

**DIFFUSION OF SOLAR PHOTOVOLTAIC SYSTEM IN KISUMU COUNTY,  
KENYA**

**BY**

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for the award of the Degree of Master of Environmental Studies (Climate Change  
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## DECLARATION

### Declaration by the Candidate:

This Research Project is my original work and has not been presented for an award or a degree in any University or Institution.

.....

Signature

.....

Date

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### Declaration by the Supervisor

I confirm that the work reported in this research project was carried out by the student under my Supervision.

.....

Signature

.....

Date

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## **EDICATION**

This work is dedicated to all the people who helped me become:

My mother Ms. Mary Gathoni Morris, and Mr. Michael Mwangi, my late father.

My circle of friends, who always lift me up.

To my soundboard and friend, Scott Remborg who made this work possible.

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## **LIST OF ACRONYMS AND ABBREVIATIONS**

<b>AOI</b>	Area of Interest
<b>COA</b>	Cluster and Outlier Analysis
<b>DOI</b>	diffusion of Innovation
<b>ESRI</b>	Environmental Systems Research Institute
<b>GHG</b>	Greenhouse Gases
<b>GIS</b>	Geographic Information System
<b>IMF</b>	The International Monetary Fund
<b>IEA</b>	International Energy Agency
<b>IPCC</b>	Intergovernmental Panel on Climate Change
<b>KNBS</b>	Kenya National Bureau of Statistics
<b>LCA</b>	Life Cycle Assessment
<b>MFIs</b>	Microfinance Institutions
<b>OLS</b>	Ordinary Least Squares
<b>OGO</b>	Optimised Getis-Ord
<b>OECD</b>	Organisation for Economic Cooperation and Development
<b>PV</b>	Photovoltaic
<b>PAYG</b>	Pay-as-you-go
<b>SHS</b>	Solar Home Systems
<b>SDGs</b>	Sustainable Development Goals
<b>SPRD</b>	Solar Panda Relational Database
<b>SP</b>	Solar Panda

## **DEFINITION OF TERMS**

### **Diffusion**

This refers to the mechanism through which innovations are transmitted among members of a social system over a period through designated channels. (Rogers, 2004).

### **Photovoltaic**

Müller et al., (2013) describes photovoltaics as a form of solar energy technology employed in solar panels. When sunlight strikes a solar panel, the photovoltaic (PV) cells within the panel absorb solar energy, generating an electric charge and initiating the flow of current.

### **Solar Home systems**

Adwek et al., (2020) describes solar home systems as compact independent photovoltaic systems, autonomous power sources suitable for both rural and urban households without access to the grid or with inconsistent power availability.

### **Climate Change**

This refers to long-term shifts in temperatures and weather patterns. They can be as result from natural activities such as large volcanic eruptions or from human activities due to burning of fossil fuels like coal and gas (Edenhofer,2014).

### **GHG Inventories**

A comprehensive list of greenhouse gas emissions associated with a specific product or process (Intergovernmental Panel on Climate Change, 2006)

### **Functional Unit**

A standardized unit of measurement used to quantify the performance of a product or system (International Organization for Standardization, 2008)

## ABSTRACT

This study investigated the diffusion of solar home systems in Kisumu East-Sub County, Kenya. The primary objectives of this study were to first identify the spatial patterns of solar home systems in Kisumu. Secondly the study sought to understand the socioeconomic factors driving the diffusion of solar home systems in Kisumu, and lastly the study sought to assess the potential of solar home systems for climate mitigation through greenhouse gas reduction. The study employed an empirical interventional design combined with geospatial tools. A cluster sampling procedure was employed. 384 households were sampled. The research identified statistically significant spatial clusters of solar home system diffusion patterns. These clusters exhibited a wave-like pattern radiating from population centres, but with a diminishing trend for the period 2016 to 2021. Using an ordinary least squares model, socioeconomic factors were analysed to understand the drivers of the spatial trends. For population density, the coefficient (-0.116) was negative but statistically insignificant ( $p$ -value = 0.531). This suggested that, on average, population density was not associated with a statistically significant change in solar home system diffusion. Regarding income, the coefficient (45.36) was positive and statistically significant at ( $p$ -value = 0.037). This indicated a positive relationship between income and solar home system diffusion. Regarding education, the coefficient (0.111) was positive but statistically insignificant at ( $p$ -value = 0.735). This suggested that, on average, an increase in education levels was not associated with a statistically significant increase in solar home system diffusion. Lastly, regarding electricity, the coefficient (0.013) was positive and statistically significant at ( $p$ -value = 0.000\*). This indicated a positive relationship between electricity rates and solar home system diffusion. The study estimated that solar home system usage in Kenya had avoided 5.875 metric tons of CO<sub>2</sub> emissions for the period 2016 to 2021, highlighting its potential for greenhouse gas reduction. Although solar home systems diffusion counts declined over time, socioeconomic factors, particularly income and electricity rates, emerged as stronger drivers of diffusion compared to population density and education level. Based on the findings the study suggests the recommendations that targeted interventions for promoting solar home system diffusion in suitable areas. Secondly the research suggests that policy makers could consider leveraging economic incentives for addressing factors related to electricity costs to encourage wider diffusion of solar home systems. Lastly the study recommends that further research is needed to implement a program for ongoing monitoring and evaluation of solar home systems impact.

## CHAPTER ONE: INTRODUCTION

### 1.1 Background Information

Significant greenhouse gas emissions caused by human activities have drawn considerable attention. The intensifying greenhouse effect has resulted in a suite of adverse consequences, such as rising sea levels, warming oceans, shifting precipitation regimes, and accelerated glacial melting. Carbon accounts for 80% of the total greenhouse gas emissions to blame for global warming (Masson-Delmotte et al., 2023).

Carbon dioxide emissions have increased over the past two centuries, particularly because of industrialization and increased demand for electricity, together with the corresponding fossil fuel burning (Canadell et al., 2018).

Energy demand is projected to increase by 1.5- to three-fold by 2050 and increasing carbon emissions have become a growing problem, resulting to an increasing trend of carbon emissions. The government has effected policies to promote it (Stefan ,2023).

Renewable energy sources for instance solar power are playing a key role in implementing the 2030 Agenda and the Sustainable Development Goals in Africa and Kenya (Rabia et al., 2015).

Solar energy is emphasized due to its renewable nature, which means it can be replenished naturally and is not depleted when used. This contrasts with fossil fuels which are finite resources and contribute significantly to greenhouse gas emissions and climate change. Solar energy offers a sustainable alternative that can help lessen the impacts of climate change while also providing a reliable source of electricity (OECD,2016).

Exploration of alternative energy sources traces its origins to the late 1990s, a period marked by the escalating prices of petroleum products. The literature underscores that transitioning from fossil energy sources to renewable alternatives is crucial for realizing a sustainable vision on a global scale (David, 2019).

In Kenya, the solar market experienced substantial growth in the 1980s, primarily due to the introduction of donor-funded large-scale home solar systems (SHS) and supportive government policies. In 2009, the market was estimated to have a capacity of 8 to 10 MWp, three-quarters of which were SHS (solar home systems).

According to (Walters et al.,2018) even though there has been a spread in the diffusion of solar energy within communities, there are still challenges that hinder the diffusion of solar technologies. Some of these challenges include high costs for many individuals and communities particularly in rural areas. Access to financing inhibits the adoption of solar technologies especially for low-income households. Inadequate infrastructure especially for the distribution continues to limit the effectiveness of solar energy deployment. Policy and regulatory framework that are inconsistent or unclear also hinder investment in solar energy projects and create uncertainty for stakeholders.

Enhancing the accessibility of carbon alternatives at an attractive cost entail comprehending the widespread diffusion of renewables. This suggests that a key strategy for enhancing, increasing, and fostering the widespread use of renewable resources is to initially grasp the diffusion patterns of the technology (OECD, 2016).

Moorthy et al., (2019) reported that the widespread adoption of renewable energy technologies was primarily driven by a confluence of environmental, social, technological, regulatory, and economic factors.

This confirms the significance of comprehending the diffusion patterns of solar photovoltaics, as it sheds light on the progress made in addressing climate change through alternative energy sources, considering policy interventions and a shifting climate.

Gillingham & Graziano (2015) suggests that understanding dispersion patterns, in particular geographical patterns, is crucial from a strategic and marketing standpoint in addition to from an academic one. He goes on to add that understanding diffusion patterns is important, especially for promising technologies like renewable energy technologies. It is therefore against this background that this study sought to study the impact solar technologies had, on the reduction of greenhouse gases following their continuous use. The study examined spatial patterns of solar photovoltaics and employed the use of geospatial models like variogram and kriging, to analyse the diffusion of solar technologies, over time. Lastly, the study quantified the amount of carbon mitigated using solar technologies, showing that switching to green technologies was a viable strategy to lessen climate change.

## **1.2 Statement of the Problem**

Climate change primarily stems from energy-related activities, contributing to around 60% of total greenhouse gas emissions. It is also a major cause of health problems, primarily through air pollution caused by burning fuel. (Masson-Delmotte et al., 2019) Recent advancements in solar photovoltaics include increased energy efficiency and stability, reduced acquisition costs, integration with PV-batteries, and the advancement of new materials and technologies that improve performance and environmental sustainability (Ockwell et al., 2018).

Walters et al., (2018) argues that solar energy remains the best answer to energy poverty. This is because it provides the most feasible answer to the reduction of GHG emissions. Solar technology has overtime gained more recognition since it is largely used as a substitute in the case where the main grid electricity is not reliable or available. Most rural communities find it affordable with the rising living costs.

Although great progress has been made towards SDG7 (affordable and clean energy), and communities are more aware of the existing solar technologies, specifically the solar home systems, there is still a challenge in comprehensively understanding the impact solar home system interventions have had.

Furthermore, although existing literature explores the benefits of solar home systems (SHSs) for energy access, a complete understanding of their spatial diffusion and the potential impact they have in mitigating climate change remains limited (Sovacool, 2014). This lack of knowledge and data hinders the advancement of guided policies and strategies, that can maximize the impact of SHS deployment in achieving these goals.

This study sought to address this gap using spatial tools, to identify and analyse spatial clusters of SHS diffusion in Kisumu. In addition, using an ordinary least squares model, the study sought to analyse the underlying factors driving the diffusion of SHS. By quantifying the greenhouse gas emissions avoided due to SHS diffusion, the study further strengthened the case for promoting the usage of solar home systems in rural communities.

