settlements, energy and industry in different cities around the world manifesting as flooding, sea-level rise, heat island effects, energy demand vulnerability with some adaptations measures such as improve infrastructure planning and design, and services, including water, sanitation, storm and surface water drainage, and solid waste collection and disposal. However, no paragraphs on how to mitigate climate change were addressed by the study. Furthermore, Mishra *et al.* (2015) have used primary station data for 217 urban areas across the globe to establish significant changes in urban climate with extreme increases of heat waves over the period 1973-2012, while the number of cold waves has decreased and extremes windy days have also declined during the last four decades by 60% in the urban areas. Although these results may be helpful in taking adaptation measures, they have not promoted any adaptive or mitigative actions. Likewise, Elias and Omojola (2015) have also investigated the challenges of climate change in Lagos using a synthesis of key literature, technical reports, and policy documents. Their findings reveal that Lagos faces several climate-related stresses, including flooding, sea-level rise, storms, extreme temperatures, and heavy rainfall. Adaptation and mitigation measures involve urban renewal programmes, climate-resilient infrastructure, and waste management strategies such as reduction, reuse, and recycling, supported by policies, infrastructure investments, and public-private partnerships.

Nevertheless, argued that climate change policies in Lagos are not consistent. Going beyond, Jones (2017) in his book "Cities Responding to Climate Change" has reviewed the impacts of climate change in the cities of Copenhagen, Stockholm and Tokyo and the decisions taken by the government to respond to its environmental damage and, showed successful policy implementation in all the three cities. However, the evidence of climate change impacts on these cities from primary data has been the limitation of this study. Moreover, Reckien *et al.* (2018) using a descriptive research method have collected and analysed existing local climate mitigation and adaptation plans across 885 cities of the EU-28 by defining A1, as not compulsory under national legislation and not developed in international climate networks plans, A2, as compulsory under national legislation and not developed in international climate networks plans, A3, as plans developed in international climate network's plans, and found that roughly 66% of EU cities have a mitigation plan, 17% have joint adaptation and mitigation plans, and about 30% have neither an A1, nor an A2 or an A3 plans and suggested that city size, national legislation and international networks can influence the development of local climate plans. However, authors did not elaborate on the impacts that these cities are confronted with, nor the nature of their adaptation or mitigation plans. Aware of the issue of climate change, Simon *et al.* (2021) have used a case study on policy analysis in small and intermediate cities of India and South Africa, and revealed that there is still a lack of policy implementation by governments and resource constraints at city level, yet author only relied on the literature, no primary data have been used in the study. Furthermore, an empirical study by Bastin *et al.* (2019) has analysed and predicted the climate conditions of 520 major cities across the world and have revealed that more than 77% of the world's cities are likely to move towards the climate conditions of another major city by 2050, whilst 22% move towards climatic conditions that are not now present in any major city in the global. But, did not discuss any action measures that cities should take to confront these changes.

2.3.2 Renewable energy and climate change mitigation

Besides contributing to anthropogenic greenhouse gas emissions, cities are also highly vulnerable to the effects of climate change and extreme weather conditions. The Intergovernmental Panel on Climate Change has thoroughly pointed out the importance of renewable energy sources in climate change mitigation by displacing emissions of GHG from fossil fuels combustion (IPCC, 2011). Moreover, Scientists state that "if just 1.2% of the Sahara Desert is covered by solar panels, we could produce enough electricity to power the entire world".

To date, there are numerous studies that have been carried out in order to reduce greenhouse gas emissions through renewable energy technologies using different approaches and techniques. For instance, Elum and Momodu (2017) have conducted a study based on literature review and discourse analysis to gather information on the potential of renewable energy in mitigating climate change impact in Nigeria, however, have not shown the actual renewable energy potential and a comprehensible way to succeed their development. Similarly, Elum *et al.* (2017) have employed a discourse analysis to explore the potential of the agricultural sector to provide bioenergy as climate change mitigation strategy in Nigeria and found that that bioenergy can promote Nigeria's economic diversification, reduce dependency on petroleum and provide a strong interaction between the agriculture and energy sectors. However, this study has shortcomings in terms of methodology, which is a literature-based, and the lack of contributions to improve policies to support the deployment of these renewable sources. More so, in light of the ongoing and impending adverse impacts of climate change, Eitan (2021) has conducted research on policy discourse analyse in Israel through quantitative and qualitative methods to examine whether renewable energy promotion is focused on climate change mitigation or climate change adaptation, and reported that 92 declarations refer to the promotion of renewable energy as a tool to cope with climate change; 59 declarations (64%) refer to renewable energy as a mitigation tool, whereas only 33 declarations (36%) refer to adaptation, but was unable to show why the statements of policymakers statements regarding focusing on mitigation over adaptation, as presented and also failed to mention the potential in renewable energy that Israel possesses.

Furthermore, Žičkienė *et al.* (2022) have performed an empirical study aiming to assess GHG reduction strategies in Lithuania using surveys and SWOT analysis and disclosed that the main barrier of the deployment of renewable energy in Lithuania is cost and, found that the government is more focus on renovation of public buildings, residential dwellings and energy infrastructure, rather than shifting from fossil fuel to renewable energy production. Unfortunately, authors have not given details on the contribution of the country regarding greenhouse gas emissions as well as the actual potential of renewable energy in the country. In the light of responding to climate change, Sims (2004) has conducted a descriptive study based on the role that the global renewable energy industries could play in reducing carbon dioxide emissions using a cost comparison between renewable energy and fossil fuels. The study revealed that achieving a liveable future world with the minimum cost necessary for adaptation climate change impact, require, among other measures, the early adoption of renewable energy to displace fossil fuels. However, this study lacked provide more details from primary sources and only focused on cost, instead of engaging the public on the benefits of adopting renewable energy to solve the climate change issue.

2.4 Examples from Other Regions/Countries

Over the last several years, there have been a number of research studies conducted across the world on the subject of how cities respond to climate change through renewable energy. For instance, Sun *et al.* (2020) have used a VAR model to capture variables such as wind capacity and policy variables for evaluating the main drivers of wind energy development to mitigate climate change in Ghana. The study showed some regions of Ghana with high wind energy potential and, states that if Ghana is to reach its target of universal electrification which was supposed to be achieved by 2020, wind energy must be given a serious attention. Sahnoune *et al.* (2013) have conducted a work to analyse the current situation in support of sustainable development and climate change issues in Algeria. The study revealed that the country of Algeria is very vulnerable to climate with more frequent droughts and the energy sector represents the highest share of GHG emissions (74%) which can be reduced by 60% through the development of renewable energy technologies.

Moreover, Krupa and Burch (2011) have administrated a number of semi-structured interviews with individuals holding senior positions in major South African companies and non-governmental organisations in regard to renewable energy development in this climate change crisis, and reported that although the traditional usage of energy has created ingrained schemes of marginalisation and environmental deterioration, corruption and poverty can likewise hinder the potential for a shift to renewable energy to enhance fundamentally sustainable development. Similarly, Keleş and Bilgen (2012) have reviewed renewable energy potential for responding to climate change in Turkey and found that the country has great potential of renewable energy, therefore, Turkish government should support domestic renewable energy sources and make efficient use of solar power plants, and reduce dependence on fossil fuels. In the light of mitigating climate change in Thailand, Udomsri *et al.* (2011) have employed research on solid waste incineration and biomass to solve the consequences of climate change in urban areas, and reported that the incineration system can handle more than 1.6 million tons of solid waste each year, leading to a reduction of CO_2 equivalent of up to 3.7 million tons per year for the Bangkok metropolitan area in Thailand. Equally, Wang *et al.* (2018) used a Divisia index approach to explore the drivers of renewable energy development in China including GHG reduction, energy security and low-carbon economy. According to the authors, the contributions of energy security, low-carbon economy and total carbon emission to renewable energy consumption were 174.12, 27.77 and 48.87 Mtoe, respectively in the last 20 years, and as a world's largest emitter of CO_2, China should focus on the use of renewable energy technologies.

To address the dual energy and climate change challenges in the city of Seoul, South Korea, Byrne *et al.* (2015) have introduced a solar city concept and methods to assess rooftop solar electric potential, and concluded that a potential equal to about 30% of the city's total annual electricity consumption can be provided by the large-scale deployment of photovoltaic rooftop systems. Furthermore, in Germany, the global pioneer in applying renewable energy and environmental technologies, Breyer *et al.* (2015) have researched a profitable solution for reducing greenhouse gases emissions in cities, and concluded that Germany has financial benefits of between 19 and 93€/tCO_2eq to mitigate GHG emissions through solar photovoltaic systems and suggested therefore, photovoltaic systems as a very interesting option for climate change mitigation. Similarly, Busch and McCormick (2014) have also exploring the motivations of mayors and key success factors for many German cities to switch to 100% renewable energy based on the “theory of planned behaviour”, and suggested that the efforts to promote renewable energy to cities should focus on the concrete benefits for cities, rather than devoting resources on explaining and advocating the “fight” against climate change.

2.5 Overview and Key Issues of the Study

Some forty years ago, anthropogenic climate change becoming a major environmental issue has captured the interest of several scientists across the world. First models of urban temperature, rainfall and wind flow were investigated for sites around London by Luke Howard between 1806 and 1830, for Paris in the 1870s by Emilien Renou, and for Berlin and Vienna in the 1890s by Gustav Hellmann and Julius Hahn, respectively (Hebbert and Jankovic, 2013). The duty to respond to climate change has become a necessary action to preserve the environment. However, it requires a close interplay between the scientific community, society and governmental institutions. The Intergovernmental Panel on Climate Change (IPCC), established in 1988, has progressively expanded to become the main United Nations organ responsible for providing this service to the nations of the world. The IPCC in its fourth assessment report concluded, “Most of the observed increase in global average temperature since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations” (IPCC, 2007). Consequently, in its report on renewable energies and climate change, IPCC emphasises the use of renewable energy sources to mitigate climate change (IPCC, 2011) .

Nigeria ratified the UNFCC in 1994, adhered to the Kyoto Protocol in 2004, and to the Paris Agreement in 2015 (NDCNigeria, 2021). Nigeria Government has also approved its National Energy Policy in 2003. The Energy Commission of Nigeria (ECN), is mandated to develop and foster renewable energy technologies in Nigeria including strategic energy plans and policy coordination. Mali has also pledged to combat climate change by joining the United Nations Framework Convention on Climate Change in 1994, the Kyoto Protocol in 1999 and the Paris Agreement in 2016. As part of its efforts to reduce the impacts of climate change, the country has established its National Energy Policy supported by the National Strategy for the Development of Renewable Energy since 2006 for developing and promoting the use of renewable energy in the whole country.

In both countries, several national and multinational institutions, private and public corporations are involved in the struggle against environmental damage and the development of renewable energies. For example, in Nigeria, the Department of Climate Change (DCC) of the Federal Ministry of the Environment is committed to the issue of climate change nationally through the UNFCCC, Kyoto Protocol and Paris Agreement. The department operates in conjunction with the Inter-Ministerial Committee on Climate Change (ICCC). Furthermore, Nigeria's Sustainable Energy for All Action Plan (SE4ALL) is a national implementation tool to support the Sustainable Development Goal (SDG) on energy. Following this perspective, and recognising the importance of renewable energy in reducing greenhouse gas emissions, the Renewable Energy Association of Nigeria (REAN) a non-profit association created by stakeholders in the renewable Energy sector in Nigeria have vowed to work together to boost the development and promotion of renewable energy up to 40% of the national energy mix by 2030. According to Sambo (2009), a private company known as Nigerian Electricity Supply Company (NESCO) has been working with the government to install eight small hydropower plants with a total capacity of 37.0 MW in Nigeria. However, notwithstanding efforts to move towards a sustainable quality of life, certain institutions have simply failed to achieve it. According to Oyedepo (2012), the Power Holding Company of Nigeria (PHCN), formerly the National Electric Power Authority (NEPA) has been unable to provide minimum acceptable international norms of energy for electricity service reliability and affordability over the past three decades. In Mali, the same targets are being set through the National Renewable Energy Action Plan (PANER), Sustainable Energy for All (SE4ALL) as well as the Agency for the Development of Domestic Energy and Rural Electrification (AMADER).

There are various programmes and activities aimed at the development of renewable energy technologies in order to mitigate climate change by reducing emissions in the energy sector, which is still the main source of greenhouse gas emissions. For instance, to mitigate climate change through the energy sector and to promote sustainable development in Nigeria, the National Renewable Energy and Energy Efficiency Policy (NREEEP) in line with the objectives of the National Energy Policy has initiated programmes and activities to install renewable energy technologies such as hydropower, solar, wind and biomass electricity with a total of 12.801 MW, 6.831 MW, 3.211 and 292 by 2030 to underpin the sustainable development in Nigeria (NREEEP, 2015). The main priorities for Mali are to ensure renewable energy development and energy efficiency, aiming to install over 100 MW by 2030 of all renewable energy sources throughout the country.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Description of the Study Area

3.1.1 Location of the study area

The Sudan Savanna region of West Africa extends between latitudes 9° 30’ and 12° 31’ N and longitudes 4° to 14° 30’ E, covering an estimated 22.8 million hectares (Manyong *et al.*, 1995). This study focuses on two selected cities, Kano in Nigeria and Bamako in Mali, both situated within this ecological zone in West Africa (Figure 3.1). Kano et Bamako were selected based on their common bioclimatic region, namely the Sudan Savanna region of West Africa. In addition, Kano and Bamako share other characteristics such as urban sprawl, population, climate, and being two large and bustling commercial cities that yield a high human activity and energy use.

Kano metropolis, the capital city of Kano State, is located between the latitudes of 11°25' N and 12°47' N and the longitudes of 8°22' E and 8°39' E, at an elevation of 472 metres above sea level. The city is bordered by Katsina State to the northwest, Jigawa State to the northeast, Bauchi State to the southeast, and Kaduna State to the southwest. It comprises eight Local Government Areas: Dala, Fagge, Gwale, Kano Municipal, Nassarawa, Tarauni, Kumbotso, and Ungogo, with a total area of about 499 square kilometres (Ozomata *et al.*, 2021).

Bamako, the capital and largest city of Mali Republic, is located between latitudes 12°30’ N to 12°45’and longitude 7°38’ W to 8°00” W. It borders the regions of Kayes to the northwest, Segou to the northeast and Sikasso to the southeast and a small part of Koulikoro to the north. The city falls within the Koulikoro region and covers an area of 245 square kilometres. Bamako consists of a large basin, surrounded in part by hills, and expands along the two banks of the Niger River that flows through it. Bamako is divided into six (6) municipalities which encompasses Commune I, Commune II, Commune III, Commune IV, Commune V, Commune VI.

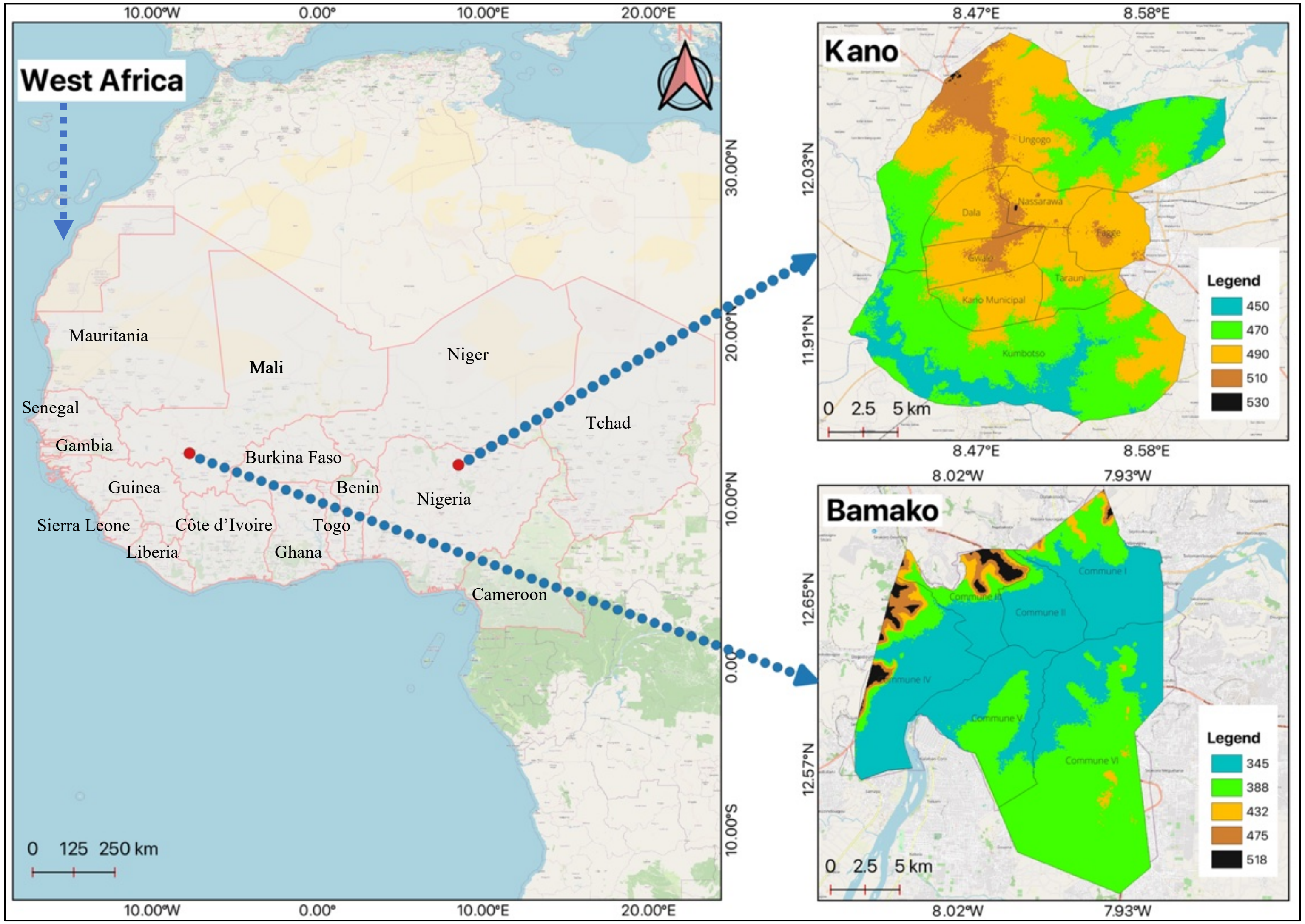


Figure 3.1 Geographical Location of the Study Area

3.1.2 Climate of the study area

Kano and Bamako belong to the Sudanian zone of West Africa (Figure 3.2), a region marked by a single rainy season each year. Annual rainfall in both cities typically ranges between 900 and 1100 mm (Figure 3.2). Geographically, the Sudan Savanna lays between the rainforest and the dry Sahel. The average monthly temperature in the rainy season ranges from 26.5 to 31.5 °C in Bamako, compared with 26.5 to 33 °C in Kano (Akinseye, 2020). In the Sudan Savanna region of West Africa, the dry season begins from November to April, and the wet season spans from May to October with a rainy peak occurring in August. The daily average temperatures are between 30 and 35°C, with maximum mean temperature of about 40°C recorded in May.

3.1.3 Soil, vegetation and hydrology of the study area

The soil of Kano is classified in three major categories: zonal, intra-zonal and azonal (Barau, 2006). The zonal type of soil is a ferruginous soil characterised by its high quantity of iron, although the intra-zonal is a well-developed soil generally determined by local factors such as the relief and the nature of the parent material. The azonal soil, on the other hand, is an immature soil that has lacked well-developed horizons. The vegetation of Kano Metropolis reflects a typical savanna landscape, with dominant grasses and interspersed trees that primarily possess fire-resistant bark, adapted to a semi-arid climate (Negbenebor *et al.*, 2018). One main watershed divides two main river basins in the metropolis, the Jakara River basin in the North and the Kano River basin in the South (Salisu Dan'azumi and Mustapha Bichi, 2010). Jakara, Kano and Challawa are the three major rivers drained in Kano metropolis (Ibrahim and Mohammed, 2016).

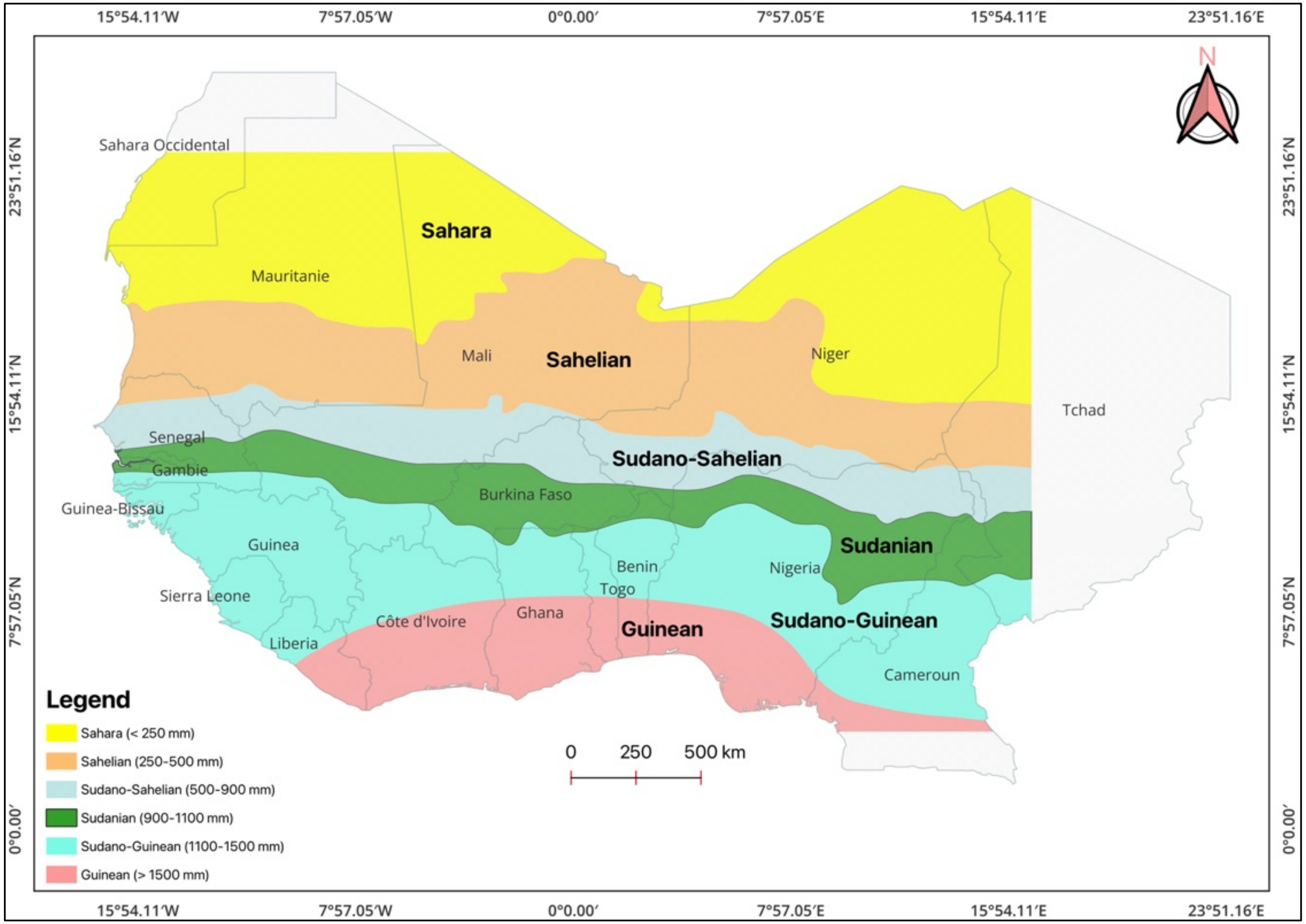


Figure 3.2 The Sudan Savanna Region of West Africa

Bamako lies on a granite basement covered with sandstone deposits. The Niger River, which is 4,200 km long and rises from Futah Jalon in Guinea, is the main river of Bamako and the longest river in West Africa. The city stretches along the two banks of the Niger River. The different types of soils encountered in Bamako are mainly gravelly and lateritic soils. They are compact and are difficult to dig or to rip. The vegetation therefore, belongs to gallery forest of savanna and rivers (Keita *et al.*, 2020).

3.1.4 Demography and socio-economic activities of the study area

The population of Kano metropolis was estimated at over 6 million in 2016 (Umar and Naibbi, 2021). Boasting a population density of around 1,000 inhabitants per square kilometres, Kano metropolis ranks as Nigeria's second-largest commercial centre after Lagos, and the largest city in Hausa land, experiencing phenomenal urban growth. This notwithstanding, commerce and agriculture remain the main activities in Kano. The metropolis is largely cantered on agricultural activities, particularly in crop production such as sorghum, millet, rice, cowpeas, wheat, groundnut, and maize. These activities contribute to making the metropolis one of Nigeria’s fastest-growing urban centres, consistently attracting new populations (Koko *et al.*, 2021).

Meanwhile, Bamako's population is estimated at roughly 3 million inhabitants, with a density of 1,115 people per km^2 (Keita *et al.*, 2020). The city is characterised by a high and uncontrolled rate with socio-economic activities being essentially based on livestock, agriculture and fishing. However, livestock is recognised as one of the most important activities because of its numerical value in exports. Agricultural activities are mainly dominated by market gardening, arboriculture, and cereal growing.

Further ongoing business expansion and together with other socio-economic activities obviously lead to population growth with a significant increase in energy use in many sectors such as transport, building and industry, and thus generate higher CO_2 emissions. Therefore, the development of renewable energy technologies in the two cities may not only contribute to reduce considerable future climate consequences, but also strengthen existing adaptation capacities.

3.2 Types and Sources of Data

This research study used two main sources of data: primary sources of data and secondary sources of data.

3.2.1 Primary source of data

Primary data was collected through fieldwork, which involved household surveys and interviews with policy makers and representatives of public and private organisations. The purpose was to identify potential barriers and opportunities in the renewable energy market such as solar, their uptake and the policy for deployment of renewable energy technologies in the selected cities.

3.2.2 Secondary source of data

In this study, secondary data including daily maximum and minimum temperatures, and relative humidity for the period from 1992 to 2022 were acquired in Microsoft Excel for Kano and Bamako through the Nigerian Meteorological Office (NiMet) and the Malian National Meteorological Agency, respectively. Over the years, these government weather forecasting agencies have been responsible for collecting and disseminating accurate data. Over the years, these government weather forecasting agencies have been responsible for collecting and disseminating accurate weather data in their respective countries. In addition, because the Landsat satellite is the only active medium spatial resolution Earth Observation (EO) system that has been providing data for 40 years, Land Use and Land Cover (LULC) mapping has been carried out using Landsat data. Surface topography data, such as the Shuttle Radar Topography

Mission (SRTM), and solar radiation data, all sourced from the National Aeronautics and Space Administration (NASA), and OpenStreetMap (OSM) were also used. In addition to the above secondary data, including protected areas sourced from UNEP-WCMC and IUCN (2024) and wind speed (https://globalwindatlas.info/en/, accessed on 12 December 2024) were also used.

3.3 Methods of Data Collection

3.3.1 Meteorological data

The data for Kano and Bamako were collected through a successful response to requests from the Nigerian Meteorological Office (NiMet) and the Malian National Meteorological Agency, respectively. The daily data, covering a period of 30 years and composed of maximum and minimum temperatures in °C and relative humidity in percentage, were subject to a thorough quality control and data homogenisation check, following the recommendations of Aguilar *et al.*(2004). This process essentially involved checking for missing values, days, months and years for each data item, as well as the consistency of the data, for example, the maximum temperature exceeded the minimum temperature.

3.3.2 Survey data

In the survey, a combination of cluster sampling and systematic sampling was used to select respondents. First, each city was divided into Local Government Areas (LGAs), which were then used as clusters. Within each LGA, wards were then randomly selected. For Kano, three neighbourhoods were randomly selected from each of the eight local government areas and, similarly, for Bamako, four neighbourhoods were randomly selected from each of the six local government areas. In furtherance of this, in each selected neighbourhood, a systematic sampling approach was used to select respondents, ensuring that individuals were chosen at regular intervals from a list of potential participants. This approach was carefully designed to maintain both the randomness and representativeness of the selection process. The data was then collected using a structured questionnaire (Appendix A), which was designed to gather information on potential barriers and opportunities in the renewable energy market, with a particular focus on solar energy. This questionnaire was designed using an advanced data collection system, KoboToolbox (https://www.kobotoolbox.org, accessed on 10 January 2023), and administered by Master's students from the Department of Geography at Bayero University and Physics at the Faculty of Science and Technology for Kano and Bamako, respectively, with standard protocols followed in order to minimise bias and ensure the accuracy of the data. In total, the survey included 960 respondents, with 480 from Kano and 480 from Bamako. For respondents below the age of 18, prior verbal consent was obtained from a parent, guardian, or responsible adult before administering the questionnaire. This ethical consideration ensured that the inclusion of minors complied with national guidelines for research involving human subjects. The overall sample size was selected in accordance with best practices in model analysis, as research suggests that larger sample sizes improve the likelihood of proper model convergence (Gagné and Hancock, 2006; Marsh *et al.*, 1998; Velicer and Fava, 1998). The spatial distribution of surveyed households in Kano and Bamako is depicted in Figure 3.3.