## **1.3 Research Questions**

1. Why do spatial patterns and clusters of solar home system exist in Kisumu East Sub-County?

2. What are the underlying socioeconomic factors driving the spatial clusters and patterns over time?
3. How much carbon emissions (CO<sub>2</sub><sup>e</sup>) have been avoided using solar home system in Kisumu East Subcounty?

## **1.4 Research Objectives**

### ***1.4.1 Broad Objectives***

The primary objective of this study was to determine the amount of Carbon emissions abated by the deployment of residential solar home systems in the Kisumu East Sub-County.

### ***1.4.2 Specific Objectives***

1. To identify spatial clusters and patterns of solar home system diffusion.
2. To analyse the socioeconomic factors driving the spatial clusters and patterns over time.
3. To calculate the amount of greenhouse gases avoided using solar home system deployment in the region of study.

## **1.5 Research Hypotheses**

1. Ho: There is no spatial clustering of SHS in Kisumu County.

Ha: Solar home system diffusion rates exhibit spatial clustering, with areas having a high percentage of SHS diffusions compared to the overall county average.

2. Ho: There is no significant association between socioeconomic factors income, education, and population density with the spatial distribution of solar home system.

Ha: There is a significant association between socioeconomic factors income, education, and population density with the spatial distribution of solar home system.

3. Ho: The use of SHS in Kisumu East Subcounty does not lead to a significant reduction in carbon emissions (CO<sub>2</sub><sup>e</sup>) compared to traditional energy sources.

Ha: The use of SHS in Kisumu East Subcounty leads to a significant reduction in carbon emissions (CO<sub>2</sub><sup>e</sup>) compared to traditional energy sources.

## **1.6 Significance of the Study**

SDG 13 emphasizes collective access to dependable, inexpensive, sustainable, and modern energy (Campbell et al., 2018). This goal is not only crucial for improving the lives of billions but also forms the foundation for achieving poverty eradication, climate action, and a sustainable future. Globally, improved energy efficiency alone could contribute to 40% of the emissions reductions needed to meet climate change targets (Edenhofer, 2014).

Existing data on the spatial variability of SHS adoption in Kenya remains scarce, limiting the understanding of this potentially transformative renewable energy resource. This study addresses this gap by analysing the spatial distribution of SHS adoption in Kisumu County. By identifying key factors influencing SHS diffusion, the research will inform future deployments of clean technologies and contribute to broader efforts for innovation uptake.

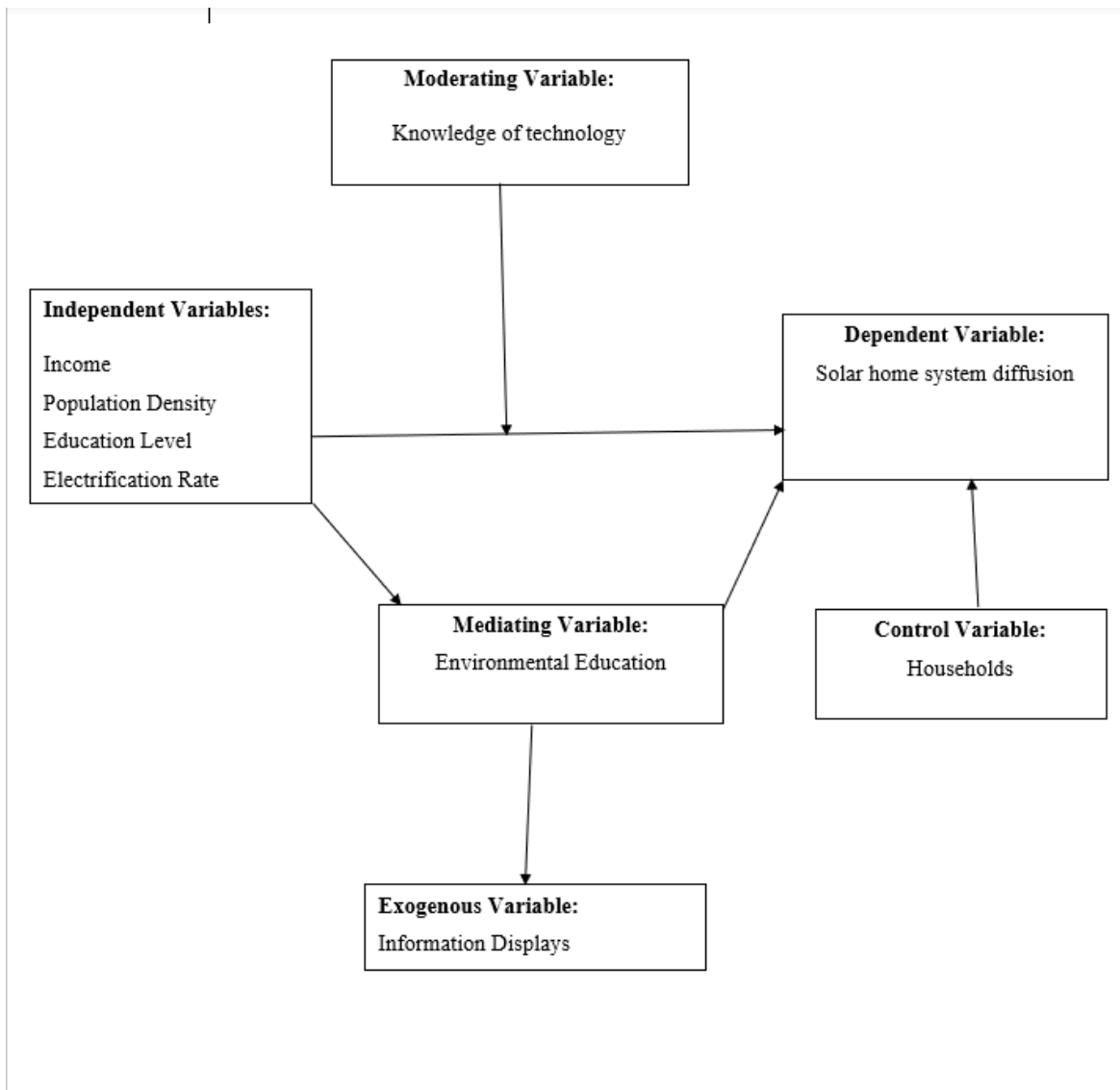
The findings from this research extend beyond the immediate context of Kisumu County. The results are valuable to various stakeholders. For energy practitioners, gaining insights into factors influencing SHS diffusion will inform targeted interventions to promote wider access.

To policy makers this research patterns will enable the development of data-driven policies to maximize the impact of SHS deployment in achieving energy access and climate goals.

For academics, this research contributes to the existing body of knowledge on SHS diffusion patterns, informing future research endeavours. For future researchers, the findings will offer a foundation for further exploration on clean energy technologies and their role in sustainable development.

## **1.7 Conceptual Framework**

A conceptual model Figure 1.1 shows the interconnected socioeconomic factors that drive SHS adoption.



**Figure 1.1: Conceptual Framework**

Knowledge of Technology moderates the connection among some independent variables and SHS diffusion. For example, in high-income areas, a lack of knowledge about SHS technology might hinder adoption. Conversely, strong knowledge of technology could incentivize adoption in lower-income areas.

Environmental Education potentially mediates the relationship between some independent variables and SHS adoption. For instance, higher education levels might lead to increased environmental awareness (environmental education) which, in turn,

could motivate individuals to adopt SHS for their environmental benefits. Information displays: this variable is exogenous in this context. Government policies, marketing campaigns, or community outreach programs can influence the availability and content of information displays about SHS. Government policies, marketing campaigns, and community outreach programs can directly impact the availability, content, and effectiveness of information displays, even in the absence of structured environmental education initiatives. In the context of SHS adoption, information displays can be influenced by a range of factors beyond formal environmental education programs. Recognizing the broader range of factors that influence information displays allows for a more comprehensive understanding of their impact on SHS adoption. These displays would not be directly influenced by the other variables in the model but could affect SHS adoption decisions.

Households: This is a control variable. The inclusion of household as a control variable in the conceptual framework aims to account for the potential influence of household-level factors on the relationship between the independent and dependent variables. For instance, since we are examining the impact of SHS adoption, controlling for household size ensures that any observed differences in energy consumption are not solely due to variations in household size.

In essence, by controlling for household characteristics, we are striving to isolate the specific effects of the variables under investigation, leading to more accurate and reliable findings.

## **1.8 Theoretical Framework**

This study uses the diffusion of Innovation (DOI) Theory (Rogers, 2004) as a theoretical framework to comprehend factors influencing the diffusion of solar home systems (SHS) in Kisumu County, Kenya. DOI theory proposes that the spread of a new idea or technology (like solar home systems) follows a predictable pattern over time through social systems.

Applying DOI theory to SHS diffusion, this study examines the influence of specific components identified within the diffusion of innovation framework.

Higher income levels are expected to have a positive correlation with SHS adoption. This can be explained by the increased relative advantage associated with greater purchasing power, making SHS a more attainable option.

Denser populations with existing SHS users can create a positive correlation through increased observability and potential cost reductions due to economies of scale in installation and maintenance. This can also influence social influence, with neighbours adopting SHS due to witnessing its benefits in their community.

Higher education levels are expected to lead to a positive correlation with SHS adoption. Increased knowledge and awareness about the benefits of SHS (relative advantage) and a better understanding of the technology (complexity) can contribute to informed decisions favouring this clean energy solution.

Electrification rates: Areas with existing electrification might have a positive or negative correlation with SHS diffusion depending on the reliability and cost of grid electricity. Unreliable grid access can incentivize SHS adoption for its relative advantage, while readily available and affordable grid electricity might create competition and hinder SHS diffusion.

### **1.9 Scope, Limitations, and Assumptions of the Study**

This study examined the diffusion patterns of solar home system in Kisumu East Sub-County from 2016 to 2021, and explored the underlying factors driving their diffusion. The study used ordinary least squares model to comprehend the drivers of solar home system diffusion in Kisumu.

The solar home system in this study were primarily used to meet only the charging and lighting needs of households, and not for commercial or industrial solar uses.

The limitations experienced in this study included lack of free, available, and open georeferenced data of small home systems not just in the country, but Kisumu County as well.

To address the limitations encountered in this study, collaborative efforts with solar panda, an organisation in the renewable energy, were made to provide data on solar home systems and inform and validate the solar panel accurate capacities. This ensured reliable GHG emissions quantification calculations avoided following their use.

## **CHAPTER TWO: LITERATURE REVIEW**

### **2.1 Introduction**

The energetic sphere is prone to many forces of change interacting in parallel. Most importantly, we recognize the environmental impact of the current energy transition, which is currently at the forefront of the environment and energy debate. In response to new discoveries, the need for “green” energy has emerged.