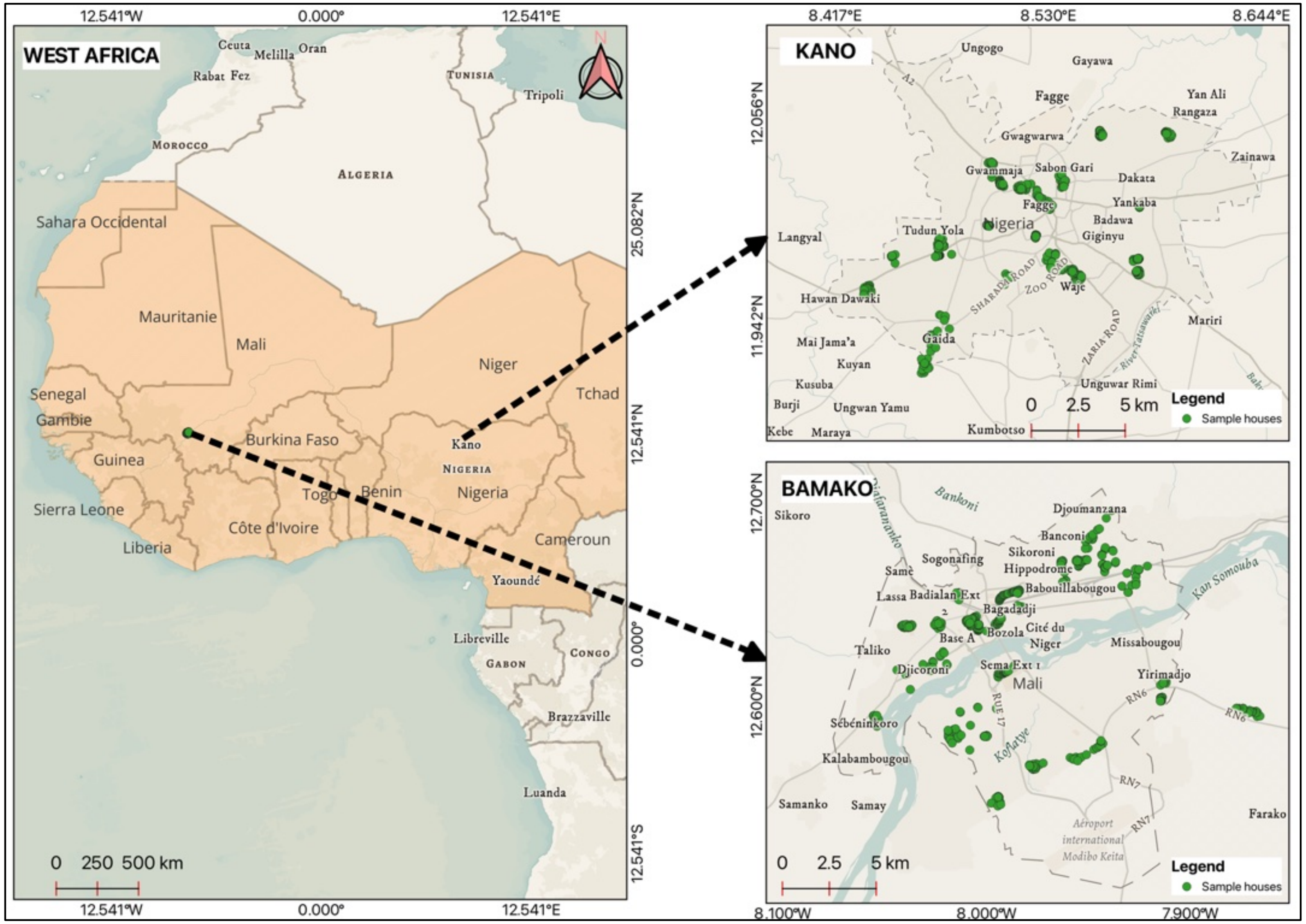


Figure 3.3 Spatial Distribution of Sampled Households in Kano and Bamako

3.3.3 Satellite imagery and remote sensing data

Three different series of Landsat imagery including Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper plus (ETM+) and Landsat 9 Operational Land Imager (OLI) were downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov, accessed on 12 February 2024) using Path 191, Row 52 for Kano and Path 200, Row 50 for Bamako. The Landsat data used were all level 2, collection 2, Tier 1 reflectance surface images. According to Masek *et al.* (2006), Masek *et al.* (2013), Vermote *et al.* (2016, 2018), and Vermote *et al.* (1997), such images consist of pixel values estimating the spectral reflectance at the Earth's surface with no atmospheric scattering or absorption effects. Consequently, neither atmospheric correction is required prior to the images being processed. Additionally, given that the study period extends from 1992 to 2022, an interval of 10 years has been considered (for example, 1991, 2002, 2012 and 2022). However, as unfortunately no Landsat images for 1992 were available, 1991 has been considered as the reference year for the study, on the assumption that there is no significant difference between 1991 and 1992. Furthermore, while every effort was made to select satellite imagery from the same season and year for both cities, the exact matching of acquisition dates, particularly the same month or day, was constrained by cloud cover, scene availability, and sensor limitations within the Landsat archive. In some instances, the best-quality imagery (for example, minimal cloud and haze) fell on slightly different dates between Kano and Bamako. Nonetheless, all selected images were acquired during the dry season, ensuring seasonal consistency, which is crucial for land use and land cover classification accuracy and comparability. An overview of the specifications of the dataset is presented in the Table 3.1.

Table 3.1 Satellite Imagery Used in the Study

Location	Satellite	Sensor ID	Path/Row	Spatial Resolution	Acquisition Date
Kano	Landsat 9	OLI	191/051	30 m	05/04/2022
Kano	Landsat 7	ETM+	191/051	30 m	18/03/2012
Kano	Landsat 7	ETM+	191/051	30 m	25/01/2000
Kano	Landsat 5	TM	191/051	30 m	10/02/1991
Bamako	Landsat 9	OLI	200/050	30 m	15/01/2022
Bamako	Landsat 7	ETM+	200/050	30 m	28/02/2012
Bamako	Landsat 7	ETM+	200/050	30 m	02/04/2000
Bamako	Landsat 5	TM	200/050	30 m	04/01/1991

Source: USGS (2024)

Further, daily solar radiation data were retrieved from the NASA-POWER Global Solar Radiation (GSR) reanalysis dataset, available through the National Aeronautics and Space Administration's Prediction of Worldwide Energy Resources (NASA-POWER) web portal at https://power.larc.nasa.gov/data-access-viewer/. These data were downloaded at a regional scale covering Kano and Bamako, with a temporal resolution of 0.5° × 0.5°. Global Horizontal Irradiance (GHI) is one of the solar radiation parameters that has been widely used to estimate solar power potential for site selection (Besharati Fard *et al.* (2022), Hasti *et al.* (2023), Noorollahi *et al.* (2022), Rekik and El Alimi (2023), Settou *et al.* (2021). In addition, 10 m digital elevation model (DEM) data sourced from the USGS, was used to gather information on the slope and terrain orientation, which are essential for assessing terrain characteristics and their influence on solar radiation exposure.

3.4 Methods of Data Analysis

3.4.1 Analyse the trends of cooling degree days and heat index between 1992 and 2022

3.4.1.1 Trends in cooling degree days in Kano and Bamako

For both Kano and Bamako, 30 years of daily maximum temperature and minimum air temperature were used to derive cooling degree days (CDD). All data were computed in Python using the Jupiter notebook. The cooling degree-days for each year were obtained by summing the positive values derived from the difference between the threshold temperature and the average temperature for each day of the year. The average temperature was calculated from the difference between the maximum and minimum temperatures on each day during the entire study period. The computation of Cooling Degree Days (CDD) is dependent on the choice of base temperature (Tb). While a Tb of 18 °C is widely used in many studies (Semmler *et al.*, 2010; Ukey and Rai, 2021; Wang and Chen, 2014), its selection often depends on the local climatic context of the study area. This choice aligns with Odou *et al.* (2023), who proposed 24 °C as a representative threshold for assessing cooling demand across West Africa, based on region-specific thermal comfort and historical temperature patterns. The cooling degree days for Kano and Bamako was therefore computed using Equations 3.1, 3.2 and 3.3.

$$CDD = \sum_{k=1}^{n} f(\varphi) \tag{3.1}$$

$$With\, f(\varphi) = T_m - T_b, if\ T_b < T_m \tag{3.2}$$

Otherwise, $f(\varphi) = 0$

$$T_m = \frac{T_{max} - T_{min}}{2} \tag{3.3}$$

where, CDD is the number of cooling degree-days, n is the number of days in a year, T_m is the average mean temperature of a day k, T_b *(°C)* is the base temperature, *Tmax (°C)* is the maximum temperature of a day *k*; *Tmin (°C)* is the minimum temperature of a day *k*.

Further, to detect changes in the CDD time series, three statistical tools were applied to the data for each station. First, we applied a linear regression technique to model the CDD evolution over time. Linear regression has been widely used over the years to study the relationship between two variables (Huang, 2023). The linear regression formula (Equation 3.4), is an affine function, expressed as follows:

$$Y = ax + b \tag{3.4}$$

where Y is the values in each year between 1992 and 2022 and x is the year over the study period 1992 - 2022. Moreover, a non-parametric Mann-Kendall test (Kendall, 1948; Mann, 1945) was used to identify the existence of a trend in the CDD time series at the 95% confidence level. The Mann-Kendall test has been extensively used to detect trends in cooling degree-days using meteorological datasets (Islam *et al.*, 2020; Sadeqi *et al.*, 2022). The Mann-Kendall test was calculated using Equation 3.5:

$$S = \sum_{k=1}^{n} \sum_{i=k+1}^{n} sgn(x_i - x_k) \tag{3.5}$$

where *n* is the sample size, and being the values of individual time series *i* and *k* respectively. The term *S* represents the sign function applied to the difference between and, indicating whether this difference is positive, negative, or zero. The sign function s is given by the following Equation 3.6:

$$\text{gn}\ (x_i - x_k) = \begin{cases} +1, if\ x_i - x_k > 0 \\ 0, if\ x_i - x_k = 0 \\ -1, if\ x_i - x_k < 0 \end{cases} \tag{3.6}$$

Furthermore, the direction and magnitude of each trend in the data were estimated using Sen’s slope estimator (Sen, 1968). The Sen’s slope is given by Equation 3.7:

$$Q_i = \frac{x_i - x_k}{\mathrm{i - k}}\ for\ i = 1, \dots, N, \tag{3.7}$$

where N represents the sample data measured at times i and k ($i>k$), respectively, and N is the number of slopes.

3.4.1.2 Trends in heat index Kano and Bamako

Daily relative humidity data over a range of 30 years from 1992 to 2022 for Kano and Bamako were used to calculate the heat index in the cities. The heat index, also known as apparent temperature, was computed according to the Equations 3.8 – 3.9, originally developed by (Steadman, 1979):

$$HI\,(°F) = -42.379 + 2.049 \times T + 10.143 \times RH - 0.225 \times T \times RH - 6.838 \times 10^{3} \times T^{2} - 5.482 \times 10^{2} \times RH^{2} + 1.229 \times 10^{3} \times T^{2} \times RH + 8.528 \times 10^{4} \times T \times RH^{2} - 1.990 \times 10^{6} \times T^{2} \times RH^{2} \quad (3.8)$$

$$°C = 5/9 \times (°F - 32) \quad (3.9)$$

where HI is the heat index (°F), T is the air temperature (°C), RH is the relative humidity (%), F stands for Fahrenheit, and C stands for Celsius. In addition, this formula gives the HI value for a given day. The HI for each year is obtained by summing up the HI values for the number of days in the year.

3.4.2 Evaluate the LULC change of the study area over 1992 to 2022

Land Use and Land Cover (LULC) change was examined for each city based on four types of land cover, including built-up areas, water bodies, vegetation, and barren land. To address the issue of Landsat tiles covering large areas rather than focusing solely on the study site, GADM (Global Administrative Areas) administrative boundaries were employed to extract the specific regions of Kano and Bamako from the satellite images using the “clip raster by mask layer” tool in Quantum GIS 3.34 software. Afterwards, colour composites were applied for defining the regions of interest. A minimum number of 100 samples per class for each year was envisaged for the training data, thereby representing 80% of the data, compared with 20% for the validation data. This approach was adopted in the consideration that increasing the training sample size has the potential to significantly improve the overall accuracy (OA) of the classifications (Burai *et al.*, 2015; Phinzi *et al.*, 2023; Ramezan *et al.*, 2021). For the entire samples selection process, Google earth high resolution images were used to support the process and ensure consistency. LULC classification was performed using the Random Forest (RF) classifier, a popular machine learning technique developed by (Breiman, 2001). Sought for its high accuracy, the RF classifier has been widely adopted in LULC studies over the last few decades (for example, Bobálová *et al.*, 2021; Ma *et al.*, 2017; Ramezan *et al.*, 2021; Talukdar *et al.*, 2020). The classification process utilised the Semi-Automatic Classification Plugin (SCP) developed by (Congedo, 2021), a robust tool within QGIS designed for geospatial analysis. The Cohen's kappa coefficient (Farr and Kobrick, 2000) and the error matrix were used to compute the accuracy assessment. To evaluate the LULC classification accuracy, traditional methods including the overall accuracy (Equation 3.10) and Kappa coefficient (Equation 3.11) have been used. Also, the annual percentage change (APC) of the different land use classes has been calculated as described in Equation 3.12. The entire LULC classification procedure is illustrated in Figure 3.4.

$$\text{Overall accuracy } = \frac{1}{k}\sum_{j=1}^{r} njj \tag{3.10}$$

where, n_{jj} represents f the true positive counts across all classes in a confusion matrix, and K is the total number of samples.

$$\text{Kappa coefficient } = \frac{K\sum_{j=1}^{r} n_{jj} \; - \; \sum_{j=1}^{r}(n_{j+} \times n_{+j})}{K^2 - \; \sum_{j=1}^{r}(n_{j+} \times n_{+j})} \tag{3.11}$$

where K represents the total number of sites in the matrix, r denotes the number of rows, n_{jj} refers to the entry at the intersection of row j and column j, is the aggregate of values in row j, and is the aggregate for column j.

$$\text{Annual percentage change } = \frac{Y_2 - Y_1}{Y_1 \times t} \times 100 \tag{3.12}$$

where Y_1 *and* Y_2 represent the areas of classes for the initial year and the final year, respectively, whilst t is the time span.

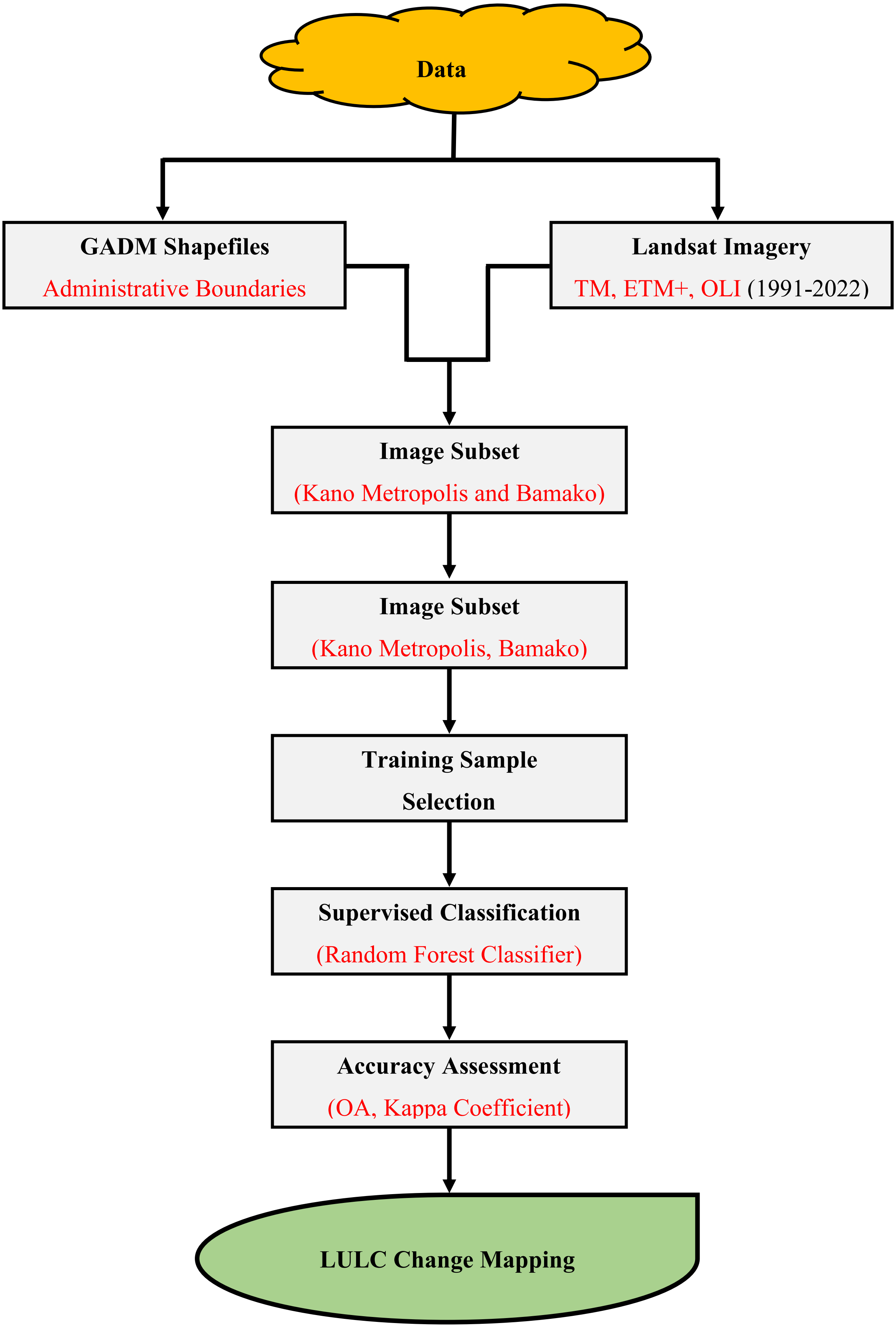


Figure 3.4 Workflow of LULC Classification based on the Random Forest

3.4.3 Identify suitable locations for installing solar powerplants

A combination of Geographic Information System (GIS) and the so-called structured decision-making method, Analytical Hierarchy Process (AHP) was used to identify the most suitable areas for the installation of solar power plants within the cities of Kano and Bamako. The Analytical Hierarchy Process (AHP) has become one of the most popular approaches for analysis and decision support. Its integration with Geographic Information Systems (GIS) has gained considerable attention for the evaluation and identification of suitable sites for solar energy development projects.

The identification of criteria was carried out according to technical, environmental, economic and social factors. These criteria include average temperature, solar irradiation, wind speed, land use, digital elevation model, slope, aspect, distance from power lines, distance from main roads, distance from railroads, distance from waterways and protected areas, whose data in raster or vector format for some has been better processed using QGIS software. A number of layers, such as wind speed and solar irradiance, have been processed further, requiring the use of Inverse Distance Weighting (IDW) due to their derivation from global climate data.

To standardise the different datasets, all the layers were transformed using fuzzy functions, and were therefore assigned a Boolean classification (0 for unsuitable, 1 for suitable). The vector layers including distance from main roads, distance from railroads, distance from waterways and protected areas, were processed by applying 500 metres buffer zones. The buffers were subsequently reclassified based on Equation 3.13. Furthermore, since no protected area falls within the Kano boundary, the protected area layer was omitted during the analysis for Kano.

$$\text{ReclassifiedBuffer} = \begin{cases} 1, & \text{Outside the buffer} \\ 0, & \text{Within the buffer} \end{cases} \tag{3.13}$$

After this process, the Analytical Hierarchy Process (AHP) was applied to determine the relative importance of the chosen criteria. A pairwise comparison matrix was constructed based on expert judgment to assign weights to each criterion. The consistency of these comparisons was validated by calculating the Consistency Index (CI) in Equation 3.14 and Consistency Ratio (CR) in Equation 3.15. The whole procedure for identifying potential site for solar powerplant is outlined in Figure 3.5.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3.14}$$

$$CR = \frac{CI}{RI} \tag{3.15}$$

where λ_{max} is the principal eigenvalue, n is the number $\text{Reclassified}_{\text{Buffer}}$ of criteria and RI is the Random Consistency Index. A *CR* value below 0.1 is considered acceptable, ensuring logical consistency in the criteria ranking (Rios and Duarte, 2021).

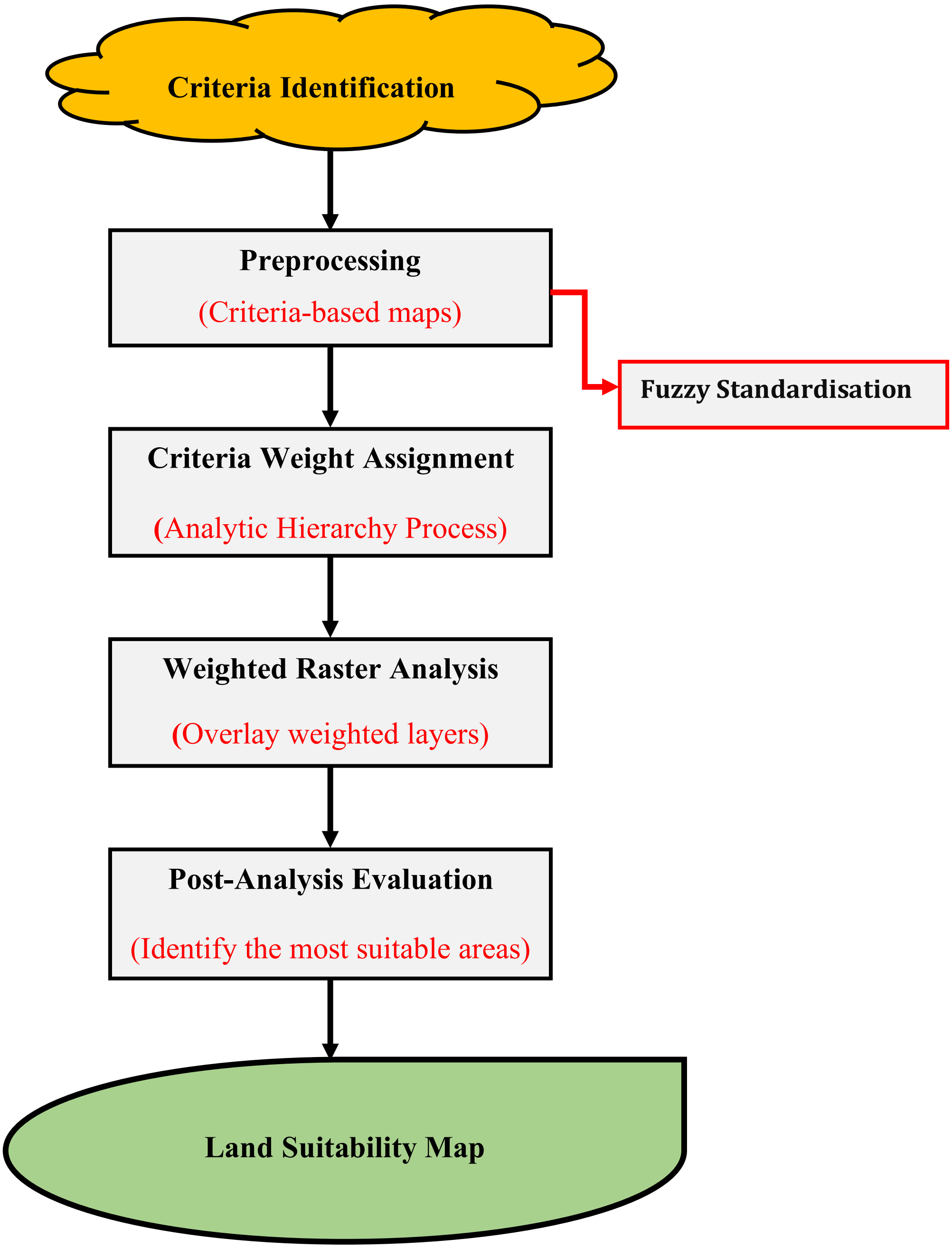


Figure 3.5 Solar Powerplant Site Suitability

For both cities, the analysis of land suitability for solar power plants was carried out according to the same criteria and restrictions. The criteria and restrictions layers used in this study are described as follows:

3.4.3.1 Average temperature

Temperature directly influences the efficiency and performance of solar energy generation systems. While the industry-standard testing conditions are based on 25 °C, this benchmark reflects temperate climate assumptions and does not correspond to typical daytime temperatures in tropical cities like Kano and Bamako, where values often exceed 30 °C. Under such conditions, the surface temperature of solar panels can rise considerably, leading to efficiency losses. Empirical studies have shown that panel output declines by approximately 0.4% to 0.5% for every 1 °C increase above the standard test condition (Yelmen and Çakir, 2016). Therefore, sites with moderate average temperatures are ideal for maximising energy output while minimising efficiency losses. Additionally, understanding temperature variations helps in estimating maintenance needs, as prolonged exposure to extreme heat can accelerate panel degradation, impacting the system's long-term reliability and lifespan. The temperature layer for both Kano and Bamako, was classified in such a way that any temperature ≥ 24° is suitable and any temperature below that is unsuitable.

3.4.3.2 Global horizontal irradiance

Global Horizontal Irradiance (GHI), measured in watts per square metre (W/m^2), is the total amount of solar radiation received per unit area over a horizontal surface. The GHI is an important factor in estimating the solar potential of a given location or region. It effectively measures the total amount of direct sunlight reaching a horizontal surface, which is crucial for solar panels to capture sunlight and convert it into electricity. For this study, a GHI value of ≥ 2150 $kWh/m^2/year$ was classified as suitable for solar development, whilst any value below this threshold was considered unsuitable.

3.4.3.3 Digital elevation model

Digital Elevation Models (DEMs) play a critical role in selecting sites for solar power plants due to their influence on solar energy performance and efficiency. Higher elevations generally enhance wind speed, helping to cool solar panels and improve their efficiency. Additionally, the reduced atmospheric thickness at higher altitudes leads to lower concentrations of particles and reflection coefficients, allowing more solar energy to reach the panels. These areas typically have higher energy potential compared to lowlands. However, elevation also affects construction and maintenance costs, posing challenges for large-scale solar projects. Recent studies underscored the importance of incorporating topographical effects in site selection to optimise energy production and reduce operational risks (Farsi *et al.*, 2024; Islam *et al.*, 2024). For both Kan and Bamako, an elevation of between 450 and 500 metres was classified as suitable for the installation of photovoltaics, and any elevation outside this range was considered unsuitable.

3.4.3.4 Land slope

Land slope is an important consideration for solar power plant site selection, as it influences both construction costs and energy efficiency. Consequently, the steeper the slope, the more difficult and expensive it can be to install and maintain solar panels. A flat site or a slightly sloping site is ideal for solar installations, making it easier to position the panels, lowering construction costs, and optimising energy capture. Consequently, since the majority of the slope of the study is less than 5°, a slope value of $\leq 5°$ was classified as flat, therefore suitable; and anything above 5° was therefore considered unsuitable.

3.4.3.5 Land aspect

Land aspect is a critical factor in identifying suitable sites for solar power plants, as it determines the direction a slope faces, influencing the amount of solar radiation it receives. The aspect, or orientation, of a land surface relative to the cardinal directions plays a pivotal role in optimising solar energy capture. It has been widely acknowledged that south-facing slopes in the northern hemisphere receive most of the sunlight throughout the day, making them ideal for solar installations (Georgiou and Skarlatos, 2016). Therefore, following the recommendations from previous studies, south-facing slopes (135°–225°) have been classified as suitable for solar farm construction, while north-facing slopes (315°–45°) were considered unsuitable.

3.4.3.6 Wind speed

High wind speeds are known to increase maintenance costs by potentially damaging panel structures and tracking systems, which necessitate additional reinforcement in wind-prone areas. While moderate wind conditions aid in passive cooling and slightly enhance panel efficiency, extreme wind zones are generally avoided in solar farm development. Consequently, regions with low to moderate wind speeds are preferred to ensure the longevity and optimal performance of solar installations. Therefore, regions with low to moderate wind speeds are preferred to ensure the longevity and optimal performance of solar installations. In this study, a value of wind speed less than or equal to 3m/s was considered to be low and one exceeding 3m/s was considered to be high.

3.4.3.7 Land use

Land use is definitely one of the most important criteria for the identification of solar site selection, as it affects land availability, environmental sustainability, and potential conflicts with other land demands.Out of the four types of land use used in this study, which are built-up, water, vegetation and bare soil; two (vegetation and bare soil) were considered suitable for solar installations, and the latter two (built-up, and water) were judged inappropriate for solar power plant facilities.

3.4.3.8 Distance from power lines

Proximity to existing powerlines or substations significantly reduces the cost and complexity of constructing new transmission lines. These lines can be expensive and logistically challenging to build. Sites closer to established powerline networks ensure more efficient energy transmission, minimising energy losses during long-distance transmission. Additionally, sites with easy access to powerlines facilitate quicker and more reliable integration of solar energy into the grid, enhancing the overall efficiency and stability of the energy supply. Furthermore, utilising existing infrastructure for power transmission helps avoid the environmental and social impacts associated with building new powerlines, such as changes in land use and disruptions to ecosystems. Therefore, when selecting locations for solar power plants, proximity to powerlines not only reduces costs but also improves the sustainability and efficiency of the energy generation and distribution process.

3.4.3.9 Distance from major roads

The distance from major roads is a crucial factor in choosing suitable sites for solar power plants. It affects both accessibility and development costs. Proximity to major roads ensures easy access for construction, maintenance, and material and equipment transportation. Solar power plants require substantial equipment, including solar panels, inverters, and transformers, which need to be transported to the site. Sites too far from major roads incur higher transportation costs and logistical challenges, potentially delaying project timelines. Moreover, the distance from major roads impacts ongoing operations and maintenance. Convenient road access allows for quicker response times to maintenance issues and regular inspections, reducing operational downtime and enhancing overall efficiency. However, while proximity to roads is important, sites too close to major roads may face noise, dust, and potential land-use conflicts. Therefore, an optimal balance must be achieved, ensuring accessibility while maintaining sufficient distance from roads to minimise disturbances.

4.4.3.10 Distance from railroads

The construction and maintenance of a solar farm necessitate the movement of substantial photovoltaic panels, electrical components, and support structures. Proximity to railways proves advantageous in reducing transportation costs. Rail connectivity facilitates the efficient delivery of materials, especially for large-scale projects that require frequent equipment transport. Regions far from rail infrastructure encounter logistical challenges, leading to increased project expenses. Therefore, areas closer to railways are often preferred due to the economic benefits of easier material transport and accessibility.

4.4.3.11 Distance from Water

Waterways influence solar power plant suitability primarily due to environmental and operational constraints. Locations near rivers, lakes, and wetlands are often avoided due to the risks of flooding and excessive moisture, which can reduce the efficiency of solar panels by increasing dust accumulation and corrosion. Additionally, land near major waterways is often designated for agricultural, ecological, or hydropower uses, making it less ideal for solar energy development. While floating solar (floating PV) technology has emerged as an alternative in some regions, traditional solar farms require stable, dry land for installation. As a result, areas situated at a safe distance from major waterways are generally preferred to ensure the long-term stability and efficiency of solar power plants.

3.4.3.12 Distance from protected areas

The distance from protected areas is a fundamental consideration in selecting sites for solar power plants to ensure that ecological integrity is maintained while supporting sustainable energy development. Solar farms, while environmentally beneficial in terms of reducing carbon emissions, can have unintended consequences if located near sensitive ecosystems. Proximity to protected areas increases the risk of disturbing local wildlife, potentially altering migration routes, breeding grounds, and food sources for protected species. Maintaining an appropriate distance from protected areas mitigates these risks and helps to align solar farm development with global biodiversity conservation goals. Additionally, protected areas often attract tourism and other local industries, and placing a solar farm nearby could result in conflicts over land use, further complicating the approval process.

3.4.4 Examine the current status of renewable energy adoption and potential barriers for renewable energy development

At first, the so-called factor analysis (FA) has been ran using "Principal Axis" method with varimax rotation in R 4.1.0 (R Team, 2020) to find out the common factors from the initial pool of 10 items. The FA was performed for each geographic region (Bamako and Kano) and then for the two regions aggregated data given the fact that items that accurately define a common factor may not may not hold consistency across regions (Balagueman *et al.*, 2023). It was assumed that a five-common factor model was sufficient to reduce the number of items in the dataset. This assumption was tested in R using the chi-square fit statistic. The five-factor model is validated when the probability (p) of the chi-square fit statistic is greater than 0.5 ($p \geq 0.5$). Furthermore, it was also assumed that each common factor displays a minimum of two items of high quality (DeVellis and Thorpe, 2021; Streiner *et al.*, 2024). High quality items are those showing factor loadings greater than 0.60 and allowing for high internal consistency on each factor (Kyriazos, 2018). The internal consistency for each common factor was measured using Cronbach's alpha index (Cronbach, 1951). The Cronbach's alpha was computed in R using the package "scales" (Wickham and Seidel, 2020). An alpha value greater than 0.50 indicates that the scale may be considered reliable to measure the construct (Kyriazos, 2018).

The Kaiser-Meyer-Olkin's (KMO) and the Bartlett's test of sphericity (Bartlett, 1951),were also computed to evaluate the quality of the FA. Bartlett's test of sphericity was performed using the “RedaS” package (Maier, 2015). The desirable KMO for the whole data should be greater than 0.5. The FA was performed using the data from 480 informants without any missed values. Furthermore, a confirmatory factor analysis (CFA) was performed to validate the common factor model for each region and for the aggregated data. CFA is a theory-driven technique that seeks to test whether the theoretical relationships between the items and underlying factors are reliable. Technically, it is about comparing a population covariance matrix with the observed covariance matrix (Schreiber *et al.*, 2010). To estimate the CFA parameters, the diagonally weighted least squares (WLSMV) method was applied. The CFA was performed using the package "lavaan" (Rosseel, 2012) in R programming software.

Following concept validation, a structural equation modelling (SEM) was carried out using the lavaan software package to test the direct and indirect structural relationship between the variables. Initially, the SEM was performed for each geographical region separately, and then replicated using the pooled data from the two regions. The measurement model in the SEM involved merely the well-fitted CFA model. A regression model was developed to test the effect of ED, ENK, SA, ARE and BRC on RED and the effect of ENK on ARE. The indirect effect of ENK on ARE was also tested. Similar to the CFA, the diagonally weighted least squares (WLSMV) method was used to estimate the model parameters. Marginal and conditional R^2 coefficients were calculated for each regression model to assess the explanatory power of the model. The convergence of the CFA and SEM models was verified based on the standards suggested by Hu and Bentler (1999) and Brown *et al.* (2005) RMSEA (≤ 0.06, 90% CI ≤ 0.06), SRMR (≤ 0.08), CFI (≥ 0.95), TLI (≥ 0.96), and the chi-square/degree of freedom (df) ratio (less than 3) (Kline, 2023).

CHAPTER FOUR

4.0 RESULTS AND DISCUSSIONS

4.1 Results

4.1.1 Trends in cooling degree days in Kano and Bamako

The trends in cooling degree days over the period 1992-2022 for Kano and Bamako are shown in Figures 4.1 and 4.2, respectively. The results revealed contrasting trends in CDD between the two cities, with a positive variation in CDD in Kano (Sen's slope = 2.308), with an increasing trend of 1.73 °C-day yr^{-1}, although this trend was not statistically significant (p = 0.444; Figure 4.1). In contrast, Bamako exhibited a decreasing trend of –3.80 °C-day^{-1}, which was marginally non-significant (p = 0.053; Figure 4.2). Gbode *et al.* (2015) reported similar evidence of increasing energy demand in Kano. The coefficient of variation (CV) for CDD was relatively low in both cities, 10.2% in Kano and 7.2% in Bamako, suggesting moderate year-to-year fluctuations.

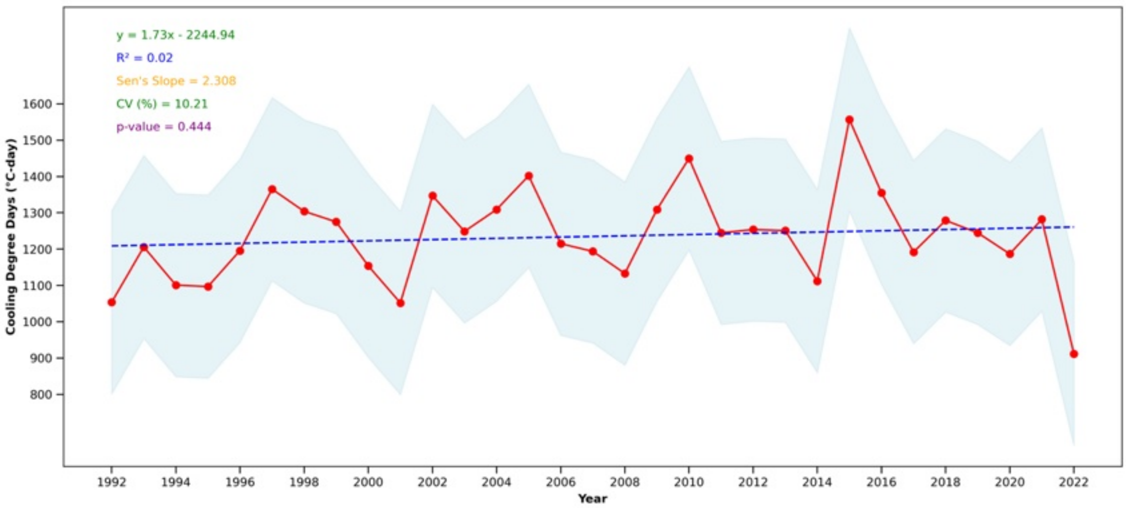


Figure 4.1 Climatology of Cooling Degree Days for Kano (1992–2022)

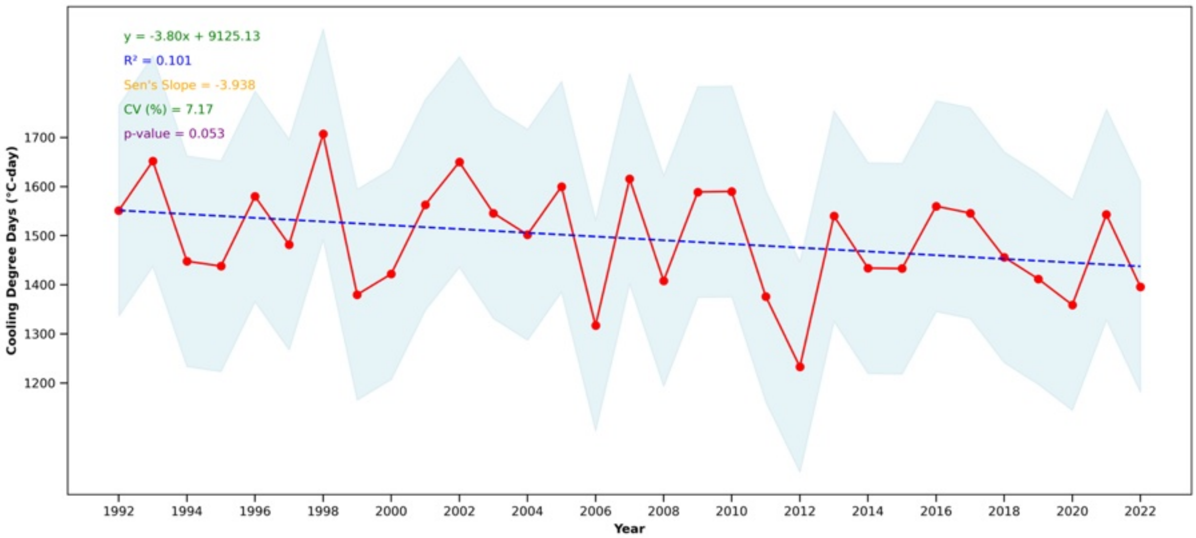


Figure 4.2 Climatology of Cooling Degree Days for Bamako (1992–2022)

Furthermore, Annual CDD values in Kano ranged from 912 °C-day to 1557 °C-day, with the highest and lowest values recorded in 2015 and 2022, respectively (Table 4.1). Bamako recorded values between 1233 °C-day and 1707 °C-day, with the peak occurring in 1998 and the minimum in 2012 (Table 4.1).

Table 4.1 Annual Cooling Degree Days for Kano and Bamako

	Kano	Bamako
Year	**CDD (°C-day)**	**CDD (°C-day)**
1992	1054	1551
1993	1206	1652
1994	1101	1448
1995	1097	1438
1996	1196	1580
1997	1365	1482
1998	1304	1707
1999	1275	1380
2000	1154	1422
2001	1052	1563
2002	1347	1650
2003	1249	1546
2004	1309	1502
2005	1402	1600
2006	1215	1317
2007	1194	1616
2008	1133	1408
2009	1309	1589
2010	1450	1590
2011	1245	1376
2012	1254	1233
2013	1251	1540
2014	1112	1434
2015	1557	1433
2016	1355	1560
2017	1192	1546
2018	1279	1456
2019	1245	1412
2020	1187	1359
2021	1282	1543
2022	912	1396

The observed trends in cooling degree days are best interpreted in relation to temperature variations, as changes in minimum, maximum, and mean temperatures directly influence their accumulation through shifts in daily thermal extremes and averages. In Kano, the annual minimum temperature showed a slight declining trend (Sen's slope = –0.025 °C/year), although this was not statistically significant (p = 0.103; Figure 4.3). In contrast, the maximum temperature exhibited a statistically significant increasing trend (Sen's slope = 0.021 °C/year; p = 0.016; see Figure 4.4). The mean temperature displayed a negligible trend over time, with no statistical significance (Sen's slope = –0.001 °C/year; p = 0.866; Figure 4.5). This suggests that the rise in daytime heat is being partially offset by cooler or stable night-time temperatures, potentially explaining why the increase in CDD is not statistically significant despite rising maximum temperatures.

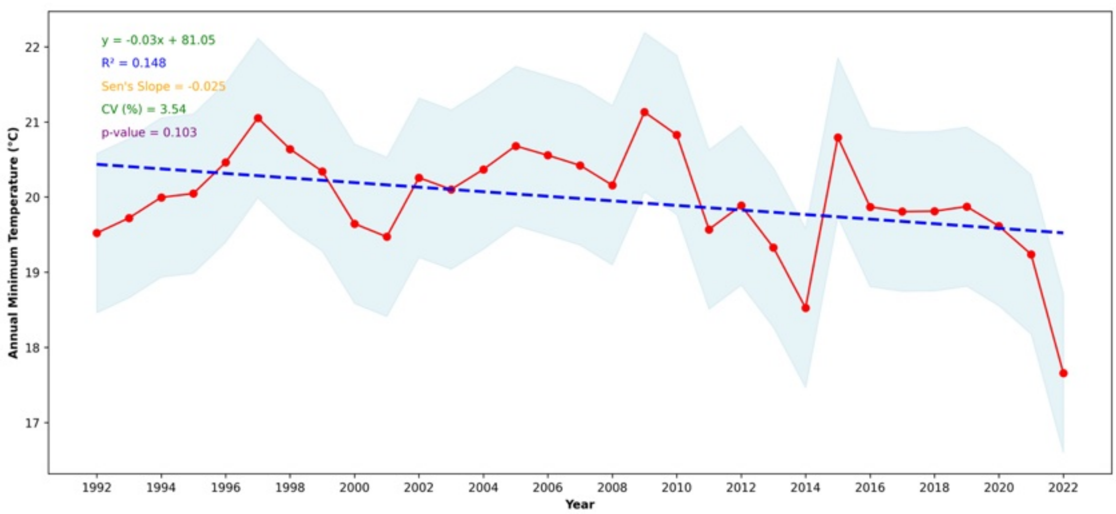


Figure 4.3 Annual Trend of Minimum Temperature in Kano (1992–2022)

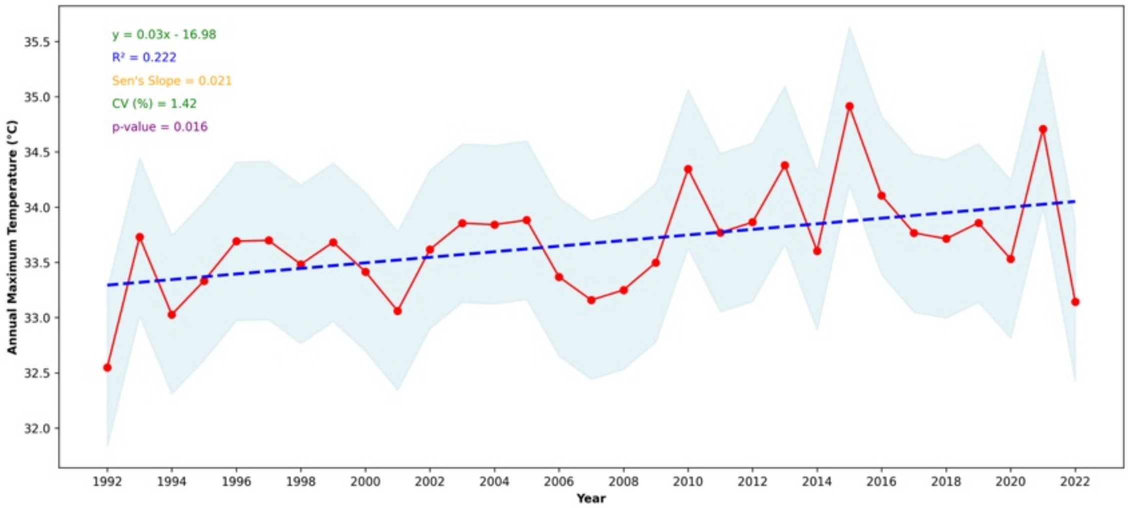


Figure 4.4 Annual Trend of Maximum Temperature in Kano (1992–2022)

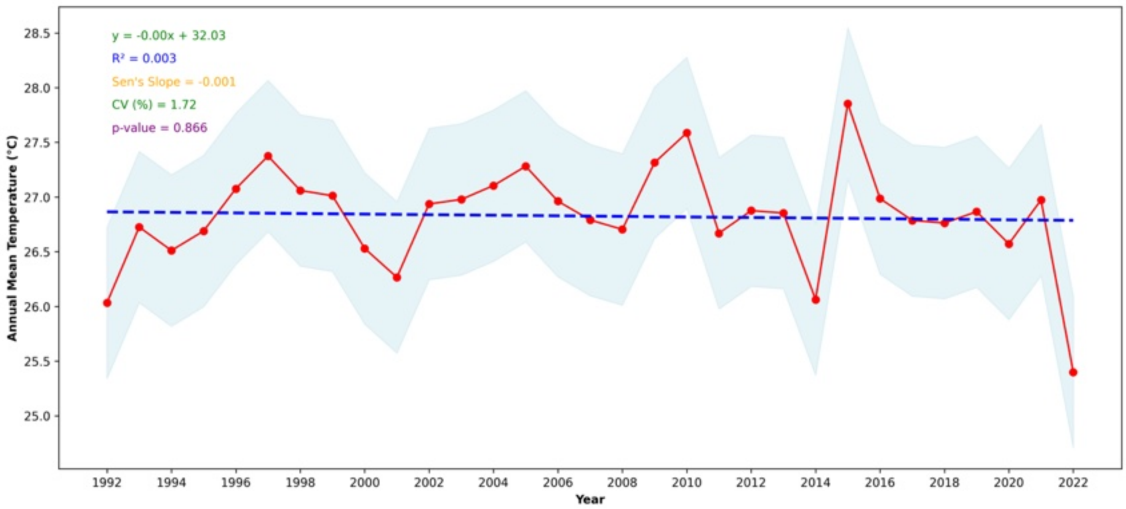


Figure 4.5 Annual Trend of Mean Temperature in Kano (1992–2022)

In Bamako, however, the temperature trends show a clearer alignment with the observed decline in CDD. A statistically significant decrease in minimum temperature was recorded (Sen's slope = –0.045 °C/year, $p = 0.001$; see Figure 4.6), followed by a slight, non-significant rise in maximum temperature (Sen's slope = 0.017 °C/year, $p = 0.083$; see Figure 4.7), and a marginally decreasing trend in mean temperature (Sen's slope = –0.012 °C/year, $p = 0.061$; see Figure 4.8).

These findings suggest that the drop in CDD is likely driven by declining night-time temperatures, which reduce the cumulative thermal stress and consequently lower cooling demand.

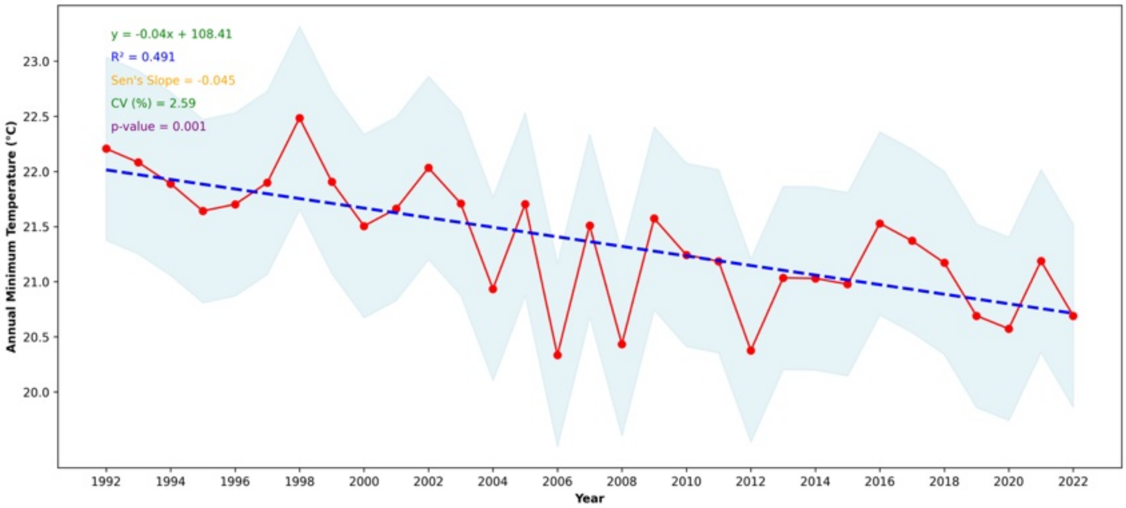


Figure 4.6 Annual Trend of Minimum Temperature in Bamako (1992–2022)

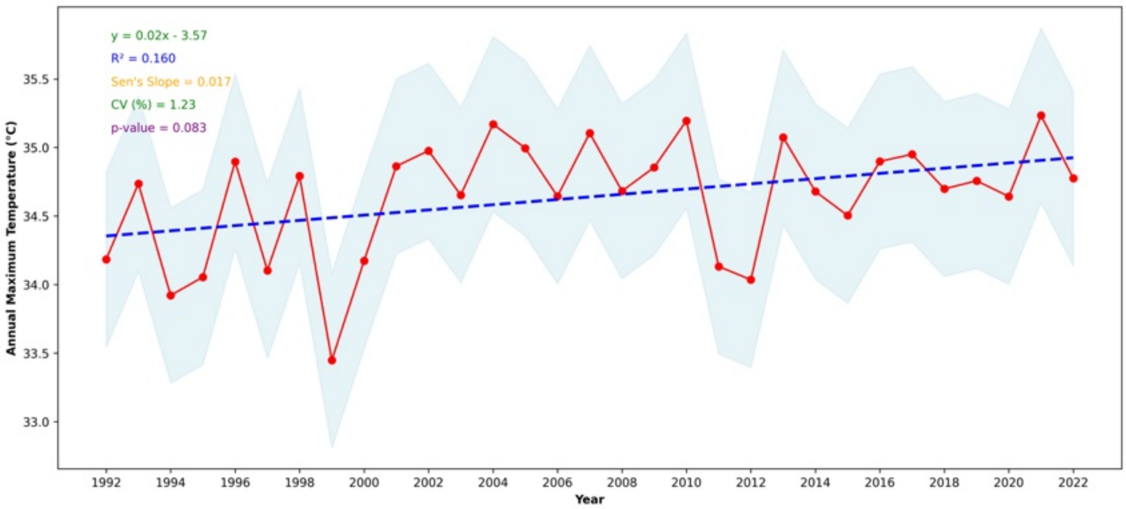


Figure 4.7 Annual Trend of Maximum Temperature in Bamako (1992–2022)

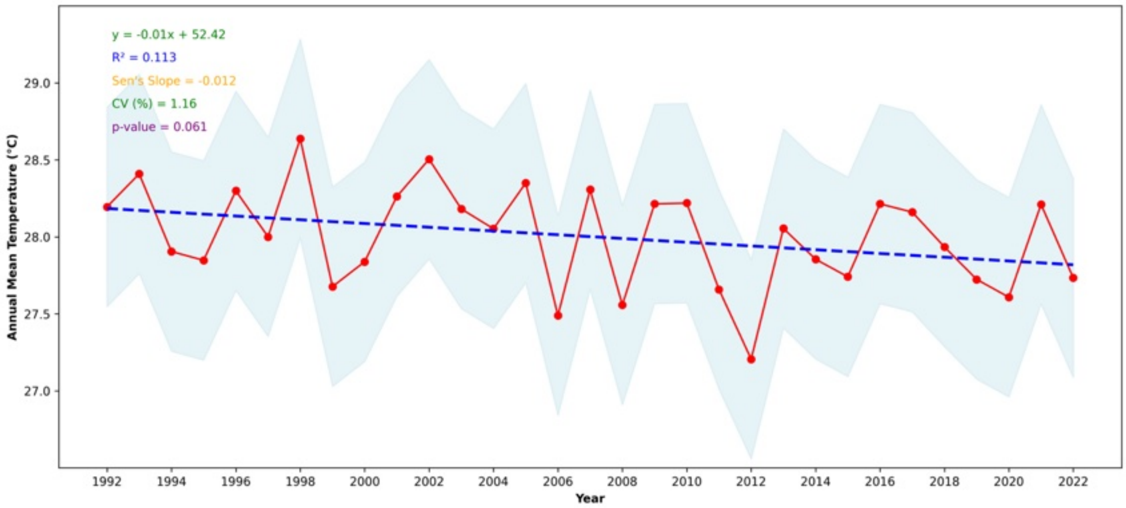


Figure 4.8 Annual Trend of Mean Temperature in Bamako (1992–2022)

The monthly Cooling Degree Days (CDD) for Kano for the period between 1992-2022, as indicated in Figure 4.9 highlights notable seasonal and inter-annual variability. Higher CDD values are predominantly observed during the late dry season and early rainy season, particularly from April to June, with May, consistently showing the highest cooling demands across the years. This pattern reflects a significant rise in cooling requirements during the hottest months, prior to the onset of substantial rainfall.

Figure 4.10 illustrates the monthly cooling degree days (CDD) for Bamako from 1992 to 2022, showing distinct seasonal patterns that correspond to variations in cooling requirements over time. Between November and February, there is little need for cooling, indicating a cooler, dry season. During April, when the temperatures are the hottest and cooling is needed most, CDD values spike significantly. There is a gradual decline in CDD from July to October, likely due to the onset of the rainy season, which moderates temperatures and reduces the need to cool.

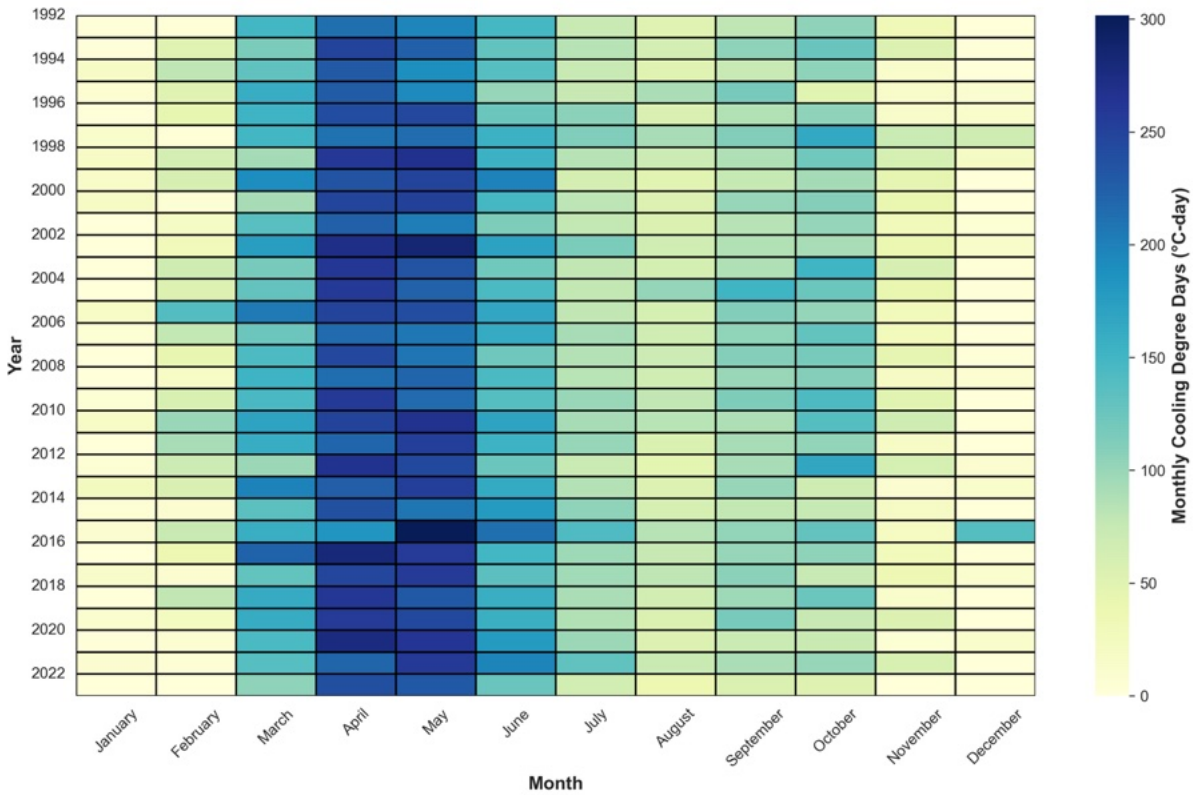


Figure 4.9 Monthly Cooling Degree Days for Kano

Over the decades, seasonal cooling demands have remained relatively stable across the years, indicating relatively stable seasonal cooling demand. The high CDD values during the pre-rainy season months highlight the importance of efficient cooling strategies to address increased energy demands and mitigate the effects of heat. This period further underscores the need for sustainable energy solutions to support Bamako’s growing cooling requirements.