Since the first oil crisis of 1973, much research has been done on renewable energy sources (OECD, 2016). According to (McCollum et al., 2017) many governments have spent significant amounts of money on renewable energy research and development, but the general reaction is that research currently reveals little data about how renewable energy is supporting climate protection efforts.

### **2.2 Renewable Energy Status and Energy Supply Mix in Kenya**

Kenya's renewable energy mix takes account of 52.1% hydro, 32.5% fossil fuels, 13.2% geothermal energy, 1.8% biogas cogeneration, and 0.4% wind (Takase & Suzuki, 2021). Cameron et al., (2015) reports that there has been public support for large-scale expansion of wind and solar PV, and geothermal energy in Kenya, to meet the national commitment under the Paris Agreement, however, a significant portion of its hydropower and geothermal sources remain untapped

Recent research in rural Kenya shows that, off-grid electrification projects managed by the private sector perform better in terms of achieving the long-term well-being of villagers and future generations (Boliko & Charles, 2019). This shows that Kenya has abundant renewable energy potential, which could contribute to improving quality of life in rural and poor urban sectors. If active emission reduction targets are set, Kenya can fully utilize its renewable energy resources to meet its climate change mitigation goals. In this case, a significant deployment of low-carbon technologies will be required (Longa & Zwaan, 2017).

### **2.3 Opportunities and Challenges of Diffusion of Solar Home System in Kenya**

Barrie et al., (2020) reported that opportunities for diffusion of solar home system in Kenya include the potential to revolutionize energy access for the poor, given a good go to market strategy, which offers affordable alternatives that are readily available for

adoption Trends (2017) further found out that household empowerment and decentralised sustainable development initiative are also a key opportunity for the diffusion of small home system. The broad adoption of renewable energy innovations remains high on each national development policy agenda. Solar home system can therefore assist national energy autonomy.

Knowledge development is another area that offers the opportunity of the diffusion of solar home system. The adoption of solar home system brings with it the education of local communities on not only the importance of adopting greener energies, but also on the need to reduce the reliance on alternatives like kerosene that cause respiratory illnesses in the long-term (Rabia et al., 2015). One of the primary obstacles to the diffusion of solar home system in Kenya is the need to keep up working capital to fund and sell more innovations. This makes the cost of distribution to be high and unsustainable in the long run (Opiyo & Ogindo, 2018).

Another major hurdle in the diffusion of solar home system is that the diffusion of solar home system relies on the PAYG model which presents the most favourable alternative for SHS distribution in Kenya. However, challenges using this model, include credit risk and its lack of connection with rural electrification policy. Private players are unable to provide this green alternative when the communities fail to honour their agreements in the payments of these solar technologies (Adenle, 2020).

#### **2.4 Spatial Clusters and Distribution Patterns of Solar Home System Diffusion**

The IEA describes renewable energy as “energy from pure processes (such as solar or wind) that is replenished faster than it is consumed” (Dechamps et al.,2023). Therefore, zero emissions from renewable energy resources are assumed.

The potential for renewable energy resources is immense, as they are theoretically infinite sources of energy. The potential for financial improvement is strongly associated with increased energy use and amplified greenhouse gas emissions. Renewable energy can ensure energy growth without increasing greenhouse gas emissions and promote sustainable development (Ahmad et al ., 2023, p.123).

Identifying and understanding spatial distribution patterns is critical not only from a scientific standpoint but also from a policy perspective. The fact that this increasingly

important technology is strongly correlated with sustainable development means that research into the existing solar home systems clusters and patterns is crucial.

(McEachern & Hanson, 2008) indicate that in any innovation diffusion process, there has to be a bridge between community adopters and policymakers and other peripheral agents of power, and by acknowledging the significance of people's discernment of intra and extra-community societal setting. He continues to further add that these components of bridging diffusion are best explored in a multi-scale geographic structure.

Research done by (Sommerfeld et al., 2017) discovered that the diffusion of PV systems was highly influenced by demographic variables, which linked up with the rural community's access to the electricity grid. This finding indicates that social interaction may influence the outcome of whether the PV system should be matched with the large body of literature on cohort effects in the transfer of spatial information

## **2.5 Examination of the Spatial Patterns in the Diffusion of Solar Home System**

The diffusion of modern technology is, for the most part, a vigorous activity that exhibits distinctive spatial patterns over time. For instance, traditional distribution models demonstrate that novel technology start at the largest population centres and are introduced in a centrifugal wavy pattern (Hägerstrand, 1952).

The process by which new technologies are created, improved, and popularized by people can be examined from various angles. The neoclassical viewpoint centres on how similar price fluctuations impact technology selection and entrepreneurial behaviour, highlighting fundamental aspects of innovation and diffusion (Stefan, 2023).

The process of novelty and dissemination is both an individual act and a collective act. Innovation is the determinant of technology choices, not only within individual companies, but also by individual actors involved in technology choice system also exists which helps and hinders this. Such an innovation system involves many variables besides price. (Stefan, 2023).

Photovoltaic technology is the latest new technology to consider (Bai et al., 2020). In 1995, around 1 terawatt-hour (Twh) was produced worldwide. This is steadily increasing, especially due to its ability to be used in off-grid environments. The widespread adoption of solar cells is currently impeded primarily by high costs, with demand being primarily driven by government initiatives.

Palm (2020) reported that new discoveries, products, and systems reportedly take time to spread. This is a reality that is often due to the diversity of potential adopters. He further elaborates on the three core classes of diffusion models: contagion, social impact and social understanding increase. Contagion refers to the fact that people are more likely to adopt if they meet other people who have already adopted it - the fact that any technological innovation spreads like an epidemic. Social clout is what people will accept when plenty of people in the group have adopted it. In other words, new technology innovation spreads through the motive of adaptation. He concludes by stating that social learning means that people adopt it after seeing sufficient empirical data to persuade them that the innovation is worth embracing, along with the evidence provided by the results of previous adopters.

Rogers (2004) argued that diffusion theory is one of the oldest models in social science. It is rooted in communication and demonstrates how ideas and products gain momentum over time and spread through specific populations and social structures. He concludes by stating that adoption implies a person doing something different from before (i.e., using or purchasing a new product, repurchasing, adopting a new behaviour). He adds that the key to acceptance is for a person to understand that the idea, action, or product is new or innovative, and therefore only this will allow it to be popularized.

The Bass model of diffusion employs Rogers' adopter classification, allowing innovators the flexibility to embrace an innovation at any moment. In contrast, the adoption timing for other groups is contingent upon the decisions made by fellow members within the social system (van der Kam, 2018)

Young (2009) showed that temporal aspects are largely ignored in social research. He contended that the inclusion of the temporal dimension highlighted the strength of diffusion studies, as it was integral to understanding the processes of innovation distribution, adopter classification, and the pace of adoption. Palm (2020) reported that the innovation diffusion process differentiated between early and late adopters, indicating that early adopters of photovoltaic technology were typically motivated by a combination of environmental consciousness and technological enthusiasm, whereas later adopters were primarily driven by economic considerations.

Ockwell et al., (2018) argues that how widely a technology spreads, depends on more than just how easy it is to use and get (the technical side). It is also influenced by cultural factors, like people's habits and beliefs, and by political factors, like government policies. This helps us understand why some technologies become widely used while others do not.

This project builds upon these theories.

## **2.6 Quantification of Greenhouse Gas Emissions Associated with SHS Diffusion**

It is reported that human activity has been estimated to have caused global warming of about 1°C. However, the report also says that a further 0.5°C of warming could be avoided by significantly reducing greenhouse gas (GHG) emissions over the next decade. The report notes that achieving the 1.5degree target will require changes in the energy sector, land, urban infrastructure, and industrial systems (Masson-Delmotte et al., 2019).

Russell (2019) Defined avoided emissions as reductions that occurred beyond the product's life cycle but were an outcome of the product's use. Tian and You (2021) argued that life cycle assessment (LCA) is a commonly used tool to measure and compare environmental effects and energy use. Russel (2019) created a setting that is neutral for evaluating and revealing the greenhouse gas (GHG) emissions and the effect of a product (good or service), in contrast to the absence of that product.

According to Tian & You (2021) the greenhouse gas (GHG) emission factor is calculated by dividing the life-cycle greenhouse gas emissions by the total power output over the entire life of the specified photovoltaic (PV) module. The greenhouse gas (GHG) emission factor is calculated by dividing the life cycle GHG emissions by the total electric power production over the entire lifespan of the specified photovoltaic (PV) module. The avoided emissions are frequently referred to as the positive differences. These positive differences have been an area of interest for businesses trying to develop and encourage low-carbon products (Kennedy et al., 2010).

The difference in product GHG inventories is how the attributable approach calculates the relative GHG impacts. The comparative is the difference between the base scenario with and without the evaluated product in terms of net GHG emissions and removals (ICCA,2013).

An attributional methodology was used to calculate the prevented emissions impact of the solar home system. The attributional methodology used in this study is a common approach in Life Cycle Assessment (LCA) to quantify the environmental impacts of products and systems. This methodology is widely recognized and applied in various fields, including climate change mitigation and sustainable development.

In this method, we compared product GHG inventories (i.e the comprehensive list of greenhouse gas emissions associated with a specific product or process). In the context of SHS, this included emissions from manufacturing, transportation, installation, and end-of-life disposal. These were then multiplied by avoided emissions per functional unit by the number of end products in use and then by the attribution factor i.e., averted emissions per functional unit, as well as the quantity of finished goods being used.

## **2.7 Knowledge Gaps**

Whereas the reviewed studies have demonstrated linkages between the independent variables including income, population density, environmental education, and electrification rates, as factors that support the diffusion of solar home system, a key knowledge gap exists regarding the impact of solar home system on climate change mitigation efforts. Existing research offers valuable insights, but a more comprehensive understanding is needed.

Furthermore, (VanderKam et al., 2018) reported that the scarcity of data supporting methodologies for measuring the impact of renewable energy interventions hindered the ability to track progress towards ambitious climate goals, such as the 1.5°C target. This highlights a limited understanding of the potential for solar home systems (SHSs) as a specific mitigation strategy. This presents the knowledge gap that this study set out to fill.

This study addressed these gaps by focusing on two key areas. First, the research used robust methodologies to estimate the actual emissions reductions achieved through solar home system diffusion in Kisumu East Subcounty.

Secondly, analysing spatial clusters and patterns of solar home system adoption and the diffusion drivers would allow for informed policy decisions regarding targeted interventions to maximize their climate change mitigation potential.