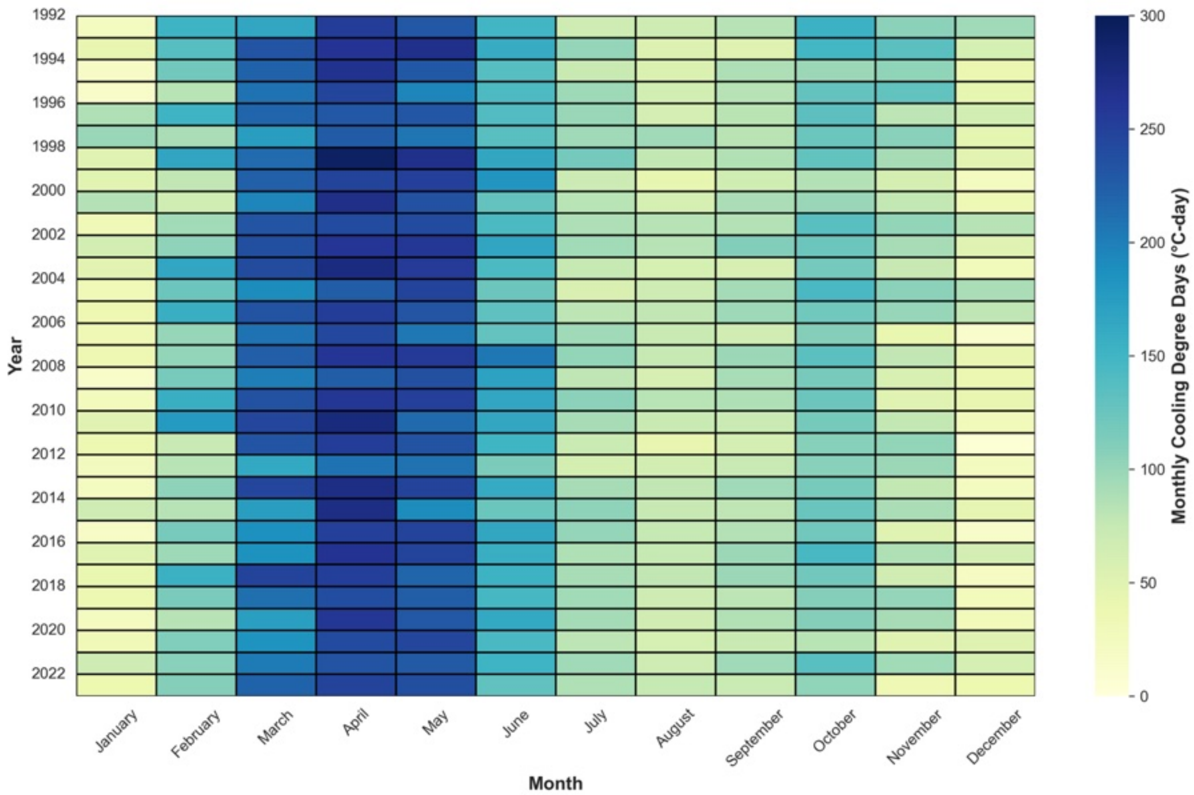


Figure 4.10 Monthly Cooling Degree Days for Bamako

Null hypothesis (Ho1): There is no significant trend in cooling degree days (CDD) between 1992 and 2022.

The statistical evidence suggests that this hypothesis is accepted. Although the CDD trend in Kano was positive, it was not statistically significant ($p = 0.444$). In Bamako, the trend was negative and nearly significant ($p = 0.053$), but does not meet the 0.05 threshold.

4.1.2 Trends in heat index in Kano and Bamako

Figures 4.11 and 4.12 shows the annual evolution of the heat index for Kano and Bamako over the period 1992-2022. For both cities, the heat index has shown less variation over the last 30 years. In Kano, heat index exhibited a positive trend with Sen's slope equal to 0.013 (Figure 4.11), although this trend is less statistically significant with a p-value greater than 0.05. Between 1992 and 2022, the heat index increased by 0.01°C every year. The coefficient of variation CV (%) is one of the most widely used summary statistics, and its values range from 0 to 0.20, very small; 0.21 to 0.40, small; 0.41 to 0.60, moderate; 0.61 to 0.80, large; and 0.81 to 1.00 for very large degree of variation (Kvålseth, 2017). The degree of variation of the heat index for Kano is 12.57% indicating a very small degree of variation.

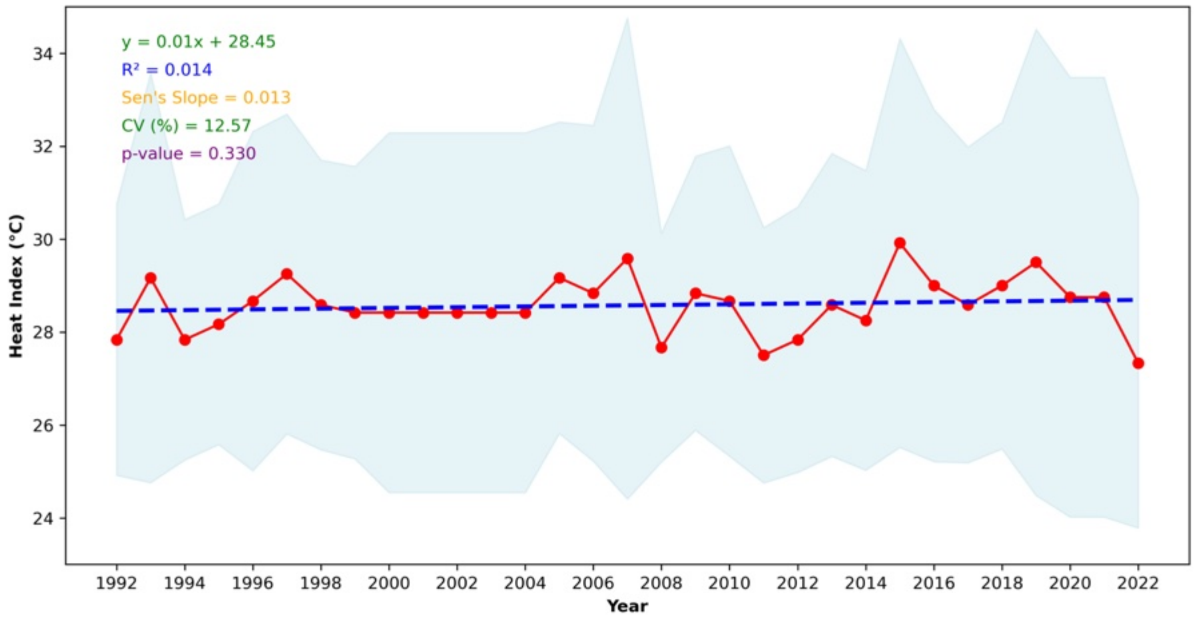


Figure 4.11 Variation of Heat Index between 1992-2022 for Kano

Meanwhile, Bamako presented a negative trend in heat index evolution over the years, as indicated by Sen's slope of -0.059, reflecting an annual change of approximately -0.06°C per year. Furthermore, the results in Bamako are statistically significant with a p-value equal to 0.005. However, a coefficient of variation of 11.87% suggests that the heat index variation is slow, and this is evident in Figure 4.12.

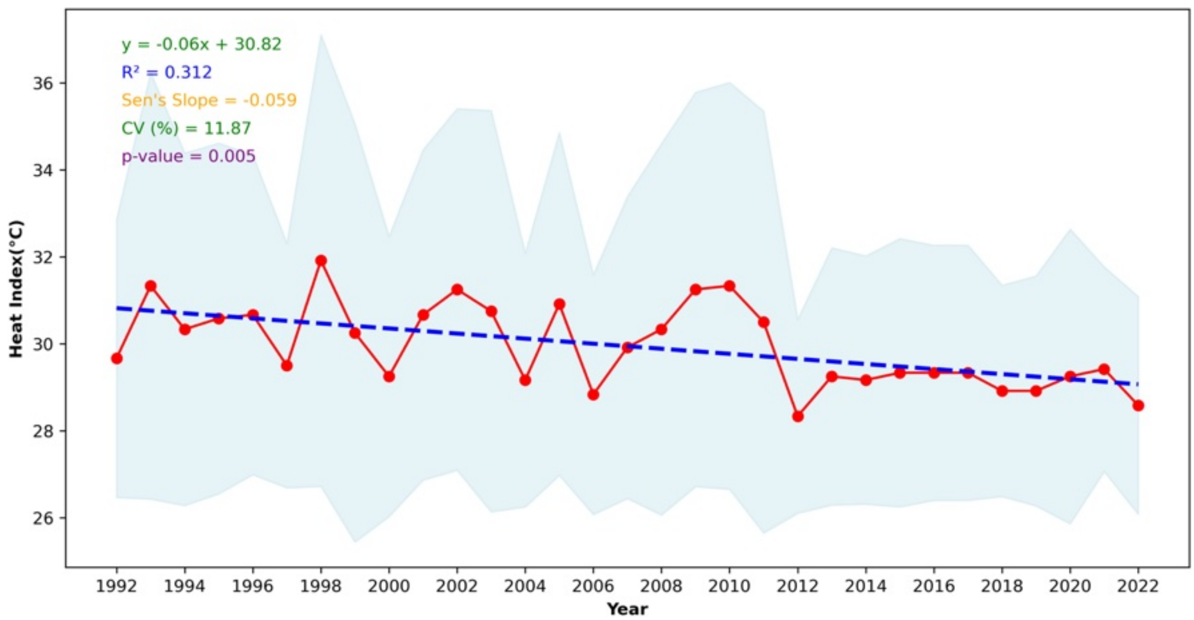


Figure 4.12 Variation of Heat Index between 1992-2022 for Bamako

Going further, the monthly average heat index values during the period 1992-2022 for Kano and Bamako are reported in Figure 4.13 and 4.14, respectively. The results as visible in the figures herein indicate the variation of heat index across the 12 months of the year, with heat index values ranging from 23 to 28°C for December, January and February in Kano (Figure 4.13). These months had lower heat index than the others, especially in 2022, when the heat index barely exceeded 24°C. Meanwhile, From April onwards, heat index values increased considerably, with an extreme value of 41 °C recorded in April 1994. On average, however, May consistently exhibited the highest monthly heat index across the study period, with mean values exceeding 35 °C. Heat values then start to decrease in July. Meanwhile, December to February were the coolest months in Kano, April to June recorded the highest heat index values over the period 1992 to 2022, witnessing unbearable heat that could cause severe discomfort to the human body. According to the National Oceanic and Atmospheric Administration (NOAA, 2024), heat index values between 27 and 32°C could cause potential fatigue in case of prolonged exposure, between 32 and 41°C to the sun exposure, heat stroke and heat cramps, from 41 to 54°C, risks of heat exhaustion and when heat index exceeds 54°C, the risk of having heat stroke is very likely.

Bamako, had similar results to Kano, with heat index values from December to February falling between 25 and 28 °C, being the months with the lowest HI values (Figure 4.14). In contrast, the highest heat index values of 31 to 42 °C were recorded between April and May.

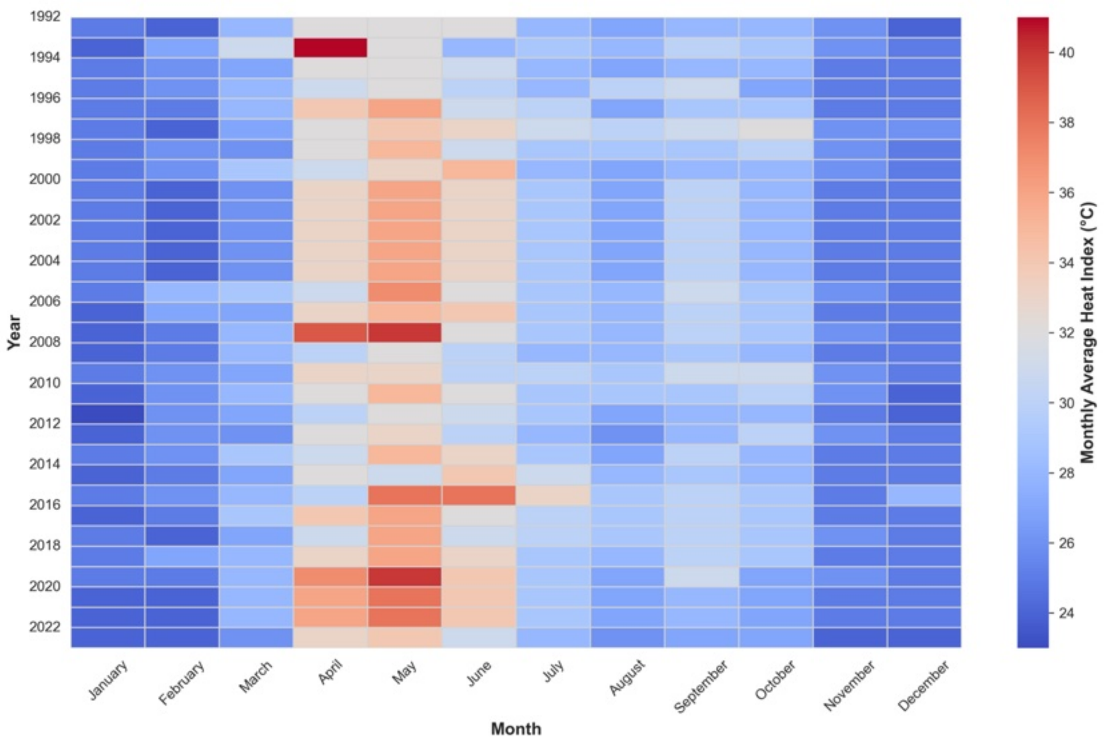


Figure 4.13 Monthly Average Heat Index between 1992-2022 for Kano

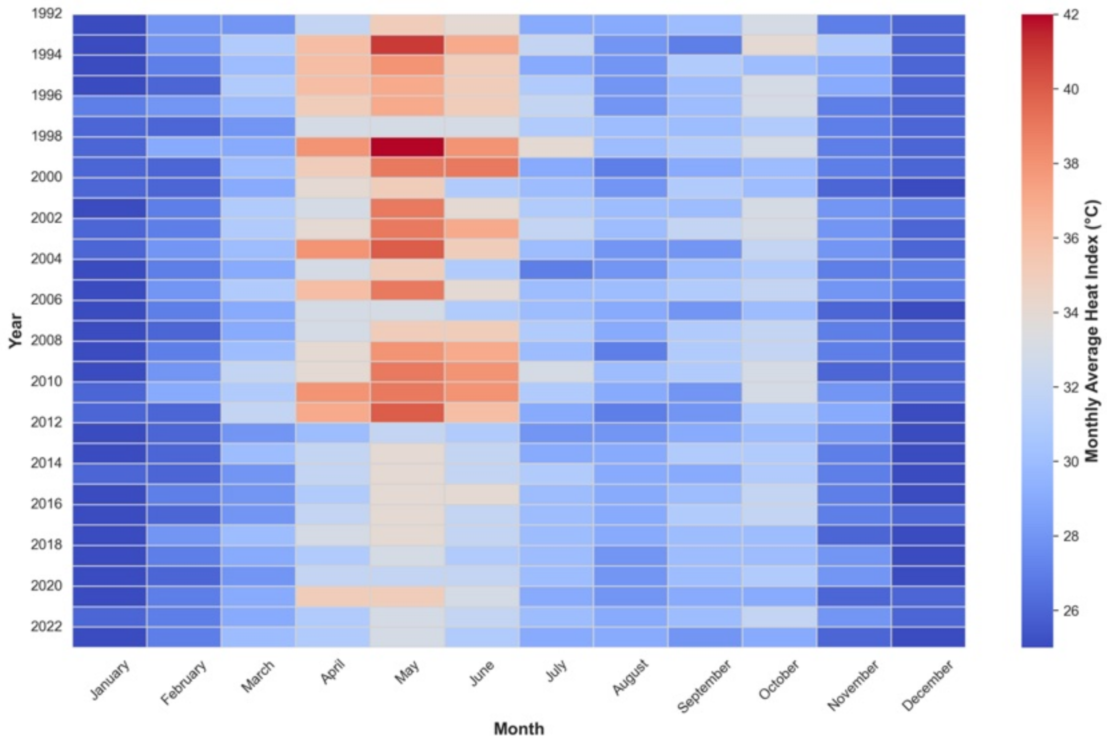


Figure 4.14 Monthly Average Heat Index between 1992-2022 for Bamako

The degree of relative humidity is a key factor in people's perception of heat, and directly impacts thermal comfort. A higher humidity leads to a warmer feeling, as sweat evaporates less efficiently. This phenomenon is best explained by Figures 4.15 and 4.16, which indicate a direct relationship between heat index and relative humidity with $r^2 = 0.20$ and $r^2 = 0.72$ for Kano and Bamako, respectively. The heat index in Kano increased by about 0.16°C, with a baseline heat index of approximately 20.80 °C at 0% relative humidity. By comparison, in Bamako, 1% increase in relative humidity can be associated with a 0.10°C increase in the heat index. According to Giannopoulou *et al.* (2014) and Steadman (1979), the impact of relative humidity on human discomfort is more pronounced in regions with warmer meteorological conditions.

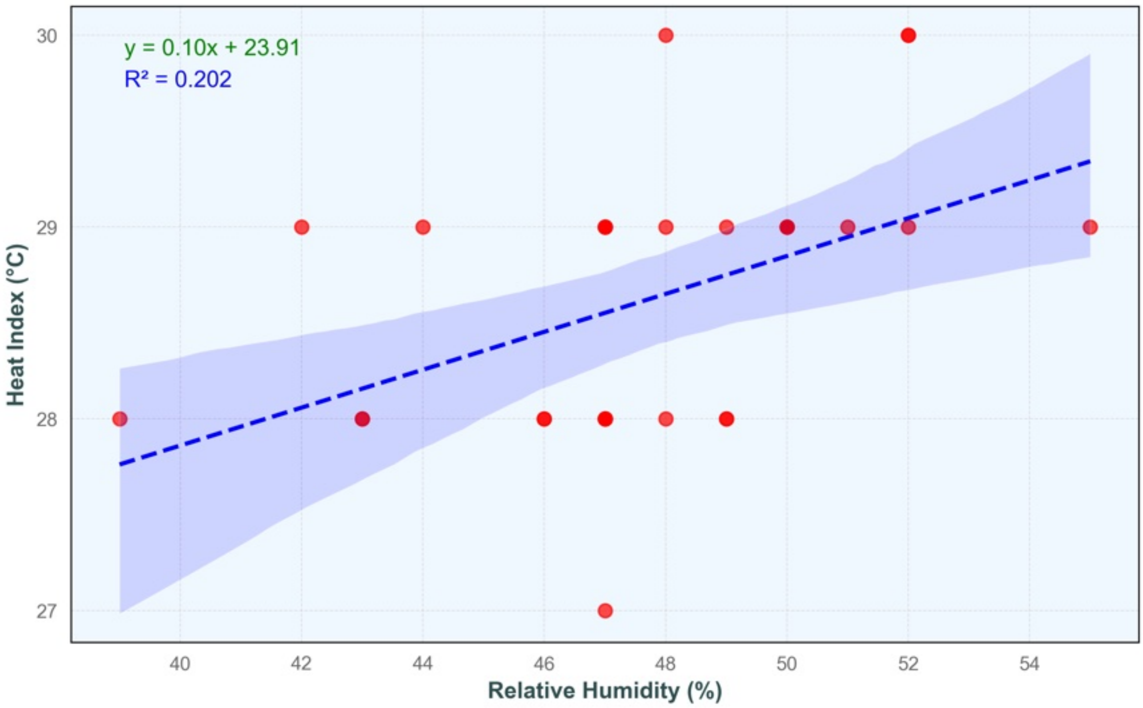


Figure 4.15 Relationship between Index Heat and Relative Humidity for Kano

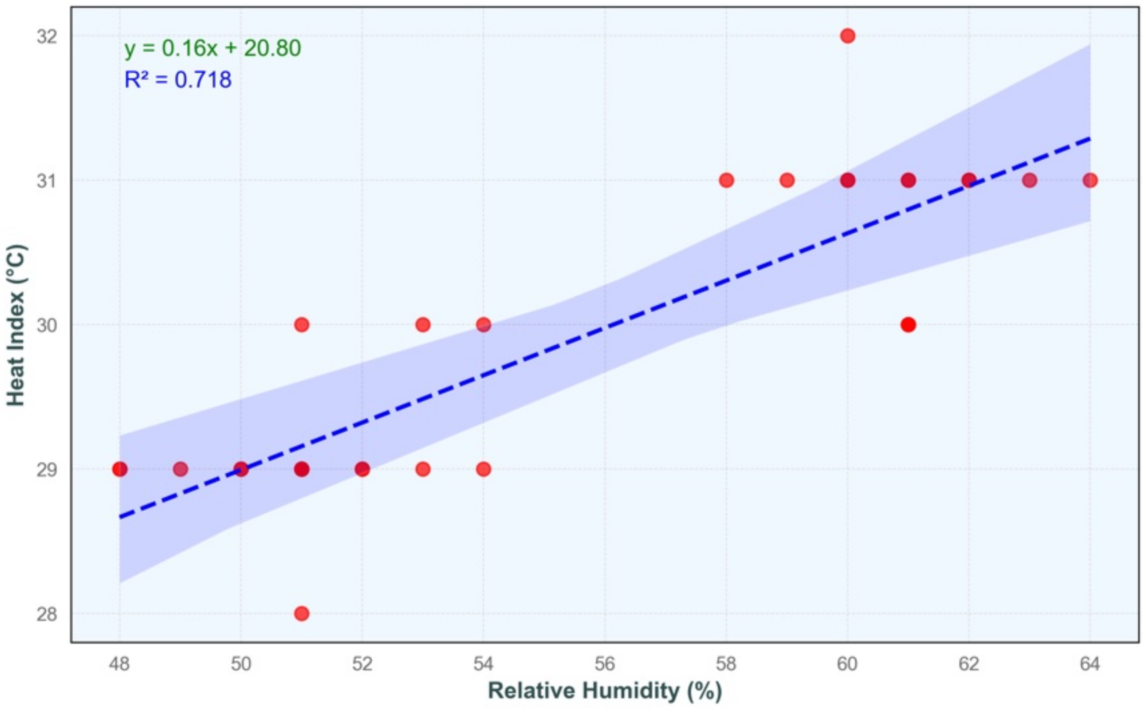


Figure 4.16 Relationship between Index Heat and Relative Humidity for Bamako

Null hypothesis (Ho2): There is no significant trend in the heat index (HI) between 1992 and 2022.

The analysis reveals that this hypothesis is partially rejected. A statistically significant decreasing trend was recorded in Bamako, while the trend in Kano was positive but not significant.

4.1.3 Assess the land use and land cover change of the study area

4.1.3.1 Analysis of spatial-temporal change

The LULC maps for Kano are shown in Figure 4.17. There is a noticeable gradual evolution of urban space at the expense of other land use classes including water, vegetation and barren land. Over the years, Kano has experienced significant land use transformation, primarily driven by rapid urban expansion. In 1991, the built-up area was concentrated in central districts such as Kano Municipal, Fagge, and Nassarawa, which served as the main urban centers. By 2002, urban growth spread outward, incorporating additional areas in Gwale, Dala, Tarauni, and Kumbotso, indicating an accelerating rate of urbanisation. This trend continued into 2012, with built-up area expanding further into Ungogo and surrounding peri-urban zones, leading to a substantial reduction in barren land. However, vegetation cover also increased more importantly during this period compared to previous years, possibly due to afforestation efforts or land conversion from barren to green use. By 2022, urban sprawl had become even more pronounced, covering nearly all major local governement areas, including Dala, Fagge, Kano Municipal, Tarauni, Gwale, and parts of Ungogo and Kumbotso. The built-up area had expanded extensively across the metropolitan landscape. Only small, fragmented patches of vegetation remained, largely confined to the peripheral zones, particularly toward the northern edges of Ungogo and also in Kumbotso LGA.

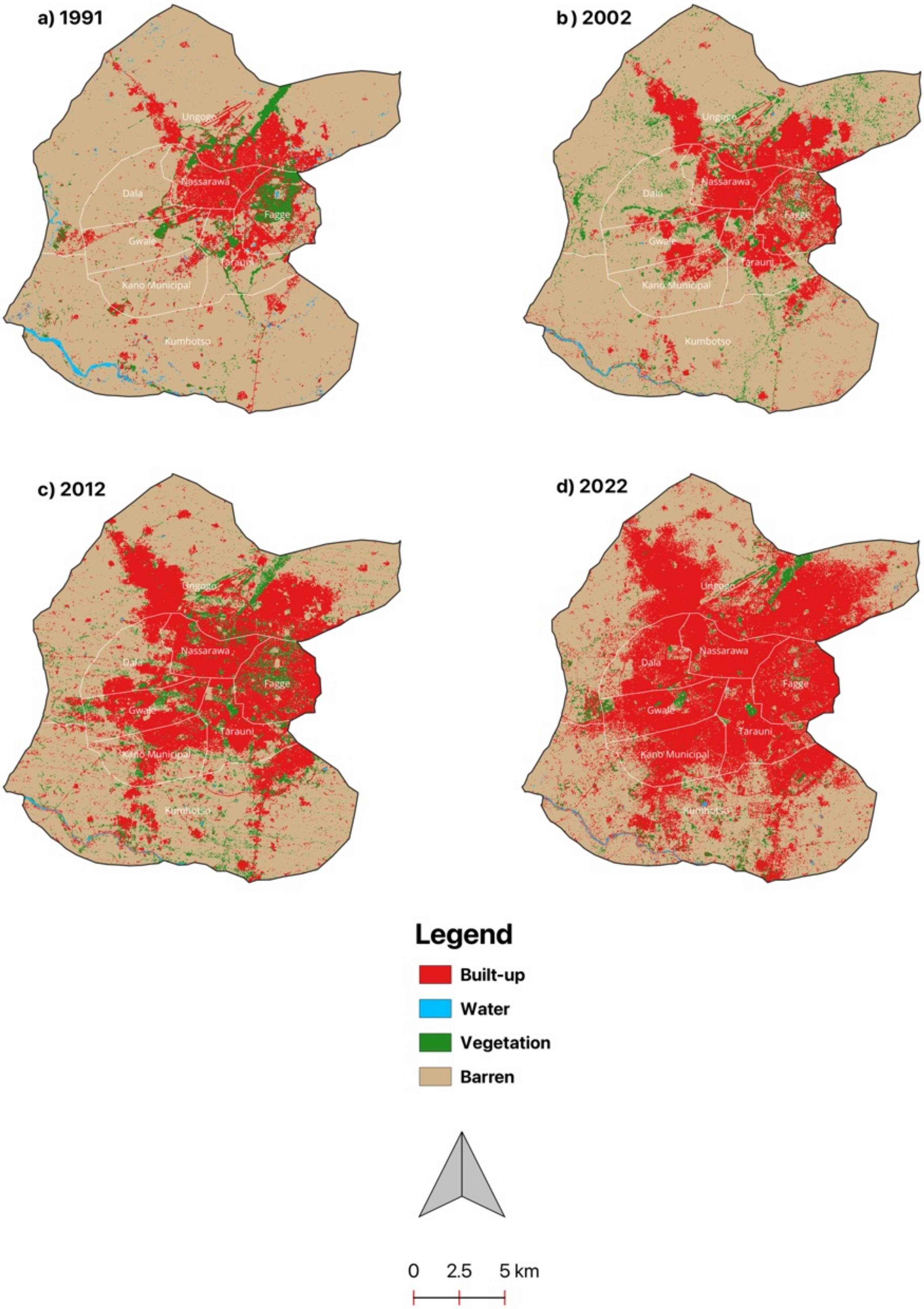


Figure 4.17 Spatiotemporal LULC Maps for Kano (1991-2022)

The LULC statistics and class distribution for Kano are detailed in Table 4.2 and illustrated in Figure 4.18. A noteworthy trend is the constant expansion of built-up areas, which have grown from 66.88 km² in 1991 to 242.53 km² in 2022, representing an average annual increase of 8.47%. This reflects the rapid urbanisation experienced in Kano over the past three decades. Conversely, all other types of land cover declined during the same time period. Compared to 1991, water bodies decreased from 5.91 km² to 1.49 km² by 2022, which translates to -2.41% less area. Although a minor recovery was observed between 2012 and 2022, when the water area increased from 1.05 km² to 1.49 km², this is likely attributable to localised flooding or drainage accumulation in rapidly urbanising areas, where the expansion of impervious surfaces disrupts natural infiltration and promotes surface water retention, particularly in low-lying zones. Likewise, vegetation cover decreased from 21.5 km² in 1991 to 17.1 km² in 2022, at a decrease rate of -0.66%. Similarly, barren land decreased from 399.59 km² to 243.94 km², representing a -1.26% annual change.

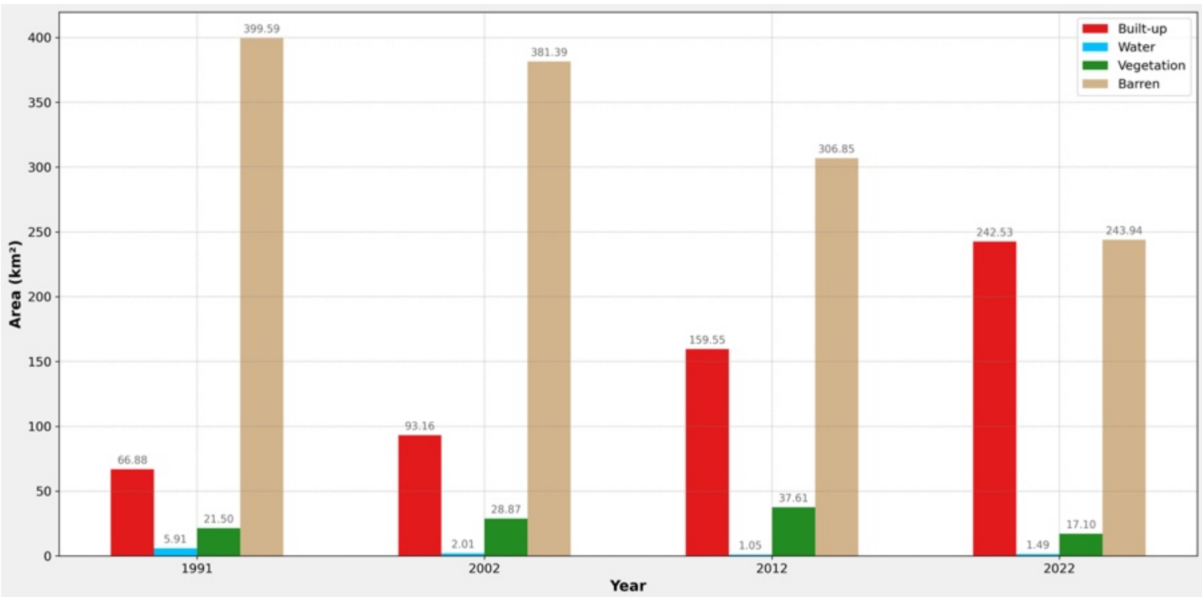


Figure 4.18 Temporal Evolution of LULC Classes for Kano (1991-2022)

Table 4.2 LULC Classes Statistics for Kano

LULC Class	1991		2002		2012		2022		AC (%)
	km^2	%	km^2	%	km^2	%	km^2	%	
Built-up	66.88	13.54	93.16	18.43	159.55	31.59	242.53	47.98	8.47
Water	5.91	1.2	2.01	0.4	1.05	0.21	1.49	0.29	-2.41
Vegetation	21.5	4.35	28.87	5.71	37.61	7.45	17.1	3.38	-0.66
Barren	399.59	80.91	381.39	75.46	306.85	60.75	243.94	48.35	-1.26

Likewise, LULC maps from 1991 to 2022 for Bamako are presented in Figure 4.19. Over the same period, the city experienced a significant physical transformation, characterised by rapid and continuous urban expansion. In 1991, built-up area was mostly concentrated in the core of the city, with large tracts of vegetation and barren land on the outskirts. A considerable outward expansion of the urban area took place in 2002, affecting the barren lands within almost all of the municipalities. By 2012, urban growth had intensified further, with built-up area expanding in the eastern and southern sectors of the city, replacing large sections of barren land and further fragmenting green spaces. By 2022, the built-up class had become the predominant land cover type throughout the metropolitan area. Urban development had saturated most of the city, leaving only scattered remnants of vegetation on the outskirts. The most notable urban expansion has taken place in municipalities I, III, and IV, where dense the built-up area has replaced previously vegetated and barren lands, especially along the Niger River.

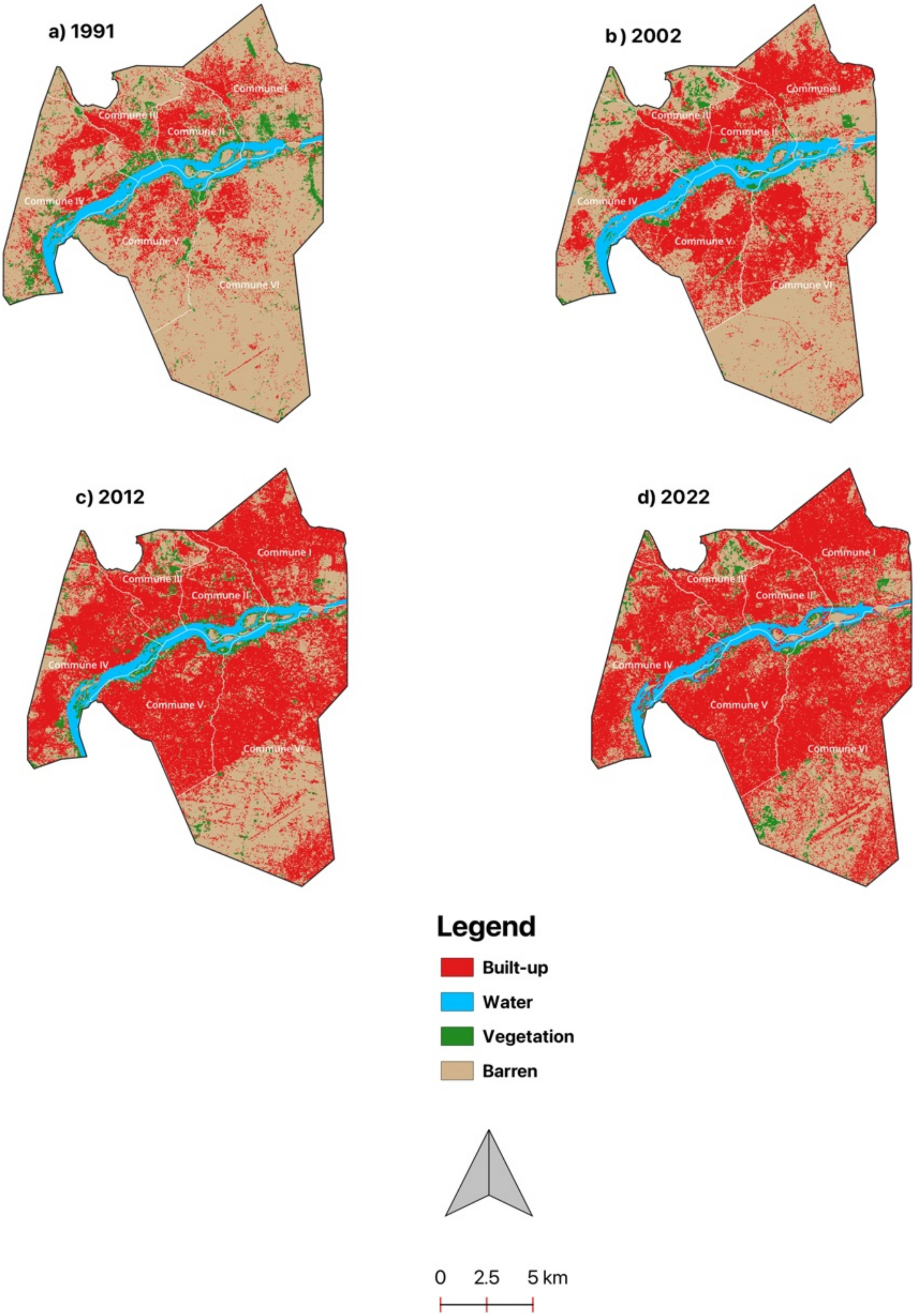


Figure 4.19 Spatiotemporal LULC Maps for Bamako (1991-2022)

Figure 4.20 and Table 4.3 present LULC statistics for Bamako between 1991 and 2022. In 1991, the built-up area covered 50.49 km², but this rose sharply to 82.17 km² in 2002, reflecting an initial trend towards urban sprawl. The rate of expansion accelerated over the following decade, reaching 114.08 km² in 2012, and peaking at 157.88 km² in 2022. This steady increase, averaging 6.86% per year, occurred to the detriment of vegetated and barren landscapes. Vegetation fell from 16.66 km² in 1991 to 13.15 km² in 2002, then decreased to 9.42 km² in 2012 and to 8.16 km² in 2022, resulting in a persistent diminution of vegetation. Similarly, barren land fell from 162.33 km² in 1991 to 130.26 km² in 2002, 98.26 km² in 2012 and finally 70.98 km² in 2022. Although water bodies have seen fewer fluctuations, the surface area has nevertheless decreased from 13.24 km² in 1991 to 11.68 km² in 2022. While this decline is less pronounced compared to other land classes, urban expansion has put increased pressure on the Niger River, particularly within the municipalities III and V, where encroachment and pollution threaten water quality. Given the central role of water resources in sustaining livelihoods, agriculture, and biodiversity, their conservation remains a critical issue.

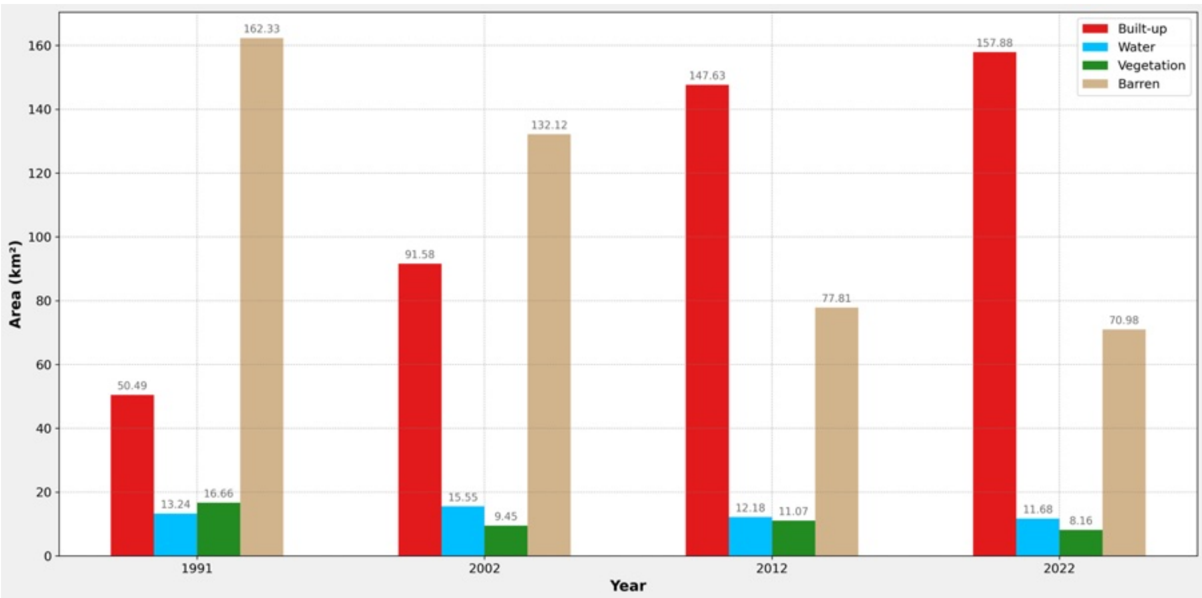


Figure 4.20 Temporal Evolution of LULC Classes for Bamako (1991-2022)

Table 4.3 LULC Classes Statistics for Bamako

	1991		2002		2012		2022		
LULC Class	km^2	%	km^2	%	km^2	%	km^2	%	AC (%)
Built-up	50.49	13.54	91.58	18.43	147.63	31.59	157.88	47.98	6.86
Water	13.24	1.2	15.55	0.4	12.18	0.21	11.68	0.29	-0.38
Vegetation	16.66	4.35	9.45	5.71	11.07	7.45	8.16	3.38	-1.65
Barren	162.33	80.91	132.12	75.46	77.81	60.75	70.98	48.35	-1.82

Over the same period, Kano and Bamako both experienced a steady growth in built-up area and a significant decrease across the other landscape classes. At the same time, barren land is the class that underwent the greatest reduction in area in Kano and Bamako over the same period.

4.1.3.2 Accuracy assessment

Table 4.4 illustrates the accuracy assessment including the overall accuracy and the Kappa coefficient for Kano between the period 1991-2022. The Cohen's kappa coefficient is a statistic used to measure inter-rater agreement (Vieira *et al.*, 2010). A value of k below 0 indicates that there is no agreement between the classified map and the observations; 0–20% indicates that there is some agreement; 21–40% means a fair agreement; 41–60% means a moderate agreement; 61–80% indicates a significant agreement, and 81–100% indicates almost perfect agreement (Loosvelt *et al.*, 2012). The confusion matrix diagonal values are used to measure overall accuracy. In spite of the desire for an overall accuracy value near 100%, a classification accuracy greater than 85% is considered acceptable (Gashaw *et al.*, 2017).

The land cover classification for Kano is highly accurate with values ranging from 0.93 to 97% and Kappa values ranging from 0.86 to 0.96%. In 1991, the overall accuracy was 0.95% and the Kappa coefficient was 0.93%. While the measurements recorded for 2002 indicate an overall accuracy of 0.96% and a Kappa coefficient of 0.95%. The results for 2012 revealed an overall accuracy of 0.97% and a Kappa coefficient of 0.96%. Furthermore, the overall accuracy and Kappa coefficients for 2022 are 0.96% and 0.95% respectively. Equally, in Bamako, an overall accuracy ratio of 0.87%, 0.93%, 0.93% and 0.92% was respectively found for the years 1991, 2002, 2012 and 2022, whereas the Kappa coefficient was 0.81%, 0.89%, 0.85% and 0.82% (Table 4.5).

Table 4.4 LULC Accuracy for Kano

Accuracy assessment	1991	2002	2012	2022
Overall accuracy (%)	0.95	0.96	0.97	0.93
Kappa (%)	0.93	0.95	0.96	0.86

Table 4.5 LULC Accuracy for Bamako

Accuracy assessment	1991	2002	2012	2022
Overall accuracy (%)	0.87	0.93	0.93	0.92
Kappa (%)	0.81	0.89	0.85	0.82

4.1.3.3 LULC transition analysis

A transition matrix is a technique used to calculate changes in land use classes over two time periods. It provides an understanding of the extent to which a given area of land has transitioned from one category to another. The matrix is a combination of rows and columns, with the rows representing the initial states and the columns the final states. The diagonal elements in the table denote areas that have remained unchanged and the non-diagonal elements are areas that have moved to different categories. Over the period 1991 to 2002 in Kano, built-up class has displayed exceptional stability with a transition probability equal to 0.728 (Table 4.6).

On the other hand, water showed considerable stability, with a transition probability of 0.979, but did not play a major role in urbanisation. Moreover, it has been established that abrupt changes occur mainly in vegetation and barren land (Kröpelin *et al.*, 2008), reflecting the significant transitions observed for vegetation and barren land, and responsible for 0.194 and 0.304 of the increase in urban space, respectively. Between 2002-2012, urban areas have continued to be more stable, with a transition probability of 0.862 (Table 4.7). Water, vegetation and barren hold transition probabilities of 0.295, 0.208 and 0.748, respectively. Water and barren did contribute significantly to the built-up area, with 0.248 and 0.192, respectively.

Eventually, during the last decennia 2012-2022, the built-up and the water have been quite stable with a probability of 0.906 and 0.448, respectively (Table 4.8). The stability of the water class during this period could reflect localised flooding or drainage accumulation in rapidly urbanising areas, where the expansion of impervious surfaces disrupts natural infiltration and promotes surface water retention, particularly in low-lying zones. Vegetation and barren, unstable contributed to the built-up expansion by 0.491 and 0.258, respectively.

Figure 4.21 provides an overview of the areas gained and lost for each class over the last three decades in Kano.

Table 4.6 Transition Matrix from 1991–2002 for Kano

Year		**2002**			
		Built-up	**Water**	**Vegetation**	**Barren**
1991	Built-up	**0.728**	0.001	0.015	0.256
	Water	0.002	**0.979**	0.018	0.002
	Vegetation	0.194	0.109	**0.266**	0.431
	Barren	0.304	0.002	0.024	**0.67**

Table 4.7 Transition Matrix from 2002–2012 for Kano

Year		2012			
		Built-up	**Water**	**Vegetation**	**Barren**
2002	Built-up	**0.862**	0.002	0.062	0.074
	Water	0.248	**0.295**	0.078	0.379
	Vegetation	0.191	0.003	**0.321**	0.484
	Barren	0.192	0.001	0.059	**0.748**

Table 4.8 Transition Matrix from 2012–2022 for Kano

Year		2022			
		Built-up	**Water**	**Vegetation**	**Barren**
2012	Built-up	**0.906**	0.001	0.01	0.083
	Water	0.306	**0.448**	0.061	0.186
	Vegetation	0.491	0.002	**0.208**	0.3
	Barren	0.258	0.003	0.025	**0.714**

Tables 4.9, 4.10 and 4.11 illustrate the transition matrices for the periods 1991-2002, 2002-2012 and 2012-2022 for Bamako, respectively. In line with the tables, it is apparent that during the first period (1991-2002), built-up and water remained virtually unchanged with transition probabilities of 0.728 for built-up and 0.979 for water. Water was the most stable class in the landscape. The high stability of the water class may be attributed to residual or semi-permanent water bodies and artificial retention systems, as well as seasonal visibility during image acquisition.

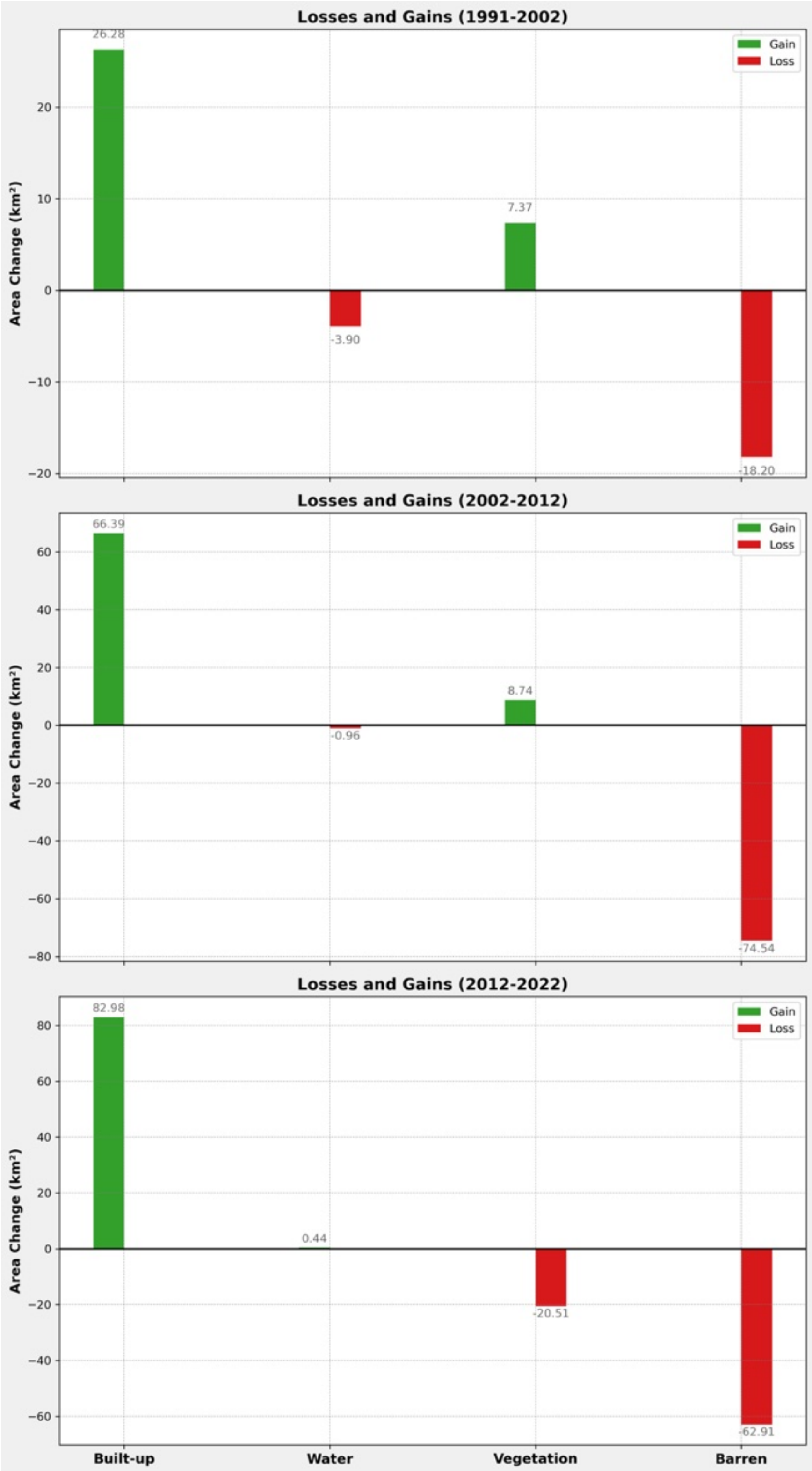


Figure 4.21 Gains and Losses in Area for Kano

Table 4.9 Transition Matrix from 1991–2002 for Bamako

Year		2002			
		Built-up	**Water**	**Vegetation**	**Barren**
1991	Built-up	**0.728**	0.001	0.015	0.256
	Water	0.002	**0.979**	0.018	0.002
	Vegetation	0.194	0.109	**0.266**	0.431
	Barren	0.304	0.002	0.024	**0.67**

Table 4.10 Transition Matrix from 2002–2012 for Bamako

Year		2012			
		Built-up	**Water**	**Vegetation**	**Barren**
2002	Built-up	**0.881**	0	0.009	0.11
	Water	0.019	**0.78**	0.152	0.049
	Vegetation	0.265	0	**0.453**	0.281
	Barren	0.486	0	0.027	**0.487**

Table 4.11 Transition Matrix from 2012–2022 for Bamako

Year		2022			
		Built-up	**Water**	**Vegetation**	**Barren**
2012	Built-up	**0.811**	0	0.007	0.182
	Water	0.052	**0.934**	0.009	0.005
	Vegetation	0.295	0.02	**0.391**	0.294
	Barren	0.441	0.001	0.034	**0.525**

Furthermore, vegetation and barren, unstable, transitioned with probabilities of 0.266 and 0.67, respectively, thereby contributing to the built-up. Between 2002-2012, the same trends were observed with a persistent stability of built-up with a transition probability of 0.881. However, water remained slightly less stable, with a transition probability of 0.78 compared with 0.979 the previous year. Vegetation and barren have maintained the same trends of instability in all the municipalities, leading to an expansion of the built-up with notably 0.265 and 0.486 contributions, respectively.

In the most recent period (2012–2022), both built-up and water classes remained highly stable, with transition probabilities of 0.811 and 0.934, respectively. However, vegetation and barren classes continued to contribute to urban expansion, with 29.5% and 44.1% of their areas transitioning to built-up, respectively. Despite this, vegetation retained a moderately high level of persistence (0.391), possibly reflecting conservation awareness or afforestation efforts in some parts of the city. Figure 4.22 presents both the gain and loss of each class in Bamako over the study period.

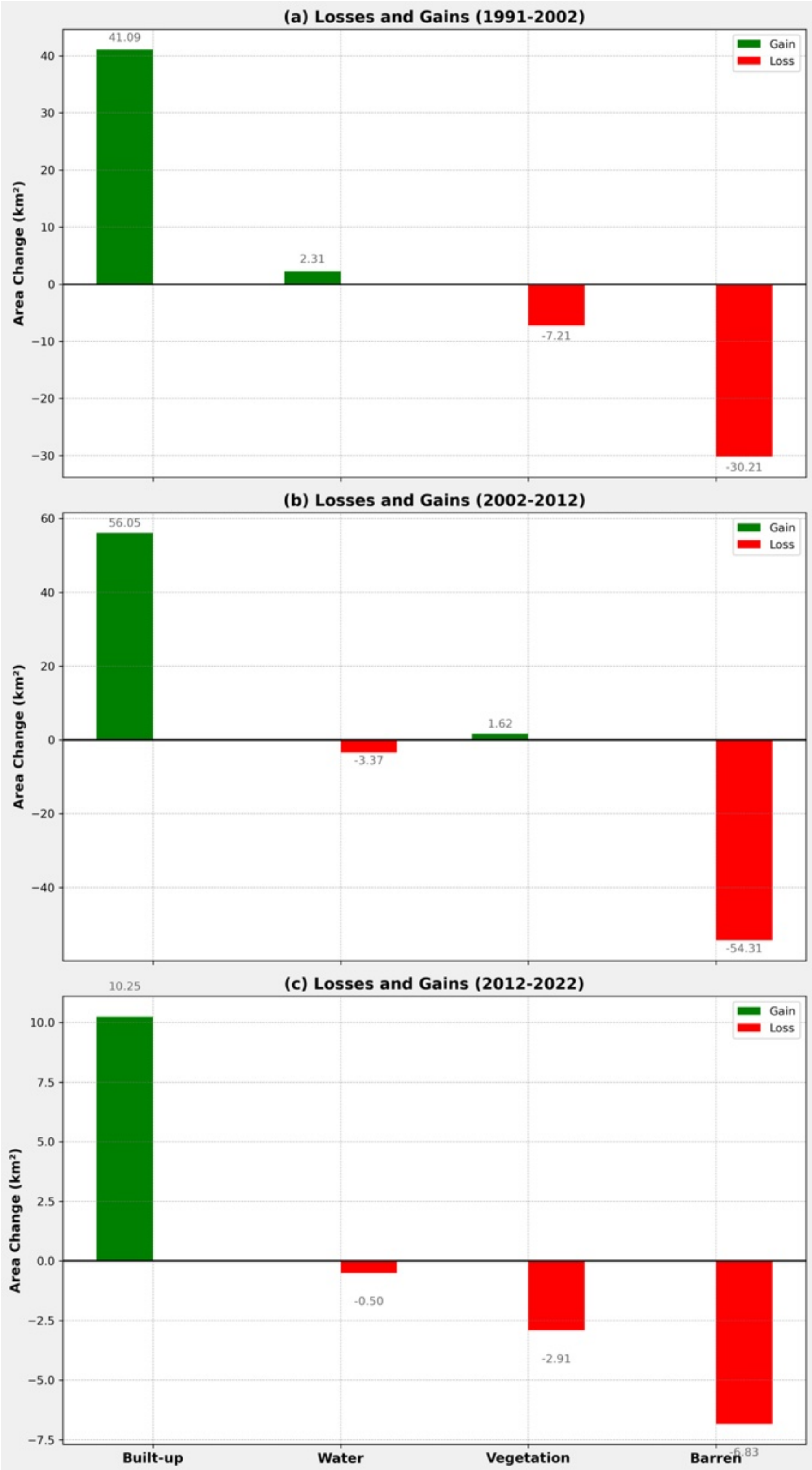


Figure 4.22 Gains and Losses in Area for Bamako

Null hypothesis (Ho3): There is no significant change in land use and land cover (LULC) in the study area between 1992 and 2022.

Evidence from the classification results suggests that this hypothesis is rejected. Both cities experienced substantial changes in LULC, particularly the expansion of built-up areas and the decline in vegetation.

4.1.4 Identify suitable locations for installing solar powerplants in Kano and Bamako

4.1.4.1 Criteria layers

The fuzzy classification results for each criterion in Kano, presented in Figure 4.23, reveal distinct spatial variations in suitability levels for solar energy development. Areas with values closer to 1 indicate optimal conditions based on the specific criterion, signifying high suitability, while values approaching 0 denote locations with limited or no potential for solar energy infrastructure.

Similarly, the fuzzy classification results for each criterion in Bamako, as displayed in Figure 4.24, illustrate the spatial distribution of suitability levels for solar energy development. Areas with fuzzy values closer to 1 indicate high suitability, reflecting optimal conditions based on specific criteria such as slope, aspect, elevation, and solar irradiance. Conversely, values closer to 0 represent locations with minimal or no potential for solar energy infrastructure.