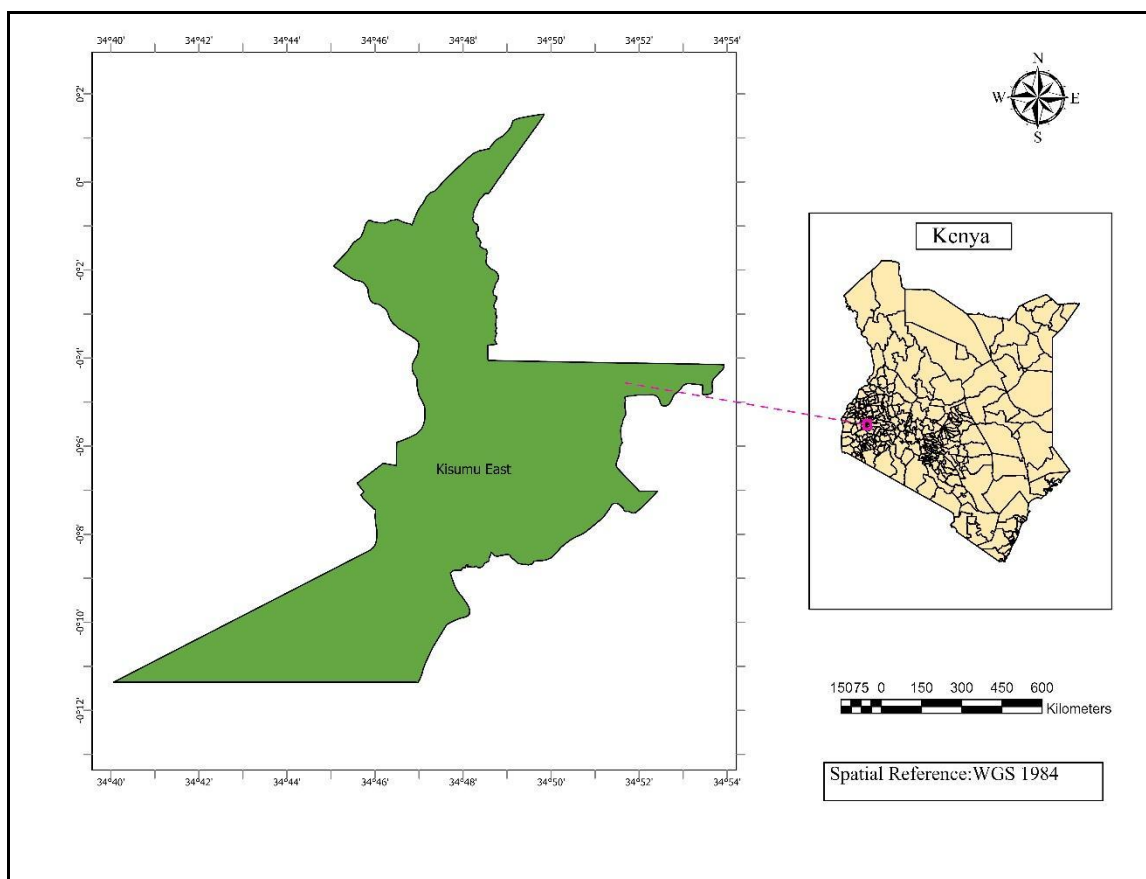
By tending to these knowledge gaps, this research aimed to contribute to a more comprehensive understanding of the role SHSs played in mitigating climate change and achieving sustainable development objectives.

## CHAPTER THREE: RESEARCH METHODOLOGY

### 3.1 Study Area

Kisumu, Kenya. Latitude and longitude coordinates are  $0^{\circ} 5' 30.1272$  S and  $34^{\circ} 46' 4.6416$  E. The total population is 1,155,574. The total area of Kisumu District is 2085.9 km. Kisumu is warm all year round, with an average annual temperature of  $23.0^{\circ}\text{C}$ . The temperature fluctuates between  $20.0^{\circ}\text{C}$  and  $35.0^{\circ}\text{C}$ , but rarely drops below  $19.0^{\circ}\text{C}$ . Kisumu has approximately 3568 hours of sunlight all through the year. On average, there are 117.33 hours of sunshine per month. (KNBS, 2019).

Kisumu was chosen because it is was the region where most past research on solar had been. Therefore, this study built upon this foundation.



**Figure 3.1: Map of the study area**

Modified from KNBS,2019

### 3.2 Study Design

An empirical interventional design was selected for this research to establish a causal relationship between solar home system (dependent variable) and income, population density, education, and electrification rates (independent variables).

An ordinary least squares model, together with spatial tools, was key, in identifying and understanding the underlying drivers of SHS diffusion across Kisumu, for the period 2016 to 2021. Regression tests in the ordinary least squares model used, allowed us to assess the strength and significance of these relationships.

This combined approach allowed the study to draw robust conclusions regarding the impact of SHS diffusion on emissions reduction.

### 3.3 Target Population

The participants in this study were drawn from the entire population of households in Kisumu East Sub-County which was 61,871. (KNBS, 2019). The study focused exclusively on household-level solar home system diffusion

### 3.4 Sampling Procedure

A cluster sampling procedure was employed.

The population was divided into smaller groups (clusters). The households with solar home system were then randomly selected among these clusters to form a sample.

Cluster sampling was chosen because the target population was large. In addition, the households that had solar home system, were geographically dispersed.

### 3.5 Sample Size

The number of households to sampled (sample size) was calculated using (Fisher, 1925) formula.

*i) Total population of households owing solar home systems in the county was above 10,000*

*Hence,*

$$n = \frac{(Z^2 * p * (1 - p))}{e^2}$$

*ii) Where; n = desired sample*

Z: Represents the standard normal deviate at the required confidence level 95%

( set at 1.96)

p: Represents the estimated proportion of the population

$$P = 0.5(50\%)$$

e: Represents the desired margin of error, which is the maximum allowable difference between the sample estimate and the population parameter (proportion in this case)

e: 0.05 (5% margin of error)

$$iii)n = (1.96^2 * 0.5 * (1 - 0.5)) / 0.05^2$$

$$n \approx 384.16$$

Therefore, a sample of 384 households was selected.

### **3.6 Data Collection Methods**

A permission letter was received from Kenyatta University following the evaluation of research tools in pilot studies. This was used in the application for a permit for research with the National Commission for Science Technology and Innovation. The letter was used to further request geospatial data from Solar Panda company, since Solar panda's data policy mandated that data be used for educational purposes only.

Geospatial data on solar home systems installations in Kisumu East Subcounty was exported from Solar Panda relational database (SPRD). Solar Panda (SP) gathered this data when communities were installing solar home systems for their homes. Communities willingly agreed to the use of the solar home system location data. For this study, private data like telephone numbers, emails and names of solar home system owner's data attributes were excluded from the exported data. This was done to protect and respect the privacy of solar home system owners.

The data was first subjected to a georeferencing process to obtain the latitude and longitude of the solar home system. To validate the above data, the spatial outlier analysis tool was used to identify any data points that fell outside of the expected location (Kisumu). Outliers were removed. The data also underwent a second validation process. A spatial overlay tool was used for this process. This was done by comparing solar home system georeferenced locations with established Kenyan National Bureau of Statistics (KNBS) households' datasets. This comparison aimed to identify any potential location inconsistencies between the two sources. No inconsistencies were found at this stage.

### **3.7 Data Analysis**

#### ***3.7.1 To Identify Spatial Clusters and Patterns of SHS.***

A geostatistical approach was employed due to the location-dependent nature of the data. This method aimed to identify and quantify the spatial structure of relevant variables, enabling the estimation of variable values based on their spatial relationships. To achieve this, two widely used spatial techniques, Optimized Getis-Ord (OGO) and Asselin's Clustering and Outlier Analysis (COA) were utilized (Ord & Getis, 1995). These methods facilitated the identification and mapping of solar home system clusters in relation to other spatial factors, providing insights into the causal factors influencing diffusion.

#### ***3.7.2 To Analyse Underlying Factors Driving Spatial Clusters and Patterns.***

##### ***3.7.2.1 Spatial-temporal Analysis***

Create space time cube, uses a fish netting method, was used to analyse the spatial clusters This made possible the visualization and analysis of the spatiotemporal data in the form of time-series analysis. It combined spatial and temporal pattern analysis, 2D and 3D visualization methods (Mitchell,2005).

Since the data consisted of time-stamped point features, it was essential to first aggregate it to comprehend spatiotemporal patterns at various places within the study area.

Fish netting was used to partition the study regions into cells of a specified size, and these cells were subsequently emphasized according to the quantity of adoptions within each one. This method was effective for illustrating diffusion patterns as it broke down the process into smaller units. The dimensions of each cell in the fishnet were set at 1km, a length that was sufficiently small to successfully break down our data yet significant enough to encompass more than one adoption within each cell.

##### ***3.7.2.2 Geospatial Modelling***

To analyse relationships between independent variables and the dependent variable, an ordinary least squares model was used.

OLS was chosen because it provided coefficient estimates which were useful in interpreting how changes in the independent variables affected the dependent variable (solar home systems). OLS was also appropriate because we were interested in the linear relationship linking the independent variable and the dependent variables. OLS

used a linear regression equation which helped describe the relationships between SHS and socioeconomic factors chosen for the study.

Secondly, OLS was chosen because the dependent variable was continuous and normally distributed across the area of study, making it appropriate for this study.

### ***3.7.3 Calculating GHG Emissions Avoided By SHS***

The carbon quantification calculations were restricted to data obtained from the solar database repository (SPRD), encompassing only domestic photovoltaic (PV) systems with a capacity of 20 watts. These domestic PV systems were exclusively used for illumination purposes.

Guided by the principles outlined in the Kenya National Climate Change Response Strategy (GOK, 2010), the emission the average carbon intensity factor for Kenya's electricity generation in 2019 was estimated at 0.35 kg CO<sub>2</sub> per kWh (International Renewable Energy Agency, 2023).

This constant value (0.35 kg CO<sub>2</sub> per kWh) represented the emissions avoided per kWh of electricity generated by the solar home systems, considering it offsets electricity that could have otherwise been drawn from the grid. The decision to use the grid's carbon intensity as a baseline for comparison with SHS emissions was based on the following; while kerosene was a common fuel used for lighting in many off-grid areas, it was important to consider the broader energy landscape and the potential for grid expansion. By using the grid's carbon intensity as a baseline, we could assess the full environmental benefits of SHS, including the avoided emissions from grid expansion and associated infrastructure development.