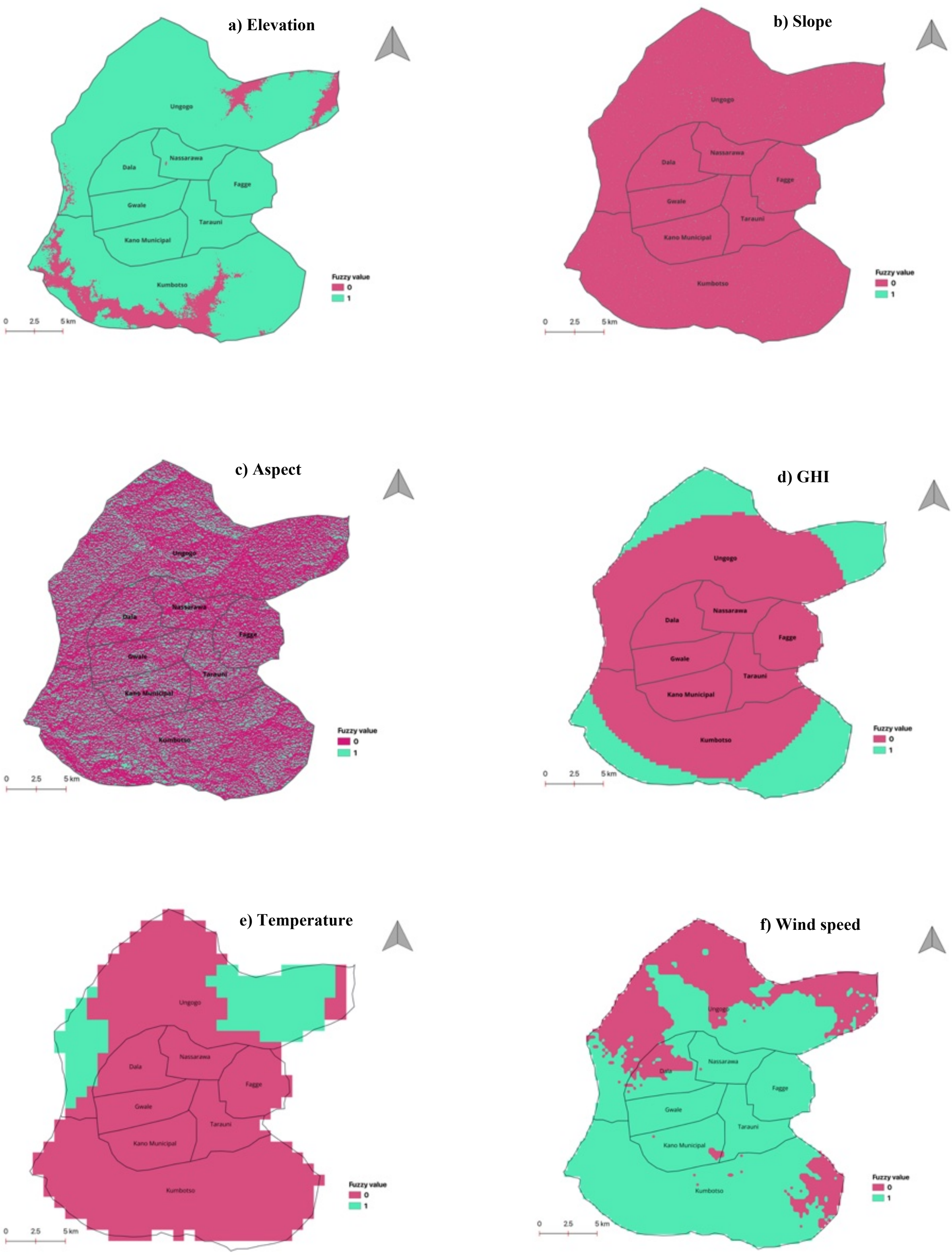


Figure 4.23 Classified Criteria Layers for Kano

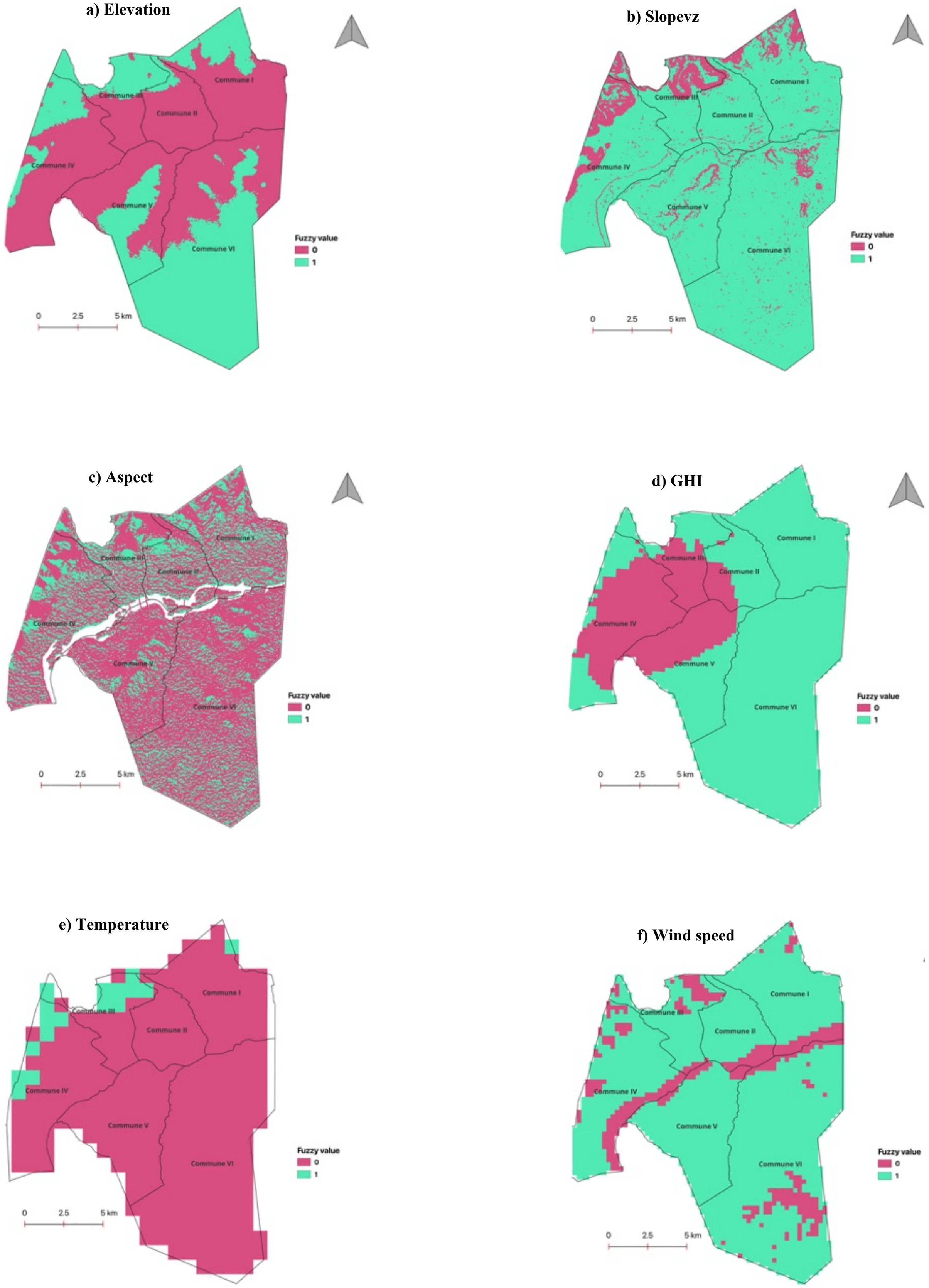


Figure 4.24 Classified Criteria Layers for Bamako

4.1.4.2 Restrictions layers

The restriction layers for Kano, illustrated in Figures 4.25 identify areas that are entirely excluded from consideration for solar energy development. These layers include proximity to roads and electricity network, and protected zones around critical infrastructure and residential areas. These restriction maps help eliminate unsuitable areas, focusing on locations with the potential for sustainable solar energy development.

Figures 4.26 illustrate the restriction layers for Bamako, which outline areas that are off-limits for solar energy development due to specific factors. These layers serve as a clear framework for eliminating unsuitable areas, thereby facilitating the identification of suitable locations for solar energy projects in Bamako.

Figure 4.25 Classified Restriction Layers for Kano

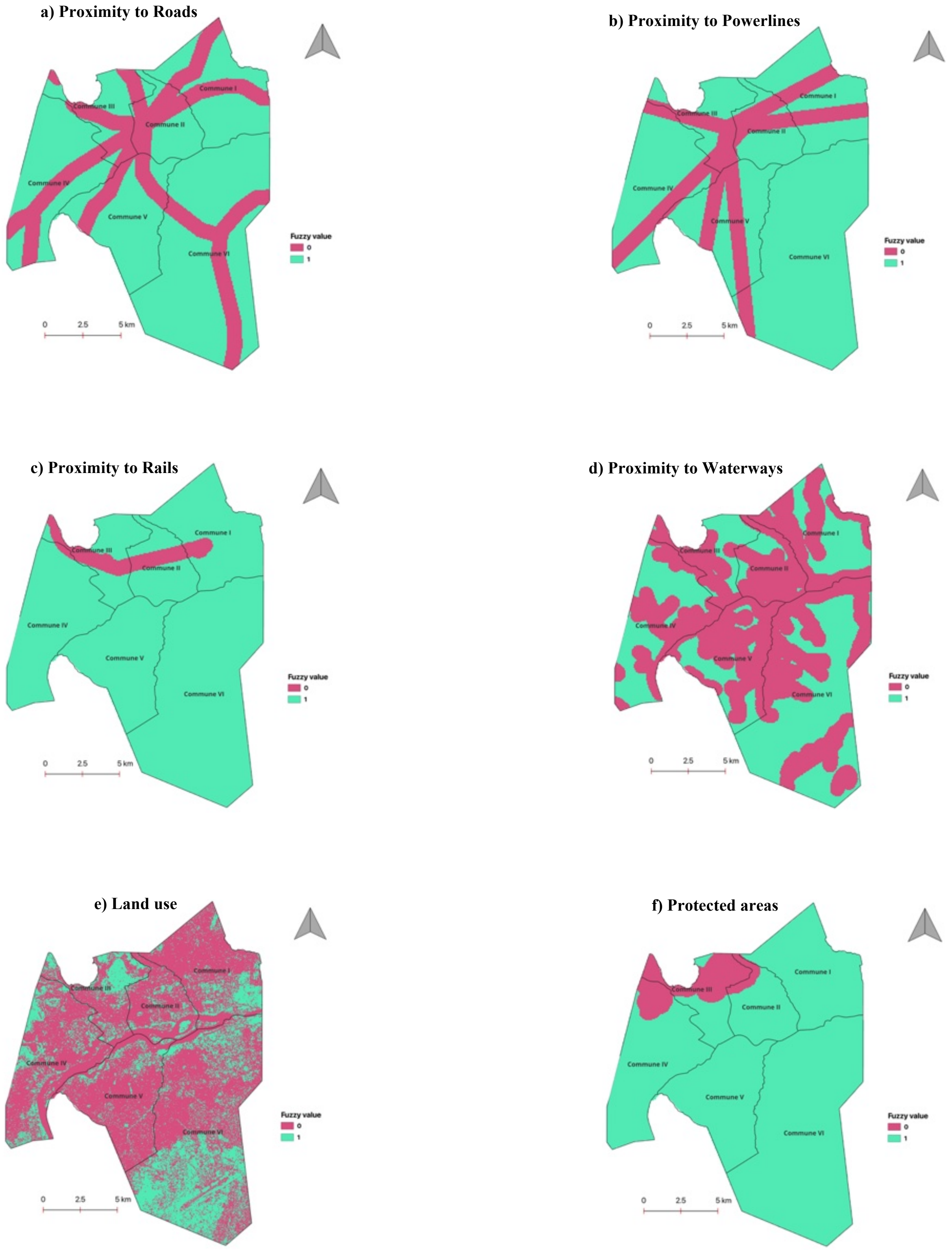


Figure 4.26 Classified Restriction Layers for Bamako

4.1.4.3 AHP pairwise comparison and criteria weights

Table 4.12 presents the normalised pairwise comparison matrix for Kano, where the relative importance of each criterion is displayed. The normalised matrix is obtained by dividing each element in the pairwise matrix (Appendix A) by the sum of its column. The values in the matrix were derived through the Analytic Hierarchy Process (AHP) by comparing each criterion against others and normalising the results to ensure consistency. Global Horizontal Irradiance (GHI) holds the highest weight (0.24), reaffirming its primary importance in solar site selection. This is expected, as areas with higher solar radiation potential yields greater energy output, making them more suitable for solar farm installation. Prior studies support this line of reasoning (Al Garni and Awasthi, 2018; Ghasemi *et al.*, 2019). Powerlines proximity follows with a weight of 0.16, signifying that accessibility to the electricity grid is a crucial factor. Solar plants need to be located near existing power infrastructure to minimise energy transmission costs and losses.

Similarly, LULC (0.12) and slope (0.08) also hold significant influence, as flat, undeveloped lands are preferable for construction and maintenance of solar panels. Conversely, factors such as aspect (0.04), temperature (0.04), and wind Speed (0.05) exhibit lower weights, suggesting that while they contribute to site selection, their impact is comparatively less than other criteria. This aligns with expectations, as aspect and temperature have secondary effects on solar panel efficiency, while wind speed is more critical in wind energy projects rather than solar applications. Interestingly, Waterways (0.10) and Railroads (0.05) have moderate weights, indicating that some degree of proximity to these features is considered beneficial, possibly for logistical reasons related to site development and accessibility.

Table 4.12 Normalised Pairwise Matrix for Kano

	GHI	Powerlines	Slope	LULC	Roads	Aspect	Temperature	DEM	WindSpeed	Railroads	Waterways	Priority Vector
GHI	0.25	0.42	0.32	0.31	0.24	0.20	0.20	0.19	0.14	0.16	0.19	0.24
Powerlines	0.08	0.14	0.19	0.21	0.18	0.16	0.16	0.14	0.14	0.16	0.19	0.16
Slope	0.05	0.05	0.06	0.05	0.12	0.12	0.12	0.10	0.10	0.11	0.05	0.08
LULC	0.08	0.07	0.13	0.10	0.18	0.16	0.12	0.14	0.14	0.11	0.10	0.12
Roads	0.06	0.05	0.03	0.03	0.06	0.12	0.08	0.10	0.10	0.11	0.10	0.08
Aspect	0.05	0.03	0.02	0.03	0.02	0.04	0.08	0.05	0.05	0.05	0.05	0.04
Temperature	0.05	0.03	0.02	0.03	0.03	0.02	0.04	0.10	0.05	0.05	0.05	0.04
DEM	0.06	0.05	0.03	0.03	0.03	0.04	0.02	0.05	0.10	0.11	0.05	0.05
WindSpeed	0.08	0.05	0.03	0.03	0.03	0.04	0.04	0.02	0.05	0.05	0.05	0.04
Railroads	0.08	0.05	0.03	0.05	0.03	0.04	0.04	0.02	0.05	0.05	0.10	0.05
Waterways	0.13	0.07	0.13	0.10	0.06	0.08	0.08	0.10	0.10	0.05	0.10	0.09

Similarly, the pair-normalised comparison matrix, obtained based on Appendix C for Bamako has been reported in Table 4.13 for Bamako. Comparable arguments were noted in Kano, with global horizontal irradiance (GHI) (0.22) and distance to power lines (0.17) emerging as the most significant factors, and therefore, reaffirming the crucial role of solar irradiance and grid accessibility in site selection. Slope and land use (0.11 each) retain a moderate influence, reflecting the importance of terrain and land-use characteristics in ensuring feasibility. Proximity to roads (0.08), aspect (0.05), temperature (0.05) and DEM (0.05) contribute to suitability, but play a secondary role to the dominant factors. Waterways, railways and protected areas each have a weight of 0.04.

Table 4.13 Normalised Pairwise Matrix for Bamako

	GHI	Powerlines	Slope	LULC	Roads	Aspect	Temperature	DEM	WindSpeed	Railroads	Waterways	ProtectedAreas	Priority Vector
GHI	0.22	0.21	0.22	0.22	0.23	0.22	0.22	0.22	0.22	0.21	0.21	0.21	0.22
Powerlines	0.18	0.17	0.17	0.17	0.19	0.16	0.16	0.16	0.17	0.18	0.18	0.18	0.17
Slope	0.11	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
LULC	0.11	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Roads	0.07	0.07	0.07	0.07	0.08	0.08	0.08	0.08	0.09	0.09	0.09	0.09	0.08
Aspect	0.05	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Temperature	0.05	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
DEM	0.05	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
WindSpeed	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04
Railroads	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Waterways	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
ProtectedAreas	0.04	0.03	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

4.1.4.4 Weighted overlay and final suitability map

Following the weighted overlay analysis, the final suitability maps for Kano (Figure 4.27) and Bamako (Figure 4.28) were classified into two categories, constrained areas and areas suitable for solar farms. Approximately 33.63% (165.5 Km^2) of land was found to be suitable for the construction of solar farms. These suitable zones were all located in Kumbotso and Ungogo Local Government Areas. Apart from these two LGAs, there is nowhere in Kano that could be used for solar farms, with the exception of the rooftops of buildings, which could also be exploited. Unfortunately, some 326.76 Km^2 (66.37%) of land in Kano is no longer suitable for solar installations due to built-up and water.

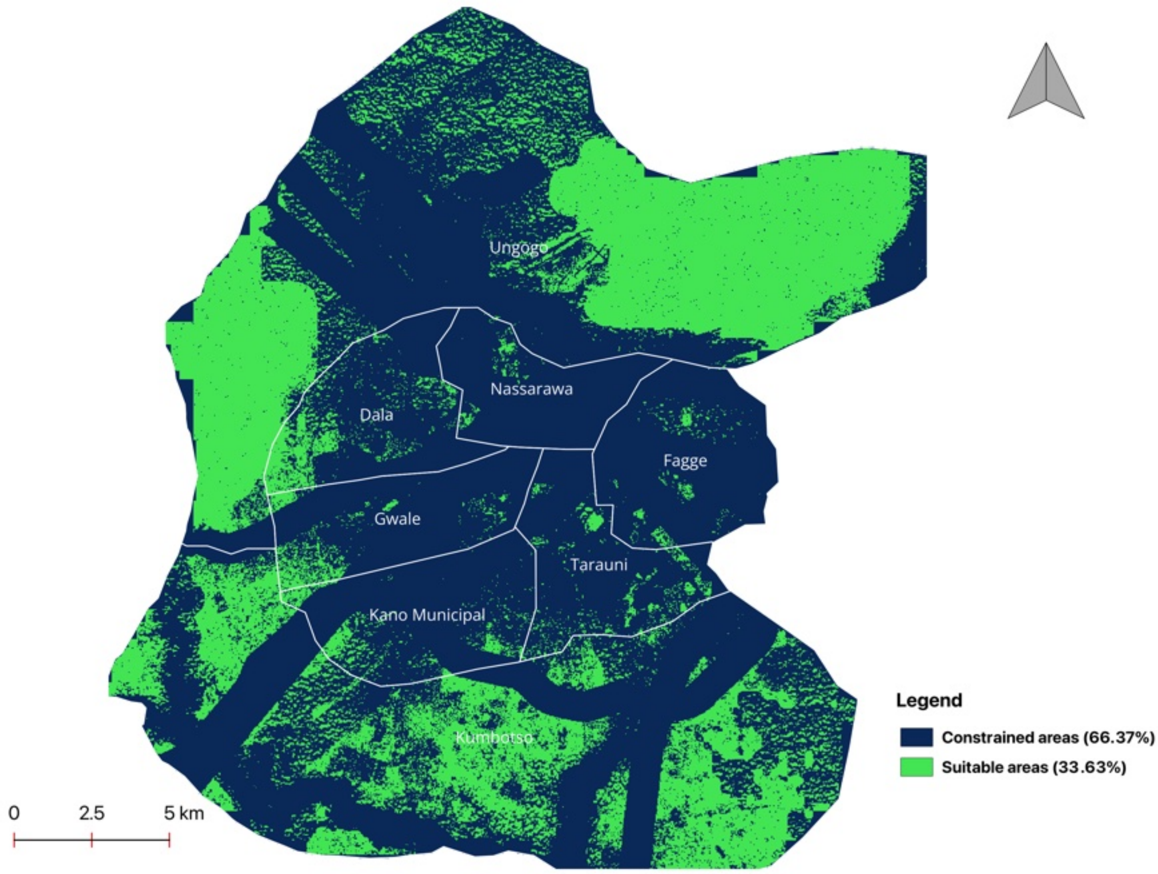


Figure 4.27 Suitability Map for Solar Plant for Kano

Further findings indicate that 75.85% of the study area in Bamako was suitable for solar farm development, while 24.15% is unsuitable due to constraints such as protected areas, high slopes, or water bodies. Most of the possible locations for solar power generation in Bamako are in Municipality VI and only a fraction in Municipality I.

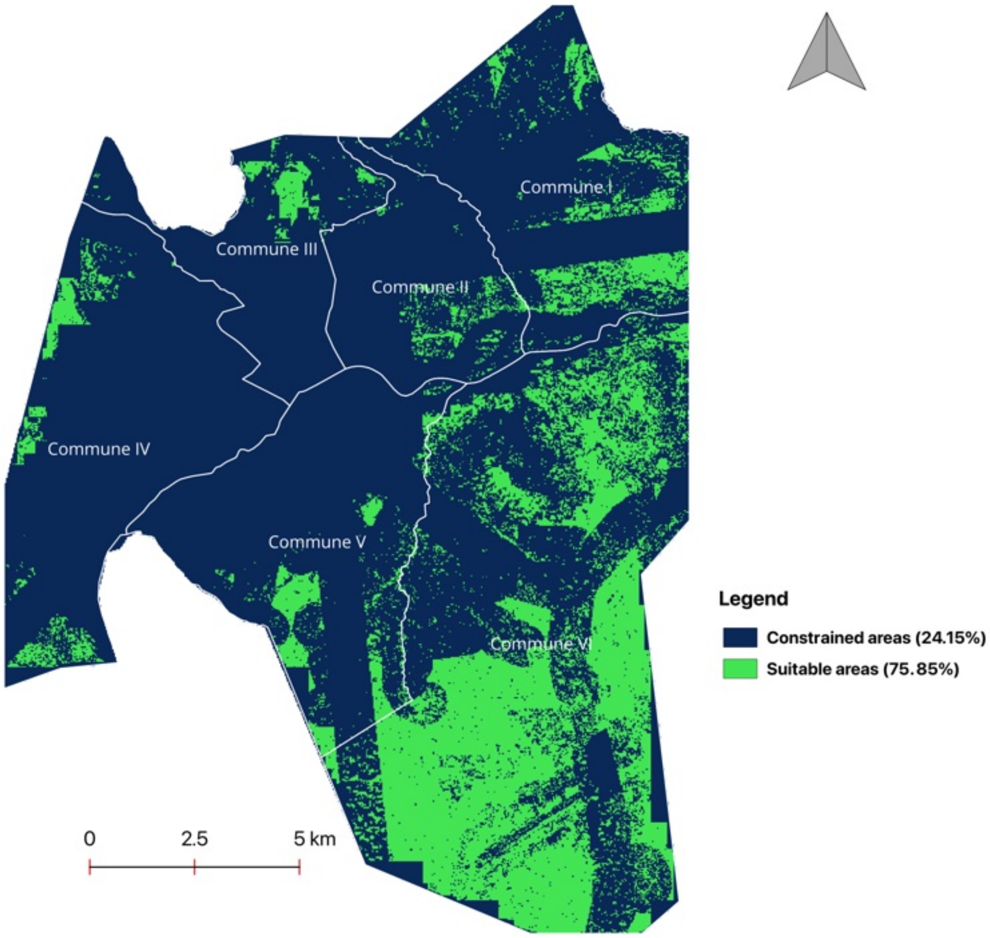


Figure 4.28 Suitability Map for Solar Plant for Bamako

Null hypothesis (Ho4): There are no significant spatial variations in the suitability of locations for solar power plant development in the study area.

The spatial modelling outcomes confirm that this hypothesis is rejected. Variability in suitability across the study area was influenced by multiple factors, including slope, land cover, and proximity to infrastructure.

4.1.5 Factors affecting renewable energy deployment in Kano and Bamako

4.1.5.1 State of renewable energy adoption

The adoption of clean energy is no longer a choice but a necessity in light of the pressing issue of climate change. A descriptive statistical approach was used to provide insights into energy types in the cities of Kano and Bamako. In Kano, household preferences for cooking energy (Figure 4.29) are mixed, with fuelwood/charcoal being the most common choice, used by 206 households (42.9%). This is followed by cooking gas, adopted by 149 households (31%), indicating a significant shift towards cleaner energy sources. In addition, 121 households (25.2%) use electricity for cooking, indicating a relatively greater reliance on modern energy sources. Kerosene is used very little (3 households, 0.6%), and other sources account for only 0.2% of households. The relatively high use of gas and electricity suggests greater accessibility and affordability of modern energy solutions in Kano.

Furthermore, the distribution of household electricity sources indicated a significant reliance on the conventional electricity grid provided by the Kano Electricity Distribution Company (KEDCO), which serves 311 households, or 64.8% of the total (Figure 4.30). In contrast, 169 households (35.2%) use solar panels as an alternative energy source. This significant proportion of solar panel users reflects a growing interest in renewable energy solutions, perhaps due to frequent grid outages and the increasingly affordable price of solar technology.

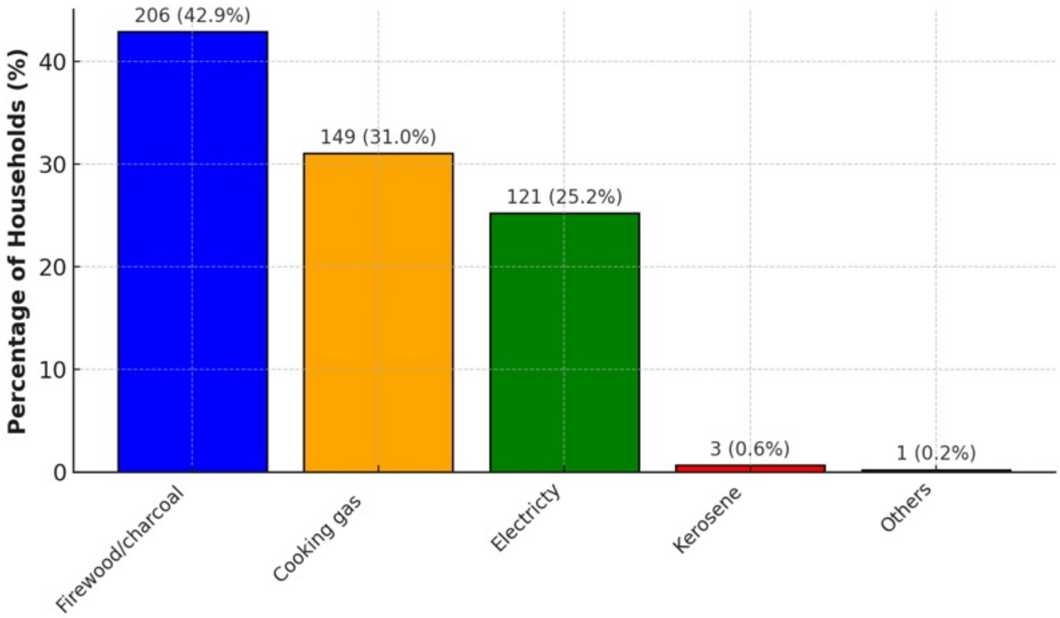


Figure 4.29 Cooking Energy Choice for Kano

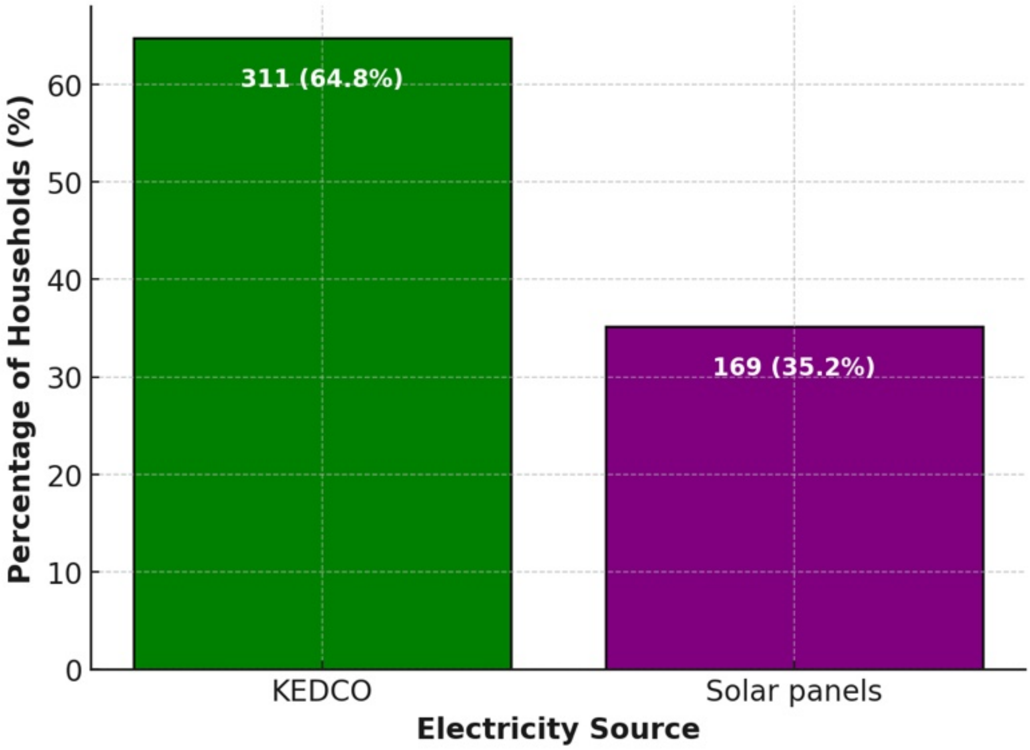


Figure 4.30 Electricity Source for Kano

Meanwhile, cooking energy in Bamako was found to be more traditional and less diverse (Figure 4.31). A majority of 435 households (90.6%) use firewood or charcoal, indicating a high dependence on biomass fuels. Only 44 households (9.2%) use cooking gas, and electricity is conspicuously absent as a cooking source. Kerosene was not used, and other sources account for only a small proportion of the total.