With this data, the quantification of greenhouse gas emissions avoided by these solar home systems was calculated by multiplying the estimated solar energy generation by the emission factor (0.35 kg CO<sub>2</sub> per kWh).

#### ***3.7.4 Data Presentation***

Data was presented visually in maps, tables, and graphs.

#### ***3.7.5 Ethical Considerations***

The investigator followed the rules of conduct when doing research. An official letter outlining the study's goal and aim was submitted by the researcher to obtain authorization to conduct it. Prior to obtaining data from Solar Panda company, the investigator obtained respondent agreement, ensuring that the data would be kept private and used solely for educational purposes.

## **CHAPTER FOUR: RESULTS AND DISCUSSION**

### **4.1 Introduction**

This chapter covered the analysis of results as acquired from the field, and their consequent discussions with evidence from past related studies. The analysis was done with the help of ArcGIS Pro, results from which are shown in both tabular and maps. For inferential analysis, ordinary least squares (OLS) which used linear regression equations for estimating coefficients of linear regression, was used to describe the link between solar home systems and the explanatory variables.

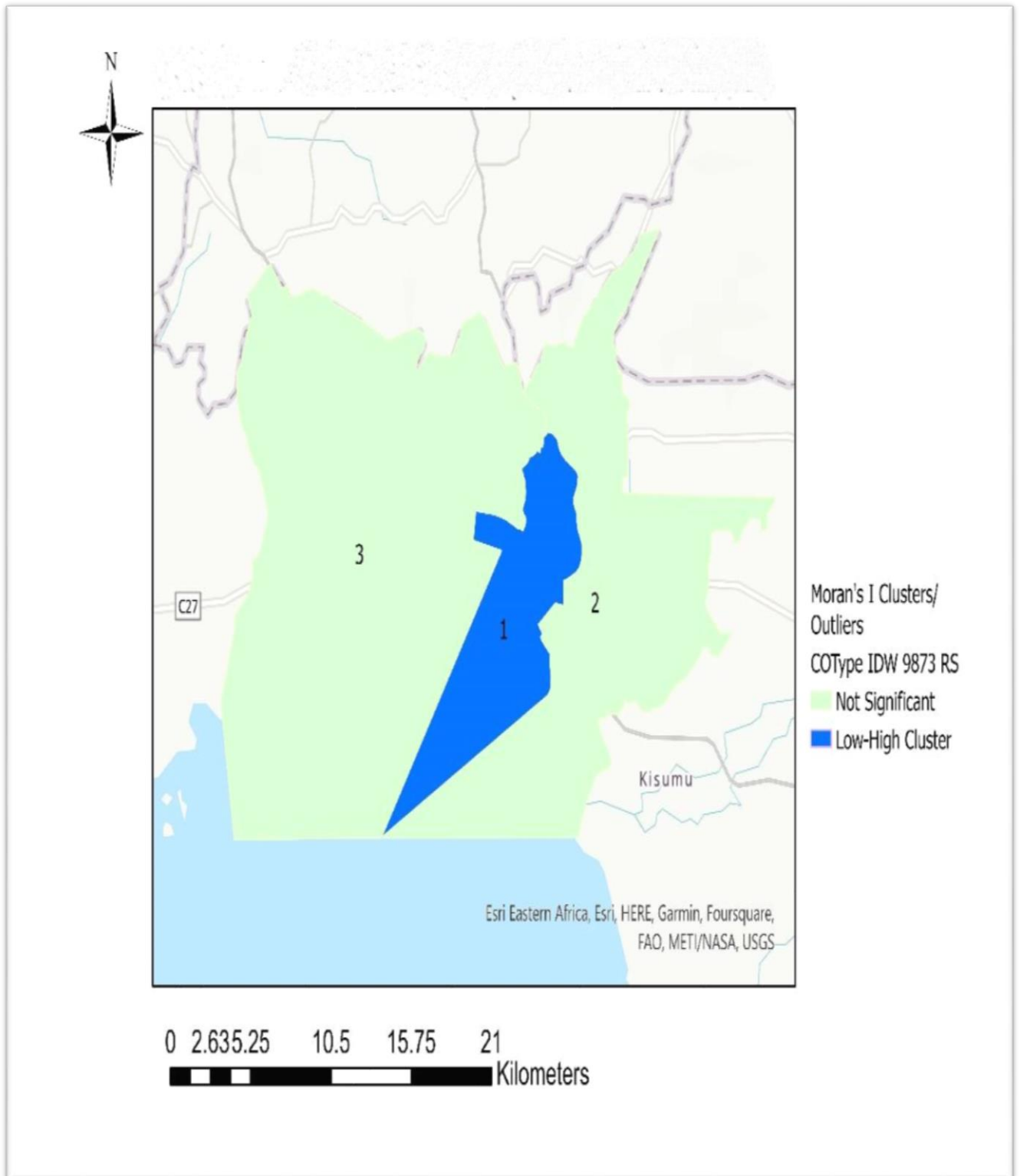
### **4.2 Spatial Clustering of Solar Home Systems**

The results from cluster and outlier and optimised hotspot analysis showed that the solar home systems had a clustering pattern. The results were consistent across cluster and outlier analysis and the optimised hotspot analysis, respectively.

The results are in the maps below.

#### ***4.2.1 Cluster and Outlier Analysis (COA)***

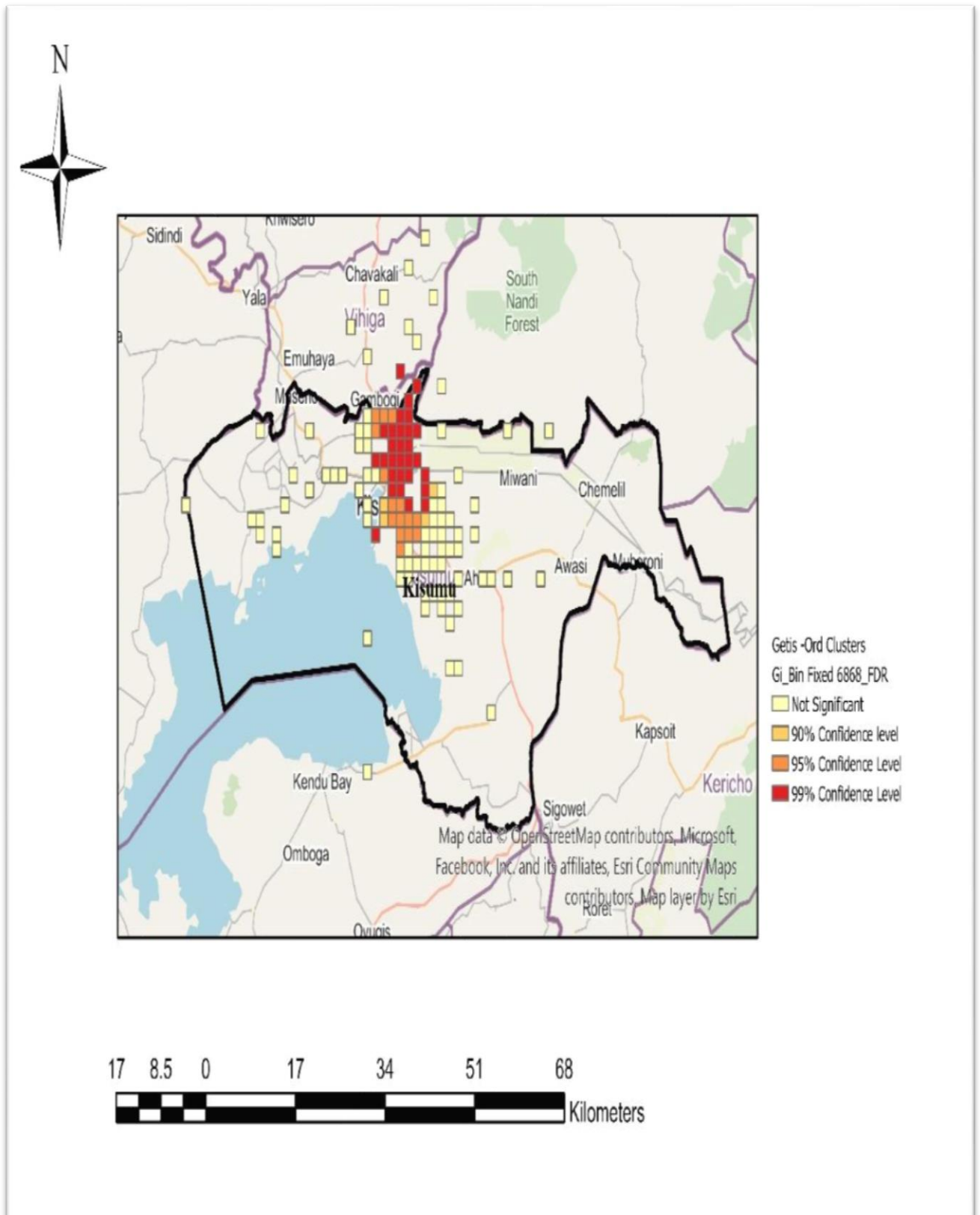
COA revealed a low -high cluster. This meant that the solar home systems revealed a pattern where a data point had a low value but was surrounded by points with high values.



**Figure 4.1: Cluster and Outlier Analysis Results.**

#### ***4.2.2 Optimised Hotspot Analysis (OGO)***

The optimised hotspot analysis as depicted in **Figure 4.1**, showed areas with statistically significant clusters of high and low values of solar home systems.



**Figure 4.2: Optimised Hotspot Analysis Results**

The optimised hotspot analysis as depicted in **Figure 4.2**, revealed significant spatial clusters of solar home systems.

In this analysis, we investigated the research question, why did spatial patterns and clusters of solar home system exist in Kisumu East Sub-County, by testing the following hypotheses:

Null hypothesis (Ho): There was no spatial clustering of SHS in Kisumu County.

Alternative Hypothesis (Ha): Solar home system diffusion rates exhibited spatial clustering, with areas having a high percentage of SHS diffusions compared to the overall county average.

To test these hypotheses, the getis-ord *Gi statistic* test was used (Ord & Getis,1995). This statistic enabled the identification of statistically significant spatial clusters of solar home systems, revealing hotspots and cold spots in the data.

The analysis resulted in a *Gi statistic* test of p-value = 0.911888. At a chosen significance level of  $\alpha=0.05$ .

Since the p-value= 0.91 was more than the chosen  $\alpha=0.05$ , the null hypothesis was not rejected. The alternative hypothesis (ha), suggesting that solar home system exhibited spatial clustering was accepted.