The electricity consumption patterns in Bamako showed a greater dependence on the national grid company, Energy of Mali (EDM S.A), which supplies electricity to 439 households, or 91.5% of the total (Figure 4.32). Only 41 households (8.5%) use solar panels, indicating a relatively limited uptake of renewable energy compared to Kano. The low use of solar energy in Bamako is associated with the high stability of the EDM SA electricity network, resulting in fewer power cuts and more loyal customers.

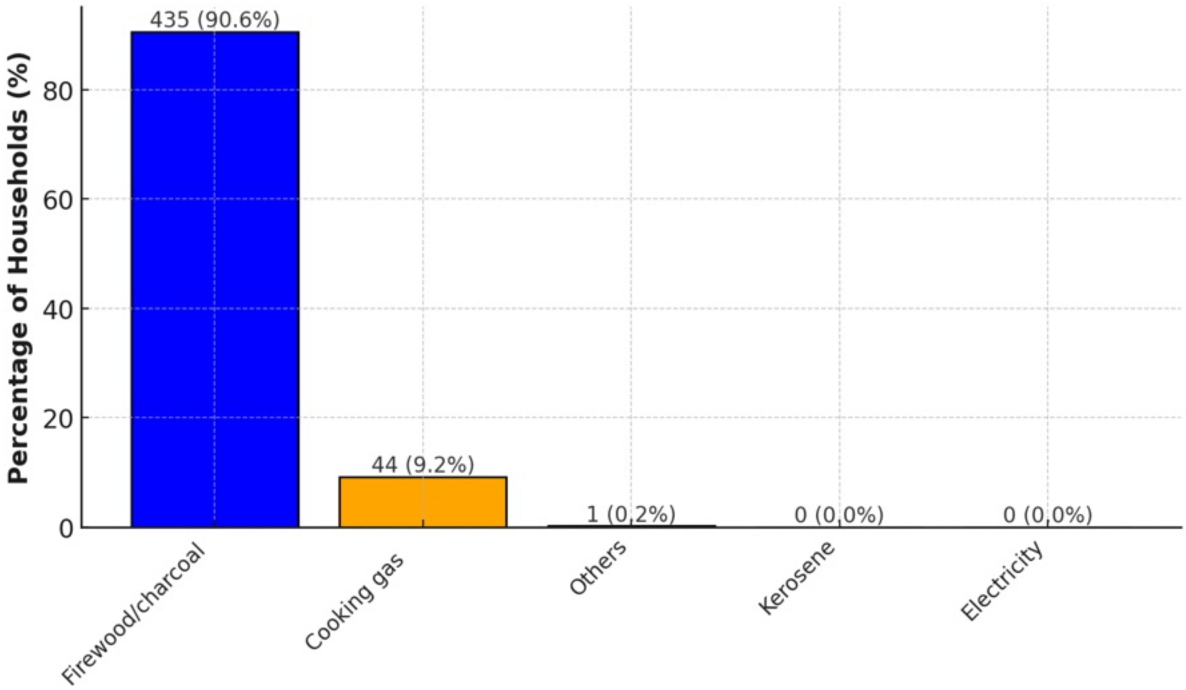


Figure 4.31 Cooking Energy Choice for Bamako

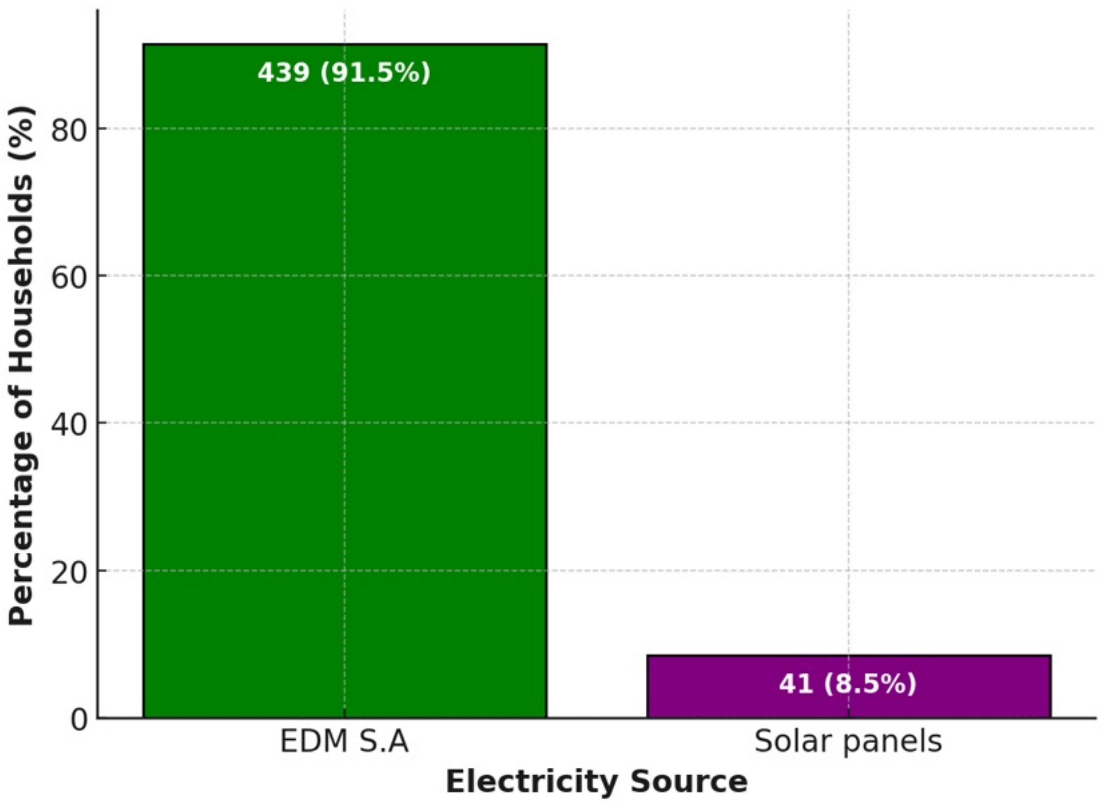


Figure 4.32 Electricity Source for Bamako

In terms of solar farms development in both cities, observations have revealed that efforts to ensure energy security have led to the construction of two solar power plants in Kano, namely Bayero University Kano with a capacity of 7.1 MW and Bayero Ado Mall with a capacity of 1 MW (Figure 4.33). In contrast, Bamako is well behind in its energy transition, with only 100 kW (Figure 4.34) on the building roofs of the Institute of Applied Sciences of Bamako.

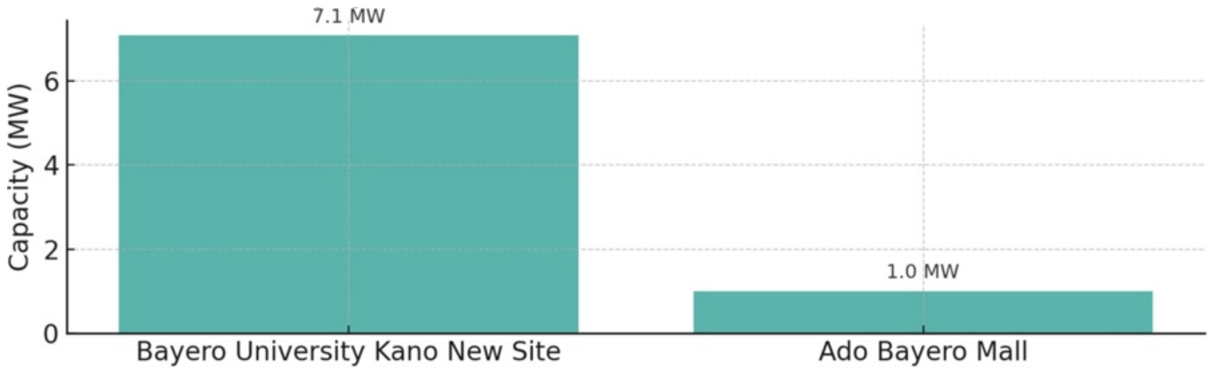


Figure 4.33 Number and Capacity of Solar Farms in Kano

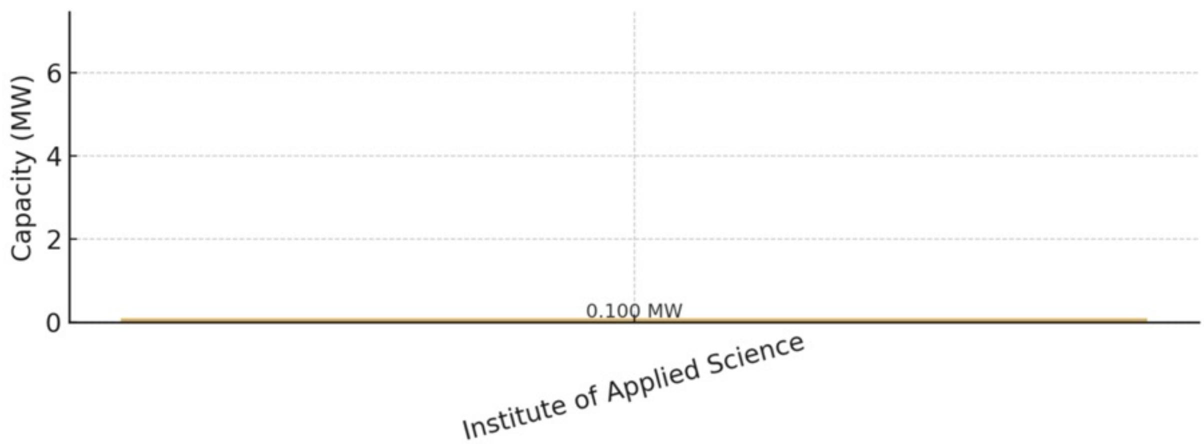


Figure 4.34 Number and Capacity of Solar Farms in Bamako

4.1.5.2 Factors model validity and reliability

In line with the hypotheses, a five-factor model was adequate to minimise the number of variables in the dataset, irrespective of geographical region and for the aggregated data ($p>0.05$, Table 4.14). The five factors accounted for 52% to 61% of the total variance in the dataset. Cronbach's alpha (α) values were above the acceptable cut-off value (0.50) for most of the common factors (α=0.50 to 0.81). Robust KMO values (0.54 to 0.61) were observed which are above the acceptable cut-off value (0.50), thereby supporting the suitability of the FA model. Moreover, Bartlett's test was significant ($p<0.05$) for each region and for the pooled data. The results showed that each concept is underpinned by a minimum of two elements whose factor loadings are above the threshold value (0.50).

The first factor (PA1), renewable energy (RE) benefits, is strongly related to beliefs about the benefits of renewable energy in all regions. The second factor (PA2), belief about the cost of renewables' is strongly related to beliefs about the cost of renewables. There was spatial variation between the items measuring factors 3 and 4. In Bamako, factor 3 (PA3) is significantly correlated with the items measuring people's RE demand, whereas in Kano and for the aggregated data, factor 3 is strongly underpinned by the items that measure people's opinion on the acceptance of renewable energy. Furthermore, factor 4 (PA4) is strongly related to the items measuring energy demand in Kano and for the aggregate data. However, in Bamako, this factor is correlated with items measuring intentions to use renewable energy and their opinion on the acceptance of renewable energy. Given that the intention and social acceptance items converged in terms of significance, this factor was considered to be "social acceptance of RE". Finally, factor 5 (PA5) reflects items that measure people's environmental knowledge in all regions and in the aggregated data.

Table 4.14 Items' Loadings from Factor Analysis (FA) and Cronbach's alpha (α)

		Bamako						Kano						Pooling data		
Items	PA1	PA2	PA3	PA4	PA5	Items	PA1	PA2	PA3	PA4	PA5	Items	PA1	PA2	PA3	PA4	PA5
ED1	0.07	0.05	**0.66**	0.01	0.09	ED1	0.06	0.01	0.07	**0.76**	0.09	ED1	0.09	0.07	0.03	**0.69**	0.10
ED5	0.05	0.02	**0.73**	0.03	-0.04	ED2	0.08	0.09	0.03	**0.74**	0.10	ED5	0.06	0.09	0.07	**0.69**	0.05
IT1	0.05	-0.06	0.02	**0.77**	0.06	IT1	**0.77**	-0.14	0.07	0.06	0.18	IT1	**0.84**	-0.03	0.06	0.07	0.17
AR1	**0.92**	0.04	0.07	0.03	0.05	AR1	**0.83**	-0.15	0.07	0.10	0.24	AR1	**0.80**	-0.06	0.07	0.11	0.15
AR2	**0.72**	0.03	0.08	0.15	0.12	AR2	0.03	0.05	**0.72**	0.07	0.05	AR2	0.03	0.05	**0.66**	0.06	0.08
SA1	0.09	0.03	0.02	**0.60**	0.05	SA1	0.08	-0.03	**0.72**	0.02	0.07	SA1	0.07	-0.04	**0.67**	0.03	0.05
CR2	0.07	**0.65**	-0.01	-0.03	0.13	CR2	-0.12	**0.84**	0.01	0.11	-0.12	CR2	-0.02	**0.85**	0.00	0.10	0.03
CR3	-0.03	**0.76**	0.08	0.01	-0.04	CR3	-0.15	**0.86**	0.02	0.01	-0.03	CR3	-0.06	**0.86**	0.02	0.10	0.01
ENK3	0.16	0.32	0.04	0.07	**0.54**	ENK3	0.22	-0.05	0.03	0.09	**0.67**	ENK3	0.17	0.11	0.06	0.06	**0.62**
ENK4	0.03	-0.05	0.02	0.06	**0.62**	ENK4	0.12	-0.07	0.08	0.10	**0.60**	ENK4	0.08	-0.06	0.06	0.08	**0.59**
α	0.81	0.65	0.65	0.63	0.50	α	0.83	0.85	0.68	0.73	0.61	α	0.81	0.65	0.50	0.65	0.50
CVar	0.14	0.25	0.35	0.45	0.52	Cvar	0.29	0.15	0.51	0.41	0.61	Cvar	0.29	0.15	0.48	0.39	0.56
KMO			0.54			KMO			0.61			KMO			0.57		
Bartlett			X^2 = 864.66***			Bartlett			1366.58***			Bartlett			2319.93***		

Cvar: Cumulative variance explained, **α:** Cronbach's alpha, **CR:** Beliefs about Renewable Energy Cost, **SA:** Social Acceptance of renewable energy, **ED:** Energy Demand, Environmental Knowledge**, ARE:** Beliefs about the advantage of renewable energy, PA1, PA 2, PA3, PA4, and PA5 are the common factors form the factor analysis. Only Items' loadings ≥ 0.5 (values in bold) were printed for the CFA.

4.1.5.3 Confirmatory factor analysis model fit indices show good fit

All the comparative fit index values for the CFA were acceptable and showed a good fit for each geographic region and aggregated data (Table 4.15). The CFI and TLI were approximately 1 which is greater than the threshold required (0.95). The RMSEA values were under the recommended threshold (0.06) as were the SRMR (< 0.09). These values combining with the p values (> 0.05) indicate that the hypothesised model appears to be a good fit to the data. No post-hoc modifications were conducted because of the good fit of the data to the model.

Table 4.15 Goodness Of Fit for the CFA

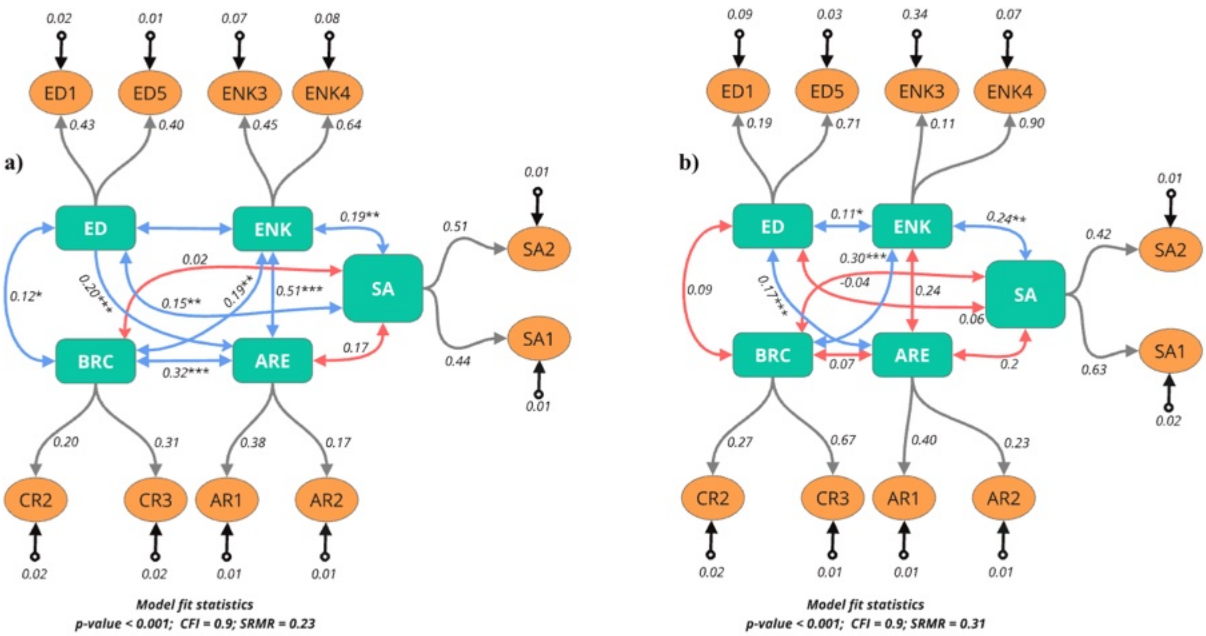
	Goodness Of Fit indices				
Region	**TLI**	**CFI**	**RMSEA**	**SRMR**	**p (Chi-square)**
Bamako	1.034	1.000	0.024	0.031	0.796 (19.020)
Kano	1.016	1.000	0.023	0.023	0.973 (13.235)
Aggregated	0.991	0.995	0.039	0.026	0.159 (31.959)

TLI: Tucker-Lewis Index**, CFI:** Comparative Fit Index, **RMSEA:** Root Mean Square Error of Approximation, **SRMR:** Standardised Root Mean Square Residual, ***p*:** probability value.

4.1.5.4 Relationship between items and their underlain constructs

Despite the good fit of the CFA, not all items accurately measured the concept. The measurement errors were all small, indicating that the concepts capture the maximum variance in the items, regardless of region. Item EK4 had the highest correlation with the underlying concept across all regions (Figure 4.35). In addition, the accuracy of some items differed from region to region. For instance, the correlation between item CR3 and its underlying construct BRC in Kano (Figure 4.35a) was notably lower than that observed in Bamako (Figure 4.35b). The same trend was observed for the ED5 item. In terms of covariance structure, the results revealed spatial variation. There were fewer covariant constructs in Bamako than in Kano. Also, some relationships between covariates became significant in Kano compared to Bamako. After aggregating the data from the two regions, there was no remarkable change in the pattern of correlations between items and constructs in relation to each geographical region (Figure 4.36). However, some changes were observed in the covariance structure.

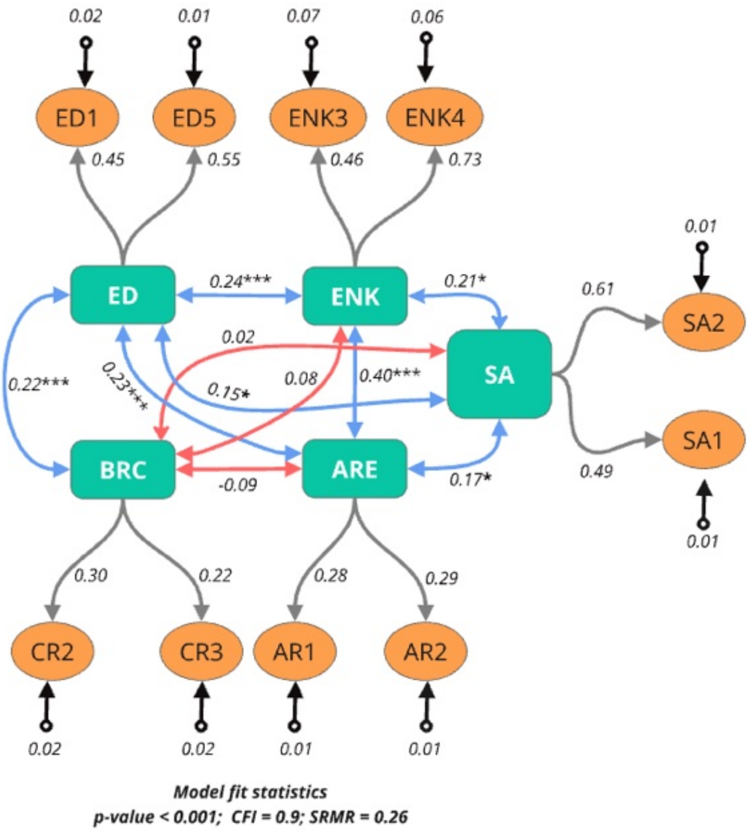
A number of relationships between covariates that were significant given the region-specific data became insignificant and vice versa Notably, the covariance relationship between SA and ARE, which was insignificant in the aggregated data, became significant in the region-specific analysis, highlighting the influence of localised factors on the relationship. This shift in the region-specific relationships upon aggregation suggests an influence of local factors unique to each region. In contrast, the emergence of new significant relationships in the pooling data reveals broader trends that were not evident in the region-specific observations. These findings highlight the importance of examining data both regionally and collectively to fully understand the interplay of constructs.



ED: Energy Demand, **ENK:** Environmental Knowledge, **SA:** Social Acceptance, **ARE:** Beliefs about the Advantage of Renewable Energy, **BRC:** Beliefs about Renewable Energy Cost

Figure 4.35 Confirmatory Factor Analysis for Kano (a) and Bamako (b) Displaying the Standardised Coefficients between the Constructs (ED, ENK, SA, ARE, and BRC) and Items (in rectangular boxes).

Note: The double-faced red arrows indicate a non-significant covariance between constructs, while the solid blue double-faced arrows indicate significant covariance. Only significant covariance coefficients (standardised values) were printed. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Values next to the light grey arrows linking items to their constructs represent standardised correlation coefficients. Values at the bottom of the black arrows pointing toward the items' boxes are the coefficients' standard errors.



ED: Energy Demand, **ENK:** Environmental Knowledge, **SA:** Social Acceptance, **ARE:** Beliefs about the Advantage of Renewable Energy, **BRC:** Beliefs about Renewable Energy Cost

Figure 4.36 Confirmatory Factor Analysis for Pooling Data Displaying the Standardised Coefficients between the Constructs (ED, ENK, SA, ARE, and BRC) and Items (in rectangular boxes).

Note: The double-faced red arrows indicate a non-significant covariance between constructs, while the solid blue double-faced arrows indicate significant covariance. Only significant covariance coefficients (standardised values) were printed. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Values next to the light grey arrows linking items to their constructs represent standardised correlation coefficients. Values at the bottom of the black arrows pointing toward the items' boxes are the coefficients' standard errors.

4.1.5.5 Structural equation modelling goodness of fit

Similarly to the CFA, all comparative fit index values for the SEM were acceptable and exhibited good fit for each geographical region and for the aggregate data (Table 4.16). The CFI and TLI were both approximately equal to 1, which is above the required threshold (0.95). The RMSEA values were below the recommended threshold (0.06), as was the SRMR

(<0.09). These values, combined with the p-values (>0.05), suggest that the hypothetical model appears to fit the data adequately.

Table 4.16 Goodness of Fit for the SEM Model

	Goodness of Fit indices				
Location	**TLI**	**CFI**	**RMSEA**	**SRMR**	**p (Chi-square)**
Bamako	0.983	0.990	0.031	0.043	0.297 (36.815)
Kano	0.993	0.996	0.044	0.035	0.226 (38.759)
Aggregated	0.972	0.983	0.032	0.039	0.217 (39.030)

TLI: Tucker-Lewis Index**, CFI:** Comparative Fit Index, **RMSEA:** Root Mean Square Error of Approximation, **SRMR:** Standardised Root Mean Square Residual***, p*:** probability value.

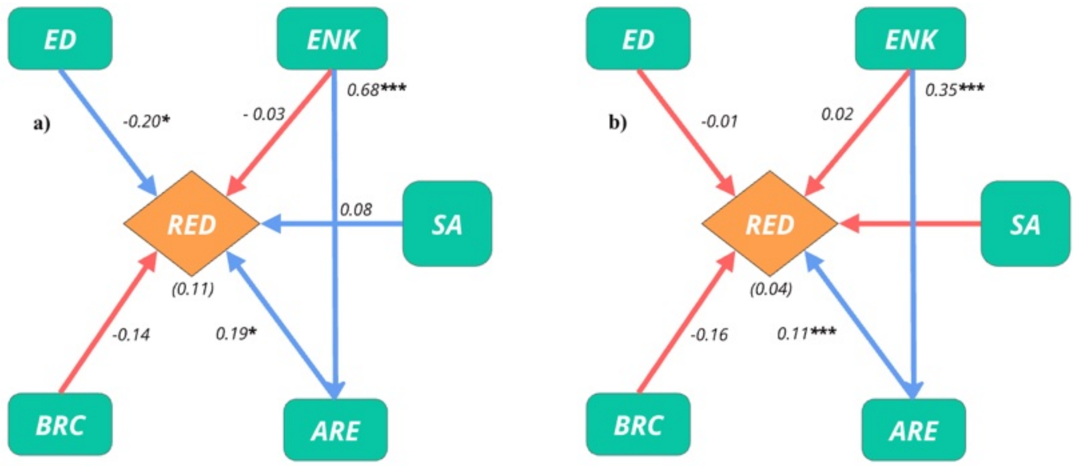
4.1.5.6 Spatial variation in determinants of renewable energy development

The study revealed a remarkable spatial variation in the determinants of renewable energy development (RED). People's beliefs about the benefits of renewable energy (ARE), energy demand (ED), and social acceptance (SA) were found to positively explain renewable energy development in Kano (Figure 4.37a), while in Bamako (Figure 4.37b), only ARE significantly influenced renewable energy development. Additionally, a positive effect of environmental knowledge (ENK) on ARE was observed in both regions, suggesting that environmental knowledge contributes to people's beliefs about the benefits of RE. This demonstrates the improving role of environmental knowledge on RED through ARE. However, we did not find a significant indirect effect of environmental knowledge on RED, as expected (Table 4.17).

Table 4.17 Structural Equation Modelling Testing the Indirect Effect of Environmental Knowledge (ENK) on Renewable Energy Development (RED) across Geographic Regions

				Bamako			Kano		
Responses	Mediators	Predictor	Effect	β	βs	p	β	βs	p
RED	ARE	ENK	Indirect	0.010	0.045	0.194	0.041	0.074	0.263

ENK: Environmental Knowledge, **ARE:** Beliefs about the advantage of renewable energy, **RED:** renewable energy development, ***β*:** non-standardised coefficient, ***βs*:** standardised coefficient*, **p***:** probability value.

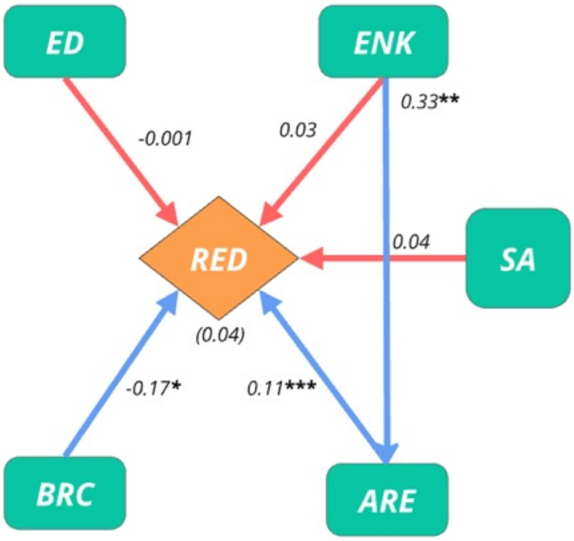


ED: Energy Demand, **ENK:** Environmental Knowledge, **SA:** Social Acceptance, **ARE:** Beliefs about the Advantage of Renewable Energy, **BRC:** Beliefs about Renewable Energy Cost, **RED:** Renewable Energy Development

Figure 4.37 Structural Equation Modelling for Kano (a) and Bamako (b) Illustrating the Determinants of Renewable Energy Development (RED)

Note: Solid blue arrows indicate significant ($p < 0.05$) relationships and red arrows indicate non-significant relationships ($p \geq 0.05$). Path coefficients (standardised values) followed by asterisks are significant: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

However, considering the pooling data, RED is positively determined by ARE but negatively by BRC (Figure 4.38). As for each region, the results demonstrated a positive effect of environmental knowledge (ENK) on ARE. There was no indirect effect of ENK on RED, as expected (Table 4.18).



ED: Energy Demand, **ENK:** Environmental Knowledge, **SA:** Social Acceptance, **ARE:** Beliefs about the Advantage of Renewable Energy, **BRC:** Beliefs about Renewable Energy Cost, **RED:** Renewable Energy Development

Figure 4.38 Structural Equation Modelling for the Pooled Data Illustrating the Determinants of Renewable Energy Development (RED)

Note: Solid blue arrows indicate significant ($p < 0.05$) relationships and red arrows indicate non-significant relationships ($p \geq 0.05$). Path coefficients (standardised values) followed by asterisks are significant: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 4.18 Structural Equation Modelling Testing the Indirect Effect of Environmental Knowledge (ENK) on Renewable Energy Development (RED) for the Pooled Data

				Total		
Responses	Mediators	Predictor	Effect	β	βs	p
RED	ARE	ENK	Indirect	-0.002	-0.014	0.588

ENK: Environmental Knowledge, **ARE:** Beliefs about the advantage of renewable energy, **RED:** renewable energy development. ***β*:** non-standardised coefficient, ***βs*:** standardised coefficient, ***p*:** probability value.

Null hypothesis (Ho_5): Increased energy demand positively influences the adoption of renewable energy.

Empirical results support acceptance of this hypothesis for Kano, where energy demand significantly influenced renewable energy development. However, the hypothesis is rejected for Bamako, where no such significant relationship was observed.

Null hypothesis (Ho_6): Environmental knowledge is expected to positively affect the implementation of renewable energy.

The structural equation modelling results suggest that this hypothesis is rejected. Although environmental knowledge was linked to positive perceptions, it did not have a direct significant impact on renewable energy implementation in either city.

Null hypothesis (Ho_7): Public acceptance positively contributes to the deployment of renewable energy.

The hypothesis is accepted for Kano, where public acceptance showed a statistically significant positive effect. It is rejected for Bamako, where this factor was not significant.

Null hypothesis (Ho_8): Positive beliefs regarding the benefits of renewable energy are likely to enhance its deployment.

The structural analysis supports acceptance of this hypothesis. In both Kano and Bamako, beliefs about renewable energy benefits were significant drivers of deployment.

Null hypothesis (Ho_9): Perceptions of renewable energy costs negatively impact its adoption.

The results validate this hypothesis. Perceptions of high cost had a significant negative effect on renewable energy adoption, highlighting affordability concerns as a key barrier.

4.2 Discussion of Results

4.2.1 Trends in cooling degree in Kano and Bamako

In light of the increase of global temperatures, the need to monitor cooling requirements is of paramount importance, particularly in regions with a warmer climate. Furthermore, recent trends in cooling degree days observed in Kano are similar to those observed in Switzerland, the United Kingdom and Norway (Miranda *et al.*, 2023).

The increase in cooling degree days in several regions of the world is expected to cause even higher energy requirements. Yet, the Sahel region is reported to have the highest levels of unmet cooling needs, highlighting a stark inequality in cooling accessibility (Falchetta and Mistry, 2021). Conversely, situations do exist where, despite global warming, cooling degree days decrease, a trend likely influenced by regional adaptations, seasonal shifts, or improvements in energy efficiency. For example, the findings have shown a decreasing trend in cooling needs in Bamako. Similar occurrences have also been observed in Shahrekord, Iran (Sadeqi *et al.*, 2022). The cooling demand is naturally responsive to temperature shifts. Therefore, the slight decrease in the number of cooling degree-days for Bamako may reflect a decrease in temperature over the last three decades, as evidenced by the statistically significant decline in minimum temperature and the marginal decrease in mean temperature, which together likely led to a reduction in overall cooling demand. Corroborating the findings, Touré Halimatou *et al.* (2017) observed a decline in warming trends for both day and night temperatures in Bamako from 1961 to 2014. The observations for this study also align with the study by (Sawadogo *et al.*, 2024), which also reported decreasing temperature trends under the SSP1–2.6 scenario in Burkina Faso, a trend that could contribute to a reduction in cooling energy requirements.

In view of the observed trends in cooling degree-days and their subsequent relationship with temperature changes, specific policy measures are necessary to meet the cooling energy demands at different locations. Although Bamako exhibits a declining trend in CDD over the past three decades, the overall CDD values remain consistently higher than those recorded in Kano. Additional financial incentives, such as tax breaks or subsidies for energy-efficient appliances and solar air-conditioning systems, may help to reduce cooling energy consumption. Furthermore, changes in construction practices and energy standards are essential to ensure better energy efficiency in new and existing buildings. This is going to help mitigating the demand for cooling energy on a long-term basis, enabling cities to adapt to rising temperatures without overburdening the energy infrastructure.

4.2.2 Trends in heat index in Kano and Bamako

Following the heat index assessment for human body precautions to prevent scorching heat, evidences of heat cramps, heat exhaustion, and heat stroke were observed in Kano and Bamako in April, May and June with values up to 41°C and 42°C, respectively. Such findings are consistent with several studies in similar climatic zones, where rising global temperatures, combined with increasing humidity levels, have contributed to an increase in thermal discomfort and potential health risks (Fotso-Nguemo *et al.*, 2023; Sylla *et al.*, 2018). Comparable extreme heat index trends were also reported in countries such as India (Choudhary *et al.*, 2024), Bangladesh (Kamal *et al.*, 2024; Rahman *et al.*, 2021), and Vietnam (Hoang *et al.*, 2022), affecting the health of millions of people around the world. Humidity is another factor that exacerbates heat stress. High humidity reduces sweat evaporation, resulting in excessive body heat accumulation. This is best illustrated by the example of the cities of Kano and Bamako where the heat index increases with humidity. Besides being direct factors affecting the human body, air humidity and the heat index are also important determinants in Sahel regions, especially for cooling due to the increased level of energy consumption. According to Kondi Akara *et al.* (2022), humidity accounted for up to 6.8% of the variability in energy consumption in Dakar.

Furthermore, it is worth considering that insignificant decreasing trends in HI were observed in Bamako. This is because, although HI values are high in April, May and June, values have become colder over the last decade in Bamako. Variations in heat index between months are quite normal, since almost everywhere on earth experienced hot and cold seasons or slightly hot and cold seasons. For example, in Brazil, rising trends in HI were observed in November, January and April, whereas a declining trend was recorded in May and August (Da Silva and Streck, 2014). The findings suggest that adaptation strategies must be developed in order to mitigate the impacts of high heat index levels. A number of initiatives could reduce the effects of rising HI, including the promotion of green spaces, the implementation of heat warning systems, and the endorsement of renewable energy solutions like solar cooling systems.

4.2.3 Spatial-temporal analysis of land use and land cover change

Research on land use and land cover changes (LULC) based on remote sensing techniques is well established in most parts of the world. In many cases, however, the methodology employed, the data used and the regions of interest often vary between studies. In addition, arguments and interpretations between authors can be quite different, and sometimes even contradictory, depending on the specific contexts studied. Nonetheless, it is crucial to understand the dynamics of LULC, as it is an essential tool for environmental monitoring, climate change impact analysis, sustainable land-use planning and natural disaster risk management. The Random Forest algorithm was adopted for its higher efficiency and accuracy, and has become very popular as one of the main tools for LULC mapping (Naushad *et al.*, 2021; Thanh Noi and Kappas, 2017).

The gradual increase in the built-up area compared to other LULC classes is likely due the increase in the population. According to the World Bank (2018) , the population of Kano is projected to reach 5.6 million by 2030. The increasing Nigerian population, likely to become a current and future debate, is the main cause of the urban sprawl of most Nigerian cities. There is evidence of urban expansion in Abuja from 1.8% in 1990 to 19.3% in 2019 (Ogochukwu *et al.*, 2022), Lagos (Kasim *et al.*, 2022), Ilorin (Rafiu Babatunde *et al.*, 2014), and Lokoja (Alabi, 2012).

Globally, the increase in built-up area is an existing trend for cities around the world. Estoque and Murayama (2017) reported similar evidence of built-up area growth in major Asian and African cities. According to Adhikari and de Beurs (2017), the pace of urban growth in cities across Asia and Africa is considerably faster than in other global regions. In most European cities, the expansion of built-up areas is growing rapidly, even in regions where the population is declining (Schiavina *et al.*, 2022). In addition to the constant increase in population, the lack of appropriate construction plans and policies in most African cities is a major factor leading to rapid urban sprawl. This is because the number of houses a person builds is often determined by their financial means. For instance, a single person with sufficient financial resources may build several properties with no limit. Such a phenomenon is very common in African cities, leading to even more construction than population growth. Furthermore, migration between rural and city is also a major driver in urban expansion. Following the outbreak of insecurity in the northern Mali since 2012, thousands of people have been forced to migrate towards the southern regions of the country, in particular Bamako. As per Ballo (2009), 33% of the population of Bamako were migrants in 2004. This trend of increasing migration to Bamako, resulting from insecurity and climate change in Mali, combined with the lack of educational and hospital infrastructures, is steadily expanding the urban space of Bamako.

4.2.4 Location of suitable areas for solar development

Identifying potential locations for solar power plants is of paramount importance as energy consumption and population continue to expand. The results of the AHP-GIS analysis of solar site suitability for Kano and Bamako revealed distinct patterns influenced by criteria weighting and spatial characteristics. Global horizontal irradiance (GHI) emerged as the most significant factor in both cities, with weights of 0.24 for Kano and 0.22 for Bamako, highlighting the importance of solar irradiance in site selection. This is in line with the same arguments of Al-Abadi *et al.* (2025).

Closeness to electricity lines ranked next, with weights of 0.16 and 0.17, respectively, highlighting the role of grid connectivity in reducing transmission losses. Kano had more fragmented suitable areas (33.63%) than Bamako, which had wider coverage (75.85%), mainly due to terrain variations and urban sprawl constraints, as evidenced by the higher impact of LULC (0.12).

Moreover, the influence of restrictions, such as protected areas and buffer zones, reduced potential sites significantly, particularly in Bamako's peri-urban zones and Kano's central district. Indeed, this is the reason why Yushchenko *et al.* (2018), believe that the restrictions zones may need to be reduced in order to consider some projected areas as suitable for off grid solar power. The present study does not support this argument, and suggests that all protected areas, regardless of their nature, should be excluded from consideration as suitable sites for solar power installations.

The normalised pairwise matrices for both cities aligned closely with suitability patterns, with criteria like GHI and powerlines having a visible spatial impact, while low-weighted factors like aspect, temperature, and wind speed played minor roles. The findings are broadly in line with most previous studies including Amrani *et al.* (2024), Fedakar *et al.* (2025), which emphasise the dominance of solar irradiation and proximity to infrastructure in site selection, while highlighting regional differences in land use constraints and accessibility.

4.2.5 State of renewable energy adoption

Notwithstanding the widely recognised benefits of renewable energy, its adoption faces considerable challenges, due primarily to a failure of national energy policies to take the issue seriously. The study reported that although Kano shows its commitment to solving its energy challenge is doing better than Bamako with two solar sites including Bayero University Kano New Site (7.1 MW) and Ado Bayero Mall (1 MW), totalling 8.1 MW, there is still more to do. For example, the shutdown of the Kumbotso solar power plant since July 2022 due to unresolved maintenance issues highlights infrastructural fragility and poor operational sustainability.

Such cases illustrate broader challenges related to weak policy implementation, institutional inertia, and corruption. As noted by Amoah *et al.* (2022), corruption continues to undermine renewable energy governance in several African countries, deterring private investment and eroding public confidence in national clean energy strategies. Without consistent political will, transparency, and enforceable regulatory frameworks, many renewable energy initiatives risk stalling or failing altogether.

The persistence of traditional biomass use, particularly for cooking, highlights the slow progress in achieving a just energy transition. A strikingly high dependence on charcoal is evident in Bamako, where 90.60% of households still rely on it as their primary cooking fuel. This aligns with findings by Dagnachew *et al.* (2020), who argue that across Sub-Saharan Africa, the transition to clean cooking remains elusive, with charcoal and firewood dominating household energy use due to affordability, availability, and policy neglect.

The comparative lack of clean cooking access in both cities highlights the continued oversight of household-level energy poverty by energy policy frameworks, particularly in informal and peri-urban settlements. To address this issue, accelerating the uptake of renewable energy requires not only grid-scale investments but also decentralised and inclusive solutions that address cooking needs, household electrification, and community-level infrastructure gaps. As suggested by (Ouedraogo, 2017), locally adapted energy policies and governance reforms that integrate technological, economic, and social dimensions are critical to expanding renewable energy access in West African cities.

4.2.6 Determinants of renewable energy development

Understanding spatial dynamics within different urban settings is crucial for designing effective strategies to enhance renewable energy (RE) adoption and efficiency. The results highlight how spatial disparities significantly influence RE development. It shows that factors such as local attitudes, knowledge, and income levels impact the adoption of RE differently across regions. In particular, spatial variations alter the impact of different factors on supply and RE acceptance. The study revealed five factors (Advantage of RE, Belief about RE Cost, Energy Demand, RE Social Acceptance, Environmental Knowledge) to capture distinct aspects related to RE acceptance (Hazrati, 2024) . This structured approach helps in understanding different dimensions influencing social acceptance across varied regions (Belaïd *et al.*, 2021; Hao and Shao, 2021).

The Cronbach's alpha values indicate moderate to good internal consistency reliability for most factors, which enhances confidence in the measurement scales used. In addition, the significance of the Bartlett's test and the adequate KMO values suggest that the factor analysis model effectively grouped related variables into meaningful constructs. This strengthens the validity of using these factors in further in addressing effective energy policy at regional differences in addressing barriers and tailor incentive appropriately (El-Karmi and Abu-Shikhah, 2013; Sen and Ganguly, 2017; Verbruggen *et al.*, 2010). Consequently, the spatial variation in energy demand and renewable energy social acceptance highlights contextual differences in how these constructs are perceived across Bamako, Kano, and at the regional scale. Local economic conditions, cultural values, environmental policies, and existing infrastructure, the social acceptance all contribute to region specific acceptance pattern. For example, in one region, high acceptance might be driven by strong environmental values, while in another, economic considerations or political support for renewable energy might play a more significant role. This aligns with findings from a spatial analysis of energy consumption patterns in Kenya (Mbaka, 2022).

A number of differences have been reported when it comes to the determinants of renewable energy development (RED) across the study area. In Bamako, for instance, beliefs about the advantages of renewable energy (ARE) were the primary factor influencing RED. Conversely, in Kano, RED was explained by ARE, energy demand (ED), and social acceptance (SA) of renewable energy (Belaïd *et al.*, 2021). Across both regions, environmental knowledge (ENK) positively influenced ARE, indicating that increased environmental knowledge enhances beliefs in renewable energy's advantages. However, ENK did not significantly impact RED indirectly, as initially expected. At the regional scale, RED was positively associated with ARE but negatively with beliefs about renewable energy costs (BRC). The lack of an indirect effect of ENK on RED across regions supports the consistent role of ENK in enhancing ARE but highlights a disconnect between ARE and RED. This finding suggests that while environmental knowledge contributes to positive attitudes towards RE, other factors may be impeding the translation of these attitudes into concrete development actions. Empirical evidence argued that, improving social acceptance of renewable energy involves several strategic approaches, based on research and best practices (Muwanga *et al.*, 2023). For example, implementing educational campaigns and integrate renewable energy topics into school curricula to build long-term support can enhance further understanding of renewable energy benefits and technologies among local communities. In addition, engaging communities helps address local concerns and increases buy-in. Therefore, involving actively communities in planning and decision-making processes, can be achieved through public consultations, community meetings, and participatory projects.

The upfront cost of renewable energy technologies, such as solar panels or wind turbines, can be a significant barrier. Although costs have been decreasing, initial investments remain a hurdle for many individuals and small businesses. Local adoption of renewable energy can face several barriers that hinder widespread implementation. These barriers often vary based on geographic, economic, and social factors. For instance, although, inadequate local incentives, such as tax credits, rebates, or grants, can deter investment in renewable energy, financial support, economic benefits of renewable energy may not outweigh the costs. In fact, limited availability of loans or financial products tailored for renewable energy projects can restrict adoption. Therefore, accessing to affordable financing options is crucial for the adoption of renewable energy technologies. Furthermore, inconsistent or unclear regulations can create uncertainty and discourage investment in renewable energy. Local policies may not always be supportive or may lack clarity on procedures and requirements. Additionally, technological limitations and lack of local expertise can impact the effectiveness and efficiency of renewable energy systems. Cultural and social factors play a significant role as local attitudes and beliefs about renewable energy can influence adoption rates. Community with limited understanding or skepticism about RE benefits may resist adopting these technologies. Infrastructure challenges such as integrating RE into existing grid can limit the effectiveness of RE implementation. Urban areas, in particular may face challenges related to space constraints for installing renewable energy systems. Addressing these multifaceted barriers requires a comprehensive approach that considers the specific context of each region and tailors' solutions accordingly.

4.3 Summary of Findings

A summary of the findings of the study consists the following:

Kano and Bamako showed contrasting trends in CDD between the two cities, with a positive variation in CDD in Kano (Sen's slope = 2.308), with an increasing trend of 1.73 °C-day yr^{-1}, whilst in Bamako, a significant decreasing trend (p=0.05) of -3.80 °C-day yr^{-1} was observed. For both cities, the heat index has shown less variation over the last 30 years. Kano exhibited a positive trend in heat index, although this trend is less statistically significant with a p-value greater than 0.05. Bamako presented a positive trend in heat index evolution over the years, as indicated by Sen's slope of -0.059, reflecting an annual change of approximately -0.06°C per year. Over the study period, both cities have faced significant land use disruption as a result of growing urban development. The built-up area rapidly increased from 66.88 to 242.53 km^2 with an annual growth rate of 8.47% in Kano and from 50.49 to 157.88 km^2 with an annual variation of 6.86% in Bamako. People's beliefs about the advantages of renewable energy positively contributed to the development of renewable energy in Bamako whereas energy demand, social acceptance and the advantages of renewable energy explained the development of renewable energy in Kano. Furthermore, in both regions, environmental knowledge reinforces people's beliefs about the advantages of renewable energy.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1. Conclusions

Big talks on climate change and how to counter its effects are certainly commonplace in the African context. However, it is not hard to notice that there is a significant gap between scientific research on climate change and concrete action to tackle the problem. This study fills part of this gap by examining trends in cooling degree days, the heat index, changes in land use, solar suitable suites and factors influencing the development of renewable energy in two West African cities, Kano and Bamako.

The study revealed crucial insights into the climatic contrasts between the two cities. In Kano, the positive trend in CDD (Sen slope = 2.308, 1.73°C-day-year^{-1}) aligning with observed increases in maximum temperature. In contrast, Bamako showed a downward trend in CDD (-3.80°C-day-year^{-1}), associated with a significant decline in minimum temperatures, suggesting reduced night-time heat burden. This disparity highlights the different climate dynamics shaping energy and climate policies in the region.

Both cities showed relatively stable heat index trends over the study period, with only minor fluctuations observed in residents' perception of the heat. In Kano, the heat index increased slightly, while in Bamako it gradually decreased. The findings highlight the critical role of sustained monitoring of the thermal environment in detecting subtle changes that may influence public health and urban development. Furthermore, the study observed notable land use changes in both cities.

The rapid urban expansion of Kano, from 66.88 km² to 242.53 km² (annual growth rate of 8.47%), and that of Bamako, from 50.49 km² to 157.88 km² (annual change of 6.86%), are contributing not only to the changing landscape, but also to increased energy demand, rising temperatures and climate resilience challenges. As cities expand, the implications for heat island effects, energy consumption and environmental sustainability become increasingly urgent.

The spatial analysis, based on a GIS-AHP approach, identified roughly 33.63% suitable land for a solar power plant in Kano, compared with 66.37% unsuitable land, whereas 75.85% of the land in Bamako was suitable, compared with only 24.15% unsuitable. These results highlight the practical potential for scaling solar infrastructure in urban West Africa using geospatially informed decision-making tools.

As far as renewable energy is concerned, the study showed that socio-cultural factors, such as public beliefs about the benefits of renewable energy, played a crucial role in the development of renewable energy in Bamako, while in Kano, energy demand and social acceptance were more influential. Both cities showed that environmental knowledge strengthened support for renewable energy. This underlines the importance of education and public awareness campaigns to encourage the uptake of renewable energy solutions in urban areas, stimulating both climate change mitigation and energy transition.

5.2. Recommendations

5.2.1 Policy improvement

To foster a sustainable energy transition, government institutions in Kano and Bamako must strengthen policy frameworks that support the deployment of renewable energy technologies. Priority should be given to enacting incentives such as subsidies, favourable tax policies, and low-interest financing to lower the cost barriers associated with solar energy systems. These efforts can be harmonised with existing frameworks like Nigeria's National Renewable Energy and Energy Efficiency Policy (NREEEP) and Mali's National Renewable Energy Action Plan (NREAP). Additionally, integrating renewable energy targets into urban planning regulations will ensure long-term alignment between infrastructure development and climate goals. Policies should also promote decentralised energy solutions to address gaps in electricity access across peri-urban and underserved zones.

5.2.2 Performance improvement

Enhancing performance across institutional and technical domains is essential to accelerate renewable energy adoption. Local governments and utilities should invest in the maintenance and upgrading of grid infrastructure to accommodate increased distributed solar generation. Programmes that target the training of technicians and local installers will build capacity and ensure the reliability of installations. Moreover, routine climate monitoring, such as temperature, heat index, and land use changes, should be institutionalised through the establishment of automated weather stations and geospatial observatories. Rooftop solar mapping of private and public buildings, including schools and health centres, should be scaled up as an effective strategy to leverage underutilised infrastructure for clean energy generation.

5.3 Contribution to Knowledge

This study revealed contrasting climatic trends in Kano and Bamako between 1992 and 2022. Kano showed an increasing trend in cooling degree days (Sen's slope = 2.31 °C-day yr^{-1}, $p = 0.444$), while Bamako exhibited a marginal decline (–3.93 °C-day yr^{-1}, $p = 0.053$). In Bamako, minimum temperature decreased significantly (–0.045 °C yr^{-1}, $p = 0.001$), whereas maximum temperature in Kano rose (0.021 °C yr^{-1}, $p = 0.016$). Land use analysis using the Random Forest algorithm demonstrated rapid urbanisation in both cities, with built-up areas expanding to 242.53 km^2 in Kano and 157.88 km^2 in Bamako.

GIS-based suitability modelling using the analytic hierarchy process identified 33.63% of Kano and 75.85% of Bamako as highly suitable for solar power plants. Structural equation modelling from 960 survey responses across both cities revealed that beliefs about the advantage of renewable energy (ARE) positively influenced renewable energy development (RED) ($\beta = 0.11$, $p < 0.001$), while beliefs about renewable energy cost (BRC) had a negative effect ($\beta = -0.17$, $p < 0.05$). Environmental knowledge (ENK) was a strong predictor overall, particularly in Kano ($\beta = 0.68$, $p < 0.001$). The findings revealed that variations in climate trends, combined with urban expansion, directly affected the spatial distribution of solar energy potential in Kano and Bamako. Furthermore, renewable energy development depended more on environmental awareness and public perceptions than just on physical land suitability in the study area.

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APPENDICES

Appendix A Survey questionnaire on the factors influencing the adoption of renewable energy in Kano and Bamako

Dear respondent, this questionnaire is designed to gather data for research on the factors influencing the deployment of renewable energy in urban areas, with a focus on Kano (Nigeria) and Bamako (Mali). Your participation is highly valued, and all responses are treated with strict confidentiality. The findings contribute to improving urban development and energy policies in both cities.

Section A: Location

1. Country

- o Nigeria
- o Mali

2. City

- o Kano
- o Bamako

If Kano,

3. Local Government Areas

- o Dala
- o Fagge
- o Gwale
- o Kano Municipal
- o Nassarawa
- o Tarauni
- o Kumbotso

- Ungogo

4. Ward/Sector: ____

5. GPS Coordinates

- Latitude (°): [ ]
- Longitude (°): [ ]
- Altitude (m): [ ]
- Accuracy (m): [ ]

If Bamako,

6. Municipalities____

- Commune I
- Commune II
- Commune III
- Commune IV
- Commune V
- Commune VI

7. GPS Coordinates

- Latitude (°): [ ]
- Longitude (°): [ ]
- Altitude (m): [ ]
- Accuracy (m): [ ]

Section B: Household and Dwelling Characteristics

1. Gender

- Male

- Female

2. Age Group

- Under 18
- 18-25
- 26-40
- 41-60
- Above 60

3. Marital Status

- Single
- Married
- Separated
- Divorced
- Widowed

4. Level of Education

- No formal education
- Primary education
- Secondary education
- Islamic education
- Vocational training
- Tertiary education

5. Occupation

- Student
- Professor
- Artisan

- Farmer
- Trader/Business Owner
- Civil/Public Servant
- Private Sector Employee
- Unemployed
- Retired

6. Monthly Household Income (₦) or (FCFA)

- Less than 50,000
- 51,000 - 100,000
- 101,000 - 150,000
- 151,000 - 200,000
- 201,000 - 250,000
- 251,000 - 300,000
- 301,000 - 350,000
- 351,000 - 400,000
- Above 400,000
- Prefer not to disclose

7. Household Size

- 1
- 2
- 3
- 4
- 5 or more

8. Type of Building

- Boys' Quarters (B-Q)
- Face-me-I-face-you
- Flat
- Duplex
- Multi-story Building

9. Ownership of Residence

- Owned by household head
- Rented apartment

Section C: Household Energy Usage

1. Cooking energy choice

- Firewood/Charcoal
- Kerosene
- Cooking Gas
- Electricity

2. Electricity source

- Solar panel
- Kano Electricity Distribution Company (DEKCO)
- Energy du Mali SA (EDM SA)

Section D: Awareness of Climate Change

1. Have you heard about climate change?

- Yes
- No

2. Which of the environmental problems are you aware of?

- o Pollution
- o Greenhouse gas
- o Global warming
- o Droughts
- o Losse of biodiversity
- o Floods

Section E: Perceptions of Renewable Energy

1. Are you familiar with renewable energy?

- o Yes
- o No

2. Do you know the benefits of renewable energy?

- o Yes
- o No

3. Do you use renewable energy at home?

- o Yes
- o No

If no,

4. Do you intend to use renewable energy in the future?

- o Yes
- o No

5. Would you support the installation of solar panels in your area?

- o Yes
- o No

If yes, why?

If no, why?

***6*. Would you accept the installation of solar power systems on your rooftop?**

- Yes
- No

If yes, why? ____

If no, why? ____

7. Does the government promote renewable energy use?

- Yes
- No
- I do not know

8. Rate the following barriers to switching to renewable energy:

Barrier	1 (Not a barrier)	2	3	4	5 (Major barrier)
High costs					
Lack of information					
Difficulty finding trustworthy suppliers					
Slow return on investment					
Political vested interests					
Rapid technological obsolescence					

9. How likely are you to recommend renewable energy to others?

0 (Not at all)

1

2

3

4

5 (Very likely)

10. Do you have any additional comments? ___________________________________

Appendix B Pairwise Matrix for Kano

	GHI	Powerlines	Slope	LULC	Roads	Aspect	Temperature	DEM	WindSpeed	Railroads	Waterways
GHI	1	3	5	3	4	5	5	4	3	3	2
Powerlines	0.33	1	3	2	3	4	4	3	3	3	2
Slope	0.20	0.33	1	0.5	2	3	3	2	2	2	0.50
LULC	0.33	0.50	2	1	3	4	3	3	3	2	1
Roads	0.25	0.33	0.50	0.33	1	3	2	2	2	2	1
Aspect	0.20	0.25	0.33	0.25	0.33	1	2	1	1	1	0.50
Temperature	0.20	0.25	0.33	0.33	0.50	0.5	1	2	1	1	0.50
DEM	0.25	0.33	0.50	0.33	0.50	1	0.50	1	2	2	0.50
WindSpeed	0.33	0.33	0.50	0.33	0.50	1	1	0.50	1	1	0.50
Railroads	0.33	0.33	0.50	0.5	0.50	1	1	0.50	1	1	1
Waterways	0.50	0.50	2	1	1	2	2	2	2	1	1
Total	3.92	7.15	15.66	9.57	16.33	25.5	24.5	21	21	19	10.5

Appendix C Pairwise Matrix for Bamako

	GHI	Powerlines	Slope	LULC	Roads	Aspect	Temperature	DEM	WindSpeed	Railroads	Waterways	Areas
GHI	1	1.2	2	2	3	4	4	4	5	6	6	6
Powerlines	0.83	1	1.5	1.5	2.5	3	3	3	4	5	5	5
Slope	0.5	0.67	1	1	1.5	2	2	2	2.5	3	3	3
LULC	0.5	0.67	1	1	1.5	2	2	2	2.5	3	3	3
Roads	0.33	0.4	0.67	0.67	1	1.5	1.5	1.5	2	2.5	2.5	2.5
Aspect	0.25	0.33	0.5	0.5	0.67	1	1	1	1.2	1.5	1.5	1.5
Temperature	0.25	0.33	0.5	0.5	0.67	1	1	1	1.2	1.5	1.5	1.5
DEM	0.25	0.33	0.5	0.5	0.67	1	1	1	1.2	1.5	1.5	1.5
WindSpeed	0.2	0.25	0.4	0.4	0.5	0.83	0.83	0.83	1	1.2	1.2	1.2
Railroads	0.17	0.2	0.33	0.33	0.4	0.67	0.67	0.67	0.83	1	1	1
Waterways	0.17	0.2	0.33	0.33	0.4	0.67	0.67	0.67	0.83	1	1	1
ProtectedAreas	0.17	0.2	0.33	0.33	0.4	0.67	0.67	0.67	0.83	1	1	1
Total	4.62	5.78	9.06	9.06	13.21	18.34	18.34	18.34	23.09	28.2	28.2	28.2