The clustered pattern of solar home system diffusion corroborated previous research findings by (Opiyo& Ogindo , 2018) in Kisumu, where he reported that 26% of Kisumu was electrified through the national grid alone, 38% through PV-based communal grids, and 26% through PV home systems.

These preliminary findings shed new light on SHS diffusion, revealing the complex interplay between population density, income, education, electricity access, and poverty.

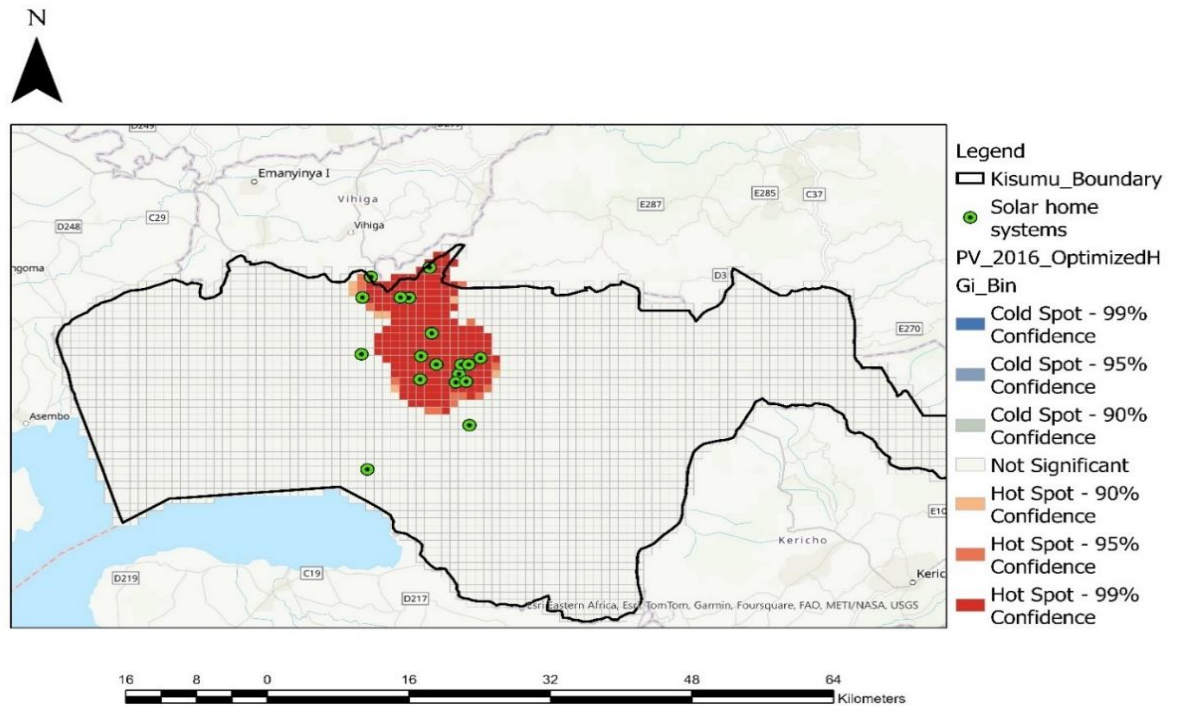
Previous research, such as (Sommerfeld et al., 2016), reinforced this perspective. They underscored the critical role of demographic and socioeconomic factors in driving solar PV technology adoption.

### **4.3 Spatiotemporal Analysis of SHS Diffusion for Period 2016 to 2021**

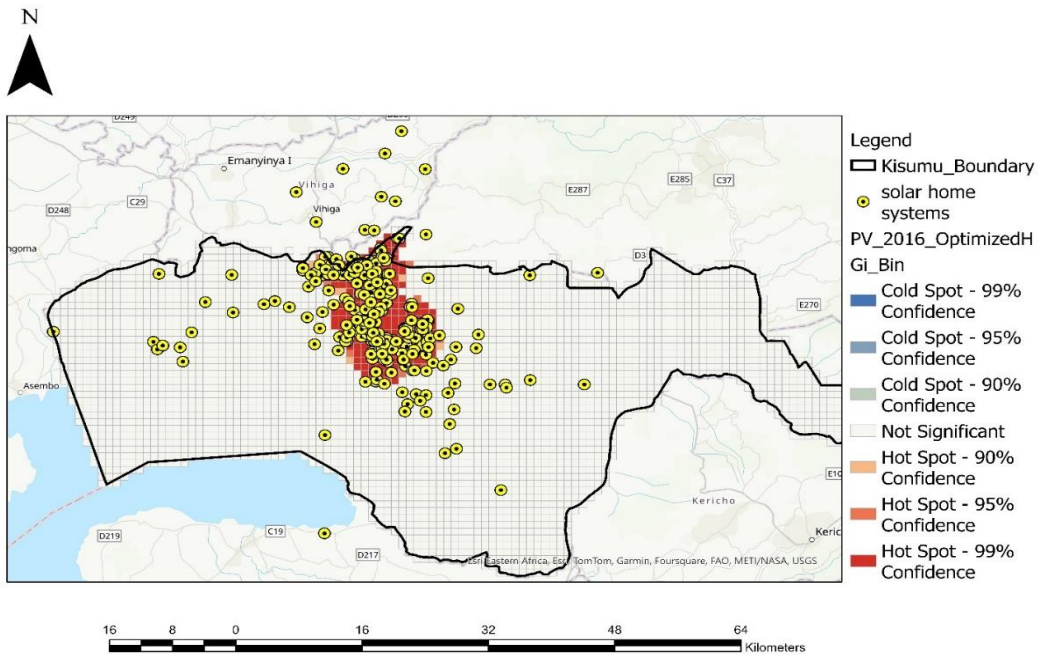
To analyse the underlying factors that contributed to the spatial clusters and patterns over time, it was crucial to first visualize the diffusion trend of SHS for the period 2016 to 2021, in Kisumu. To do this, a space time cube tool was used.

The space-time cube consolidated 463 points into 13,430 fishnet grid positions across 72 time-step intervals. Each grid location measured 1 kilometre by 1 kilometre square. The entire spatial-temporal cube covered an expanse of 85 kilometres from west to east

and 158 kilometres from north to south. The time step intervals each spanned 1 month, resulting in a total time of 72 months for the entire space-time cube. The space time cube results were presented Figures (4.3) and (4.4).



**Figure 4.3: SHS Diffusion Patterns in 2016**



**Figure 4.4: SHS Diffusion Patterns in 2021**

The findings indicated a spatial diffusion pattern characterized by a wave-like propagation from a primary diffusion center, as visualized in Figures (4.3) and (4.4), before subsequently spreading to other areas.

These results aligned with traditional diffusion models, indicating a wave-like pattern of technology adoption, commencing from more extensive population centres, as proposed by Hägerstrand (1952) a well-established concept in geography and innovation studies.

The "wave-like pattern" referred to the spatial diffusion of innovation, where the adoption of a new technology, such as solar home systems (SHS), spread outward from an initial point of origin. As revealed in Figures (4.3) and (4.4), the diffusion seemed to emanate from the central parts of the study area, before spreading to the outer areas. This pattern was characterized by a gradual increase in adoption rates over time, as the technology diffused from early adopters to later adopters (Sovacool, 2014).

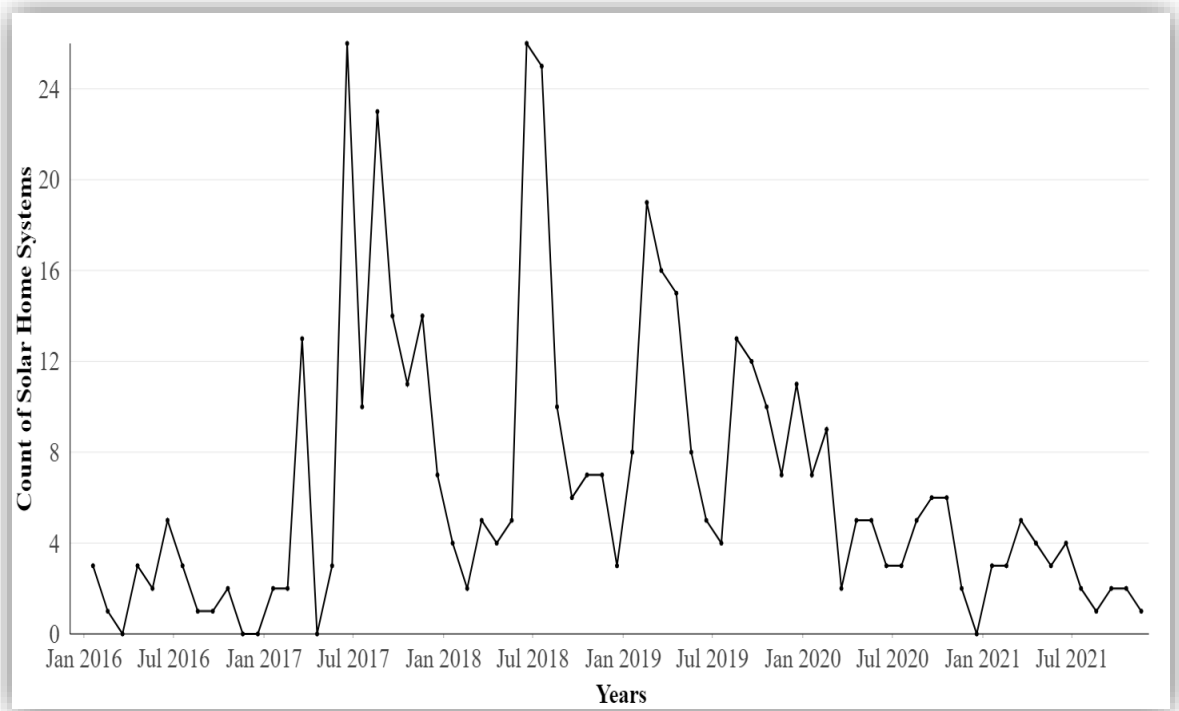
Similarly, the results aligned with research by (Riss et al., 2023), which similarly observed matches in the evolution of social actions across various domains, pinpointing a consistent wave-like pattern in their development. The study highlighted that any multiagent social action fundamentally involved the adoption of innovation. Due to the wave-like nature of this process, social actions in turn unfolded in a wave-like way.

This finding was further confirmed by (Sommerfeld et al., 2017) where he confirmed the influence of socio-economic explanatory variables of photovoltaic solar energy adoption.

#### ***4.3.1 Diminishing Effect Over Time***

Building on the spatial clustering identified above, we further investigated the temporal trend of SHS diffusion, from the wave-like pattern. To understand this pattern more comprehensively, we analysed whether the overall trend in SHS diffusion across the county showed a substantial increase in counts, for the period 2016 to 2021.

The results were presented in the graph below.



**Figure 4.5: SHS Diffusion Revealed a Decreasing Spatial trend from 2016 to 2021.**

The analysis in Figure 4.5 revealed an interesting trend in SHS diffusion patterns. Although there was not a statistically significant overall increase or decrease throughout the study period (2016-2021), the data suggested an initial rise in adoption followed by a slowdown. This was evident in the diffusion counts dropping towards the later stages (July 2021).

#### 4.4 Analysing Socioeconomic Factors and SHS Diffusion with OLS Regression.

**Table 4.1: OLS Analysis of Population Density, And Income**

<b>Variable</b>	<b>Coefficient (a)</b>	<b>Std Error</b>	<b>t-Statistic</b>	<b>Probability [b]</b>	<b>Robust_ SE</b>	<b>Robust PR [b]</b>	<b>VIF [c]</b>
Intercept	-257.9	157.9	-1.633	0.196	146.3	-1.763	0.171
Pop Density	<b>-0.116</b>	0.167	-0.698	0.531	0.149	-0.781	1.048
Income	45.36	13.38	3.388	<b>0.037*</b>	12.95	3.504	<b>0.032*</b>

Given the lack of statistically significant change in SHS counts over time, explanatory variables like population density, income levels, education level, and electricity access were tested to comprehend the relationships between solar home system diffusion patterns and the identified socioeconomic factors.

**Table 4.1: OLS analysis of population density, and income**

Source: Survey Data (2023)

\*Indicates a significant result from the model .

We investigated the research question, on what underlying socioeconomic factors were driving the spatial clusters and patterns, by testing the following hypotheses:

Null hypothesis (Ho): There was no significant association between socioeconomic factors income, education, and population density with the spatial distribution of solar home system.

Alternative hypothesis (Ha): There was a significant association between socioeconomic factors income, education, and population density with the spatial distribution of solar home system.

To test the hypotheses, linear regression analysis was used. T-test statistical test was used to assess the significance of individual explanatory variables, determining their impact on the dependent variable (solar home systems).

The analysis as shown in **Table 4.1** revealed the following results.

Population Density with a coefficient (-0.116) was negative but statistically insignificant (p-value = 0.531). This suggested that, on average, population density was not linked to a statistically significant change in SHS diffusion.

The low t-statistic (-0.698) and high p-value further indicated that the relationship between population density and SHS diffusion was weak and statistically uncertain in this model.

Income with a coefficient (45.36) was positive and statistically significant (p-value = 0.037). This indicated a positive relationship between income and SHS diffusion. On average, a one-unit increase in income (referring to higher income levels) was associated with a 45.36 unit increase in SHS diffusion.

The relatively high t-statistic (3.388) and statistically significant (p-value = 0.037), supported the conclusion that this relationship was not due to chance.

Therefore, null hypothesis was not rejected, and the alternative hypothesis ( $H_a$ ) was accepted. This meant that there was significant association between socioeconomic factors income, and population density with the spatial distribution of solar home system.

The negative correlation between SHS diffusion and population density was consistent with the findings of (Graziano et al., 2015) where he discovered that diffusions decreased with population density. He further argued that the diffusion of new technologies was not solely determined by population density. Small and medium-sized population centers were equally important for the diffusion of PV systems.

Income had a statistically significant positive correlation. This outcome was consistent with a study by (Adenle ,2020) where he found out that diminished income levels dissuaded households from contemplating the adoption of solar energy technology.

This finding was also consistent with the research by (Wassie et al., 2020) and (Bai et al., 2020) where the researchers found out that individuals with higher socioeconomic status were more likely to adopt SHS technology at an earlier stage

**Table 4.2: OLS Analysis of Education and Electricity**

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_P [b]	VIF [c]
Intercept	-85.26	33.21	-2.567	0.082	34.54	-2.468	0.089	
Education	<b>0.111</b>	0.305	0.364	0.735	0.221	0.499	0.646	1.300
Electricity	<b>0.013</b>	0.007	16.79	<b>0.000*</b>	0.004	26.95	<b>0.000*</b>	1.067

Source: Survey Data (2023)

\*Indicates a significant result from the model.

The model results in Table 4.2 showed that education, with a coefficient (0.111) was positive and statistically significant (p-value = 0.735). This suggested that, on average, an increase in education levels was associated with a statistically significant increase in SHS diffusion.

The high standard error (0.305) and low t-statistic (0.364) further indicated that the relationship between education and SHS diffusion was weak and statistically uncertain in this model.

Electricity, with a coefficient (0.013) was positive and statistically significant (p-value = 0.000\*). This indicated a positive relationship between electricity rates and SHS diffusion. On average, a one-unit increase in electricity rates (reflecting higher costs) was associated with a 0.013(Coefficient) unit increase in SHS diffusion.

The high t-statistic (16.79) and very low (p-value = 0.000), strongly supported the statistical significance of this relationship.

Therefore, the null hypothesis was not rejected, and the alternative hypothesis (Ha) was accepted. This meant that there was significant relationship among socioeconomic factors education, and electricity rate with the spatial distribution of solar home system.

While showing a positive trend, neither education nor population density significantly impacted the distribution of SHS diffusion. Furthermore, the two made the least contribution to the overall model. Income and electrification rates emerged as the strongest drivers of SHS diffusion.

The positive relationship between SHS diffusion and education was attributed to increased awareness of renewable energy benefits. A study by (Moorthy et al., 2019) recounted that if gains were known to the villagers, then the education had the ability to accelerate the diffusion of off-grid solar energy.

A study by (Arif ,2013) reported that typically, communities with a greater environmental consciousness, demonstrated heightened concerns about climate change, were more inclined to adopt solar power compared to the average community.

The positive relationship between electricity access and SHS diffusion aligned with previous research by (McEachern et al., 2008) where a string of unfulfilled grid promises led to decreased trust in politicians' promises and increased interest in SHS. Furthermore, a study by (Walters et al., 2018), reported that the rapidly increasing retail electricity rates further accelerated the demand for residential solar PV.

This discovery was also consistent with a study by (Mugisha et al., 2021) in Ethiopia where he reported that the primary problem in the sustainable development of off-grid PV technology was the inability of energy users to make payments. He additionally emphasized that addressing such challenges could be imperative to progress toward achieving universal power access.

#### **4.5 Robustness Checks of OLS Model Results**

The table 4.1 included the robust standard errors, t-statistics, and p-values used for robustness checks. Here, both regular and robust p-values for income were significant, suggesting the results were reliable.

VIF (Variance Inflation Factor): The VIF values (**1.048** for population density and **1.039** for income) indicated no significant multicollinearity between the independent variables, which was acceptable for the OLS regression results.

Similar to table 4.1, Table 4.2 also included robust standard errors (Robust\_SE), robust t-statistics (Robust\_t), and robust p-values (Robust\_Pr). These were helpful for checking the reliability of the results in case of potential issues like heteroscedasticity (unequal variance of errors). Since the regular and robust p-values for electricity rates were both highly significant (**0.000**), it suggested the results were reliable.

VIF (Variance Inflation Factor): The VIF (**1.067** for electricity rates and **1.300** for education, although not statistically concerning in this case) indicated no significant multicollinearity between the independent variables, which was a good condition for OLS regression.

#### **4.6 The Potential Impact of SHS on Carbon Emissions**

To calculate the carbon emissions avoided by utilizing a 20-Watt solar panel instead of other electricity generation sources, including hydroelectric power, the following steps were employed:

i)Determined the emission factor for all other sources of electricity.

$$=0.35\text{kg CO}_2 \text{ per kWh}$$

ii)Determined the energy output for a 20-Watt panel

$$=0.02 \text{ kilowatt hours of energy per day}$$

iii)Calculated the emissions avoided for a single panel installed

$$=0.02\text{kwh} * 0.35\text{kg CO}_2^\circ = 0.007\text{kg CO}_2^\circ/\text{day}$$

iv)Calculated emissions avoided in 1 year per Panel/per household

$$0.007\text{kg CO}_2 * 365 \text{ days} = 2.555\text{kg CO}_2$$

v)Calculated emissions avoided for the period (2016-2021)

$$2.555\text{kgCO}_2 * 384 \text{ panels} * 5 \text{ yrs} = 5875 \text{ kg CO}_2^\circ .$$

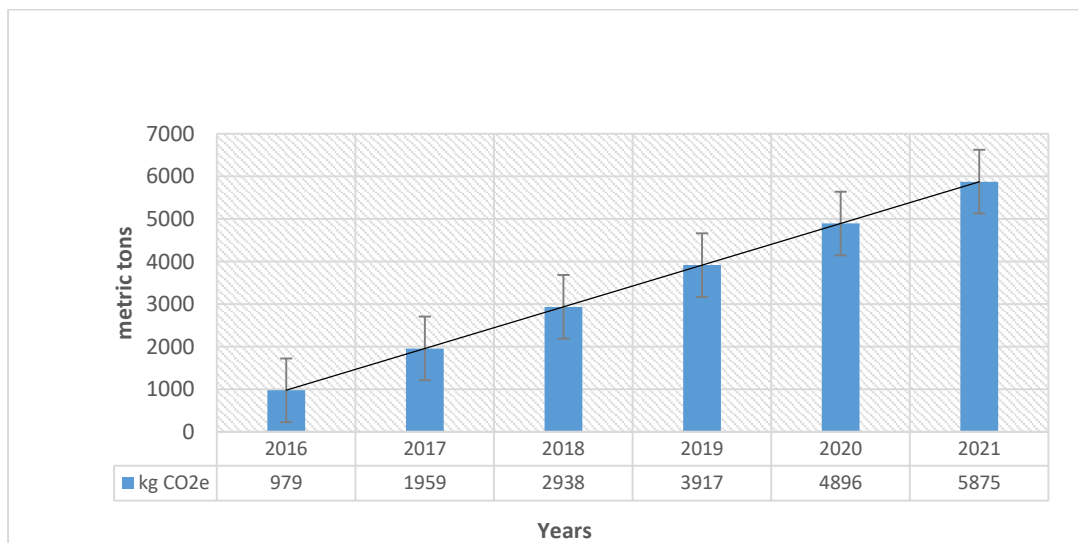
vi)Calculated total emissions avoided for households with solar home system

$$5875 \text{ kg CO}_2^\circ$$

$$1\text{kg CO}_2^\circ = 0.001 \text{ metric tonne}$$

Therefore,

$$5875 \text{ kg CO}_2^\circ = 5.875 \text{ metric tons CO}_2 \text{ emissions}$$



**Figure 4.6: Total Emissions Avoided for The Period 2016-2021**

In this analysis, we investigated the research question how much carbon emissions (CO<sub>2</sub><sup>°</sup>) had been avoided using solar home system in Kisumu East Subcounty, by testing the following hypotheses:

Null hypothesis (H<sub>0</sub>): The use of SHS in Kisumu East Subcounty did not lead to a significant reduction in carbon emissions (CO<sub>2</sub><sup>°</sup>) compared to traditional energy sources.

Alternative Hypothesis (Ha): The use of SHS in Kisumu East Subcounty led to a significant reduction in carbon emissions ( $\text{CO}_2^\text{e}$ ) compared to traditional energy sources.

To test these hypotheses, an emission factor calculation was used (International Renewable Energy Agency, 2023). This was because the use of solar home systems translated into a corresponding amount of carbon dioxide equivalent emissions ( $\text{CO}_2^\text{e}$ ). Multiplication was used to estimate emissions, based on the solar home systems data and the emission factor (0.35 kg  $\text{CO}_2$  per kWh).

384 households in Kisumu East had solar home systems (SHS) for the period 2016-2021. These installations resulted in an estimated avoidance of 5.875 metric tons of  $\text{CO}_2$  emissions during the study period as visualized in Figure 4.6.

Consequently, the null hypothesis was not rejected, and the alternative hypothesis (Ha) was accepted. This meant that the use of SHS in Kisumu led to a considerable decrease in carbon emissions ( $\text{CO}_2^\text{e}$ ) compared to conventional energy sources.

A study by (Shahsavari et al., 2018) reinforced the findings, by affirming that solar energy served as an appealing option for mitigating climate change and fostering low-carbon development. He concluded by underscoring that renewable energy technologies, particularly solar energy, could have the potential to yield lasting economic and environmental gains.

The adoption of renewable energy sources was therefore crucial for sustainable development and could be pursued through all available avenues. This extends not only to the present generation but also to the well-being of future generations.

## CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

### 5.1 Introduction

The aim of this research was to identify the main factors affecting the diffusion of solar PV systems over time and space, as well as to quantify the amount of carbon emissions that have been mitigated due to the diffusion of SHS ,for the period 2016-2021. Geospatial analysis and regression analysis, detailed data on SHS PV systems in Kisumu, along with socioeconomic and demographic information, was employed to elucidate the principal drivers.

### 5.2 Summary of Key Findings

On the first objective, the study sought to evaluate the spatial diffusion patterns of solar home systems in Kisumu County, and the impact they had in mitigating climate change effects caused by greenhouse gases. The analysis revealed a clustered pattern, with areas of high and low SHS diffusion existing in proximity. This suggested a non-random distribution.

Overall, SHS diffusion rates did not show statistically significant increase or decrease throughout the study period. However, there appeared to be an initial rise followed by a slowdown in later years (July 2021). This trend suggested potential saturation in some areas or a need for renewed efforts to promote SHS diffusion.

On the second objective, the study investigated the influence of various socioeconomic factors on SHS diffusion. Income and electricity rates emerged as the most significant drivers. Higher income levels were associated with a statistically significant increase in SHS diffusion (coefficient = 45.36), indicating affordability as a key factor. Higher electricity rates were also linked to increased SHS diffusion (coefficient = 0.013), suggesting that high electricity costs might have incentivized residents to seek alternative energy sources. Education level (coefficient=0.111 and population density (coefficient= -0.116) had minimal influence on the spatial distribution of SHS in this study .

On the third and final objective, the study found out that SHS had an immense effect in mitigating climate change (5.875 metric tons). Strategic deployment and incentivization of communities were potentially strong drivers of not only SHS diffusion, but also important contributors to the overall SDG goal on climate action.

### **5.3 Conclusions**

Drawing upon the findings of that study, the research concluded that socioeconomic factors were pivotal determinants influencing the diffusion patterns of Solar Home Systems (SHS).

Specifically, income emerged as a highly significant factor, demonstrating a robust positive correlation with increased SHS diffusion. This observation underscored the critical role of enhanced financial capacity in facilitating the initial investment required for SHS technology adoption within communities.

Furthermore, electrification rates were found to have exerted a substantial influence on SHS diffusion. The analysis indicated that regions experiencing higher electricity rates were concurrently associated with greater SHS diffusion. This suggested a compelling incentive for communities to actively seek alternative energy solutions, positioning SHS as a viable and attractive option in such contexts.

Conversely, that research established that population density and education level, while generally considered influential in technology adoption, did not emerge as primary drivers of SHS diffusion in that specific context. Therefore, while these factors may have contributed to the broader landscape of energy access, they were not the sole or predominant determinants governing the widespread dissemination of SHS.

Ultimately, that study affirmed that the provision of innovative technologies such as Solar Home Systems held immense potential for contributing to global environmental objectives, specifically in reducing greenhouse gas emissions and significantly enhancing energy efficiency. The findings strongly suggested that SHS represented an affordable, highly scalable, and increasingly accessible solution, empowering communities and countries to transition towards cleaner, more resilient economies.

### **5.4 Recommendations**

Following the result that solar home system seemed to exhibit a clustering pattern, it is recommended to develop targeted outreach and subsidy programs specifically focused on these areas. This strategic approach can bridge the gap in SHS adoption and accelerate the overall diffusion of solar home systems within Kisumu County.

Building on the study's findings that income levels and electricity rates influenced SHS diffusion, it is recommended to foster partnerships with microfinance institutions

(MFIs), the local government, and local businesses. These partnerships could focus on developing innovative financing options for SHS acquisition. This collaborative approach can address the financial barriers for potential adopters, particularly low-income households, and ultimately accelerate the diffusion of SHS technology within Kisumu County. These findings highlighted the importance of considering socioeconomic factors, particularly income levels and electricity costs, when designing policies and interventions to promote SHS diffusion.

Third, to ensure the continued success of solar home systems (SHS) in reducing emissions and increasing diffusion rates, it is recommended to implement a program for ongoing monitoring and evaluation of their impact. This will allow for adjustments to be made to the intervention strategies if necessary, maximizing their effectiveness in achieving the desired environmental and accessibility goals.

### **5.5 Further Research**

The study relied on existing data for socioeconomic variables. This did not capture the full picture of factors influencing adoption, such as social norms, risk perception, or cultural preferences. Surveys or focus groups to gather in-depth qualitative data on the social and cultural factors influencing SHS adoption decisions in different communities could be conducted in future to explore this.

The analysis focused on overall SHS numbers, not accounting for potential variations in usage patterns. Further research on how SHS usage patterns (e.g., lighting hours) vary across socioeconomic groups and how this translates to actual GHG emission reduction could be done to account for usage patterns.

The study focused on Kisumu County. The findings might not be generalizable to other regions with different socio-economic contexts or energy infrastructure. Comparative studies in other regions with varying economic development and pre-existing electricity access to assess the generalizability of the findings could be conducted to ensure regions with different socio-economic contexts are accounted for.

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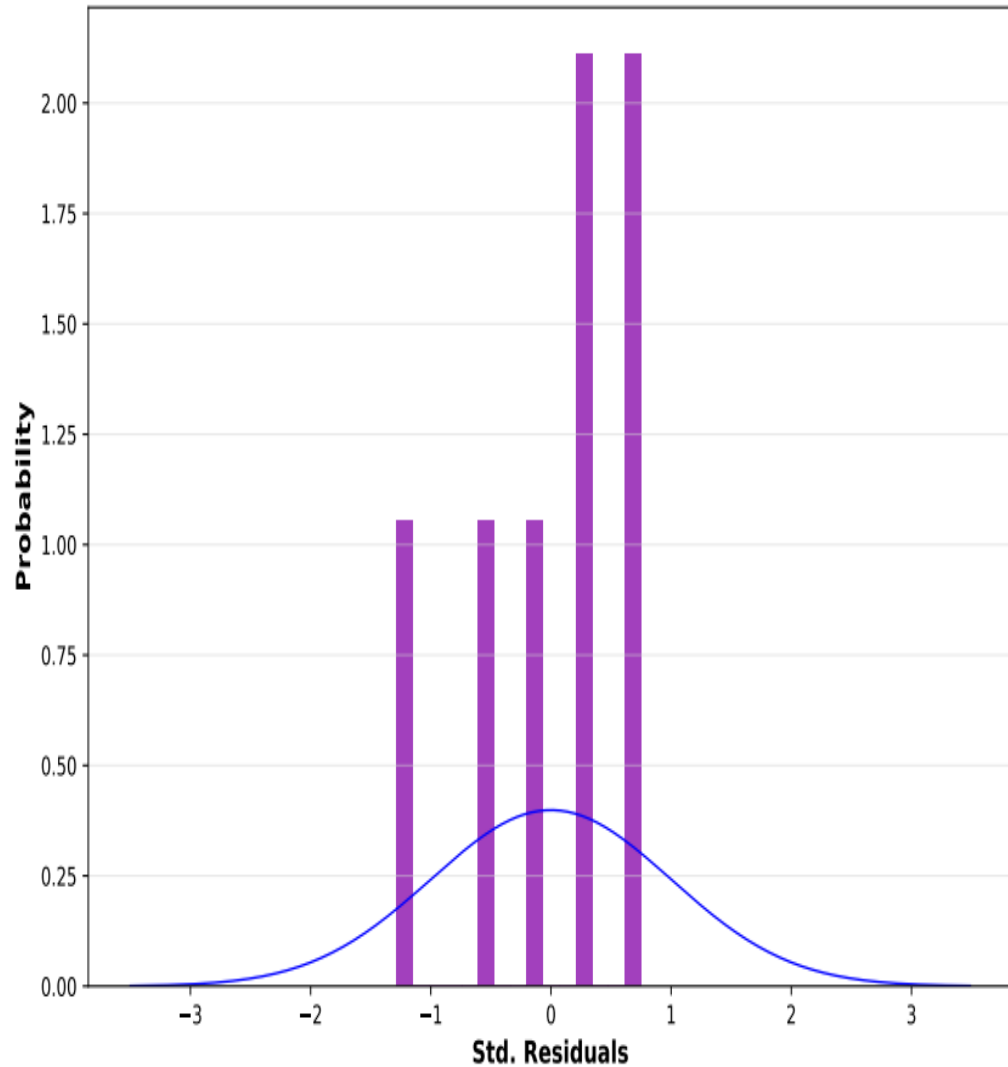
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## APPENDICES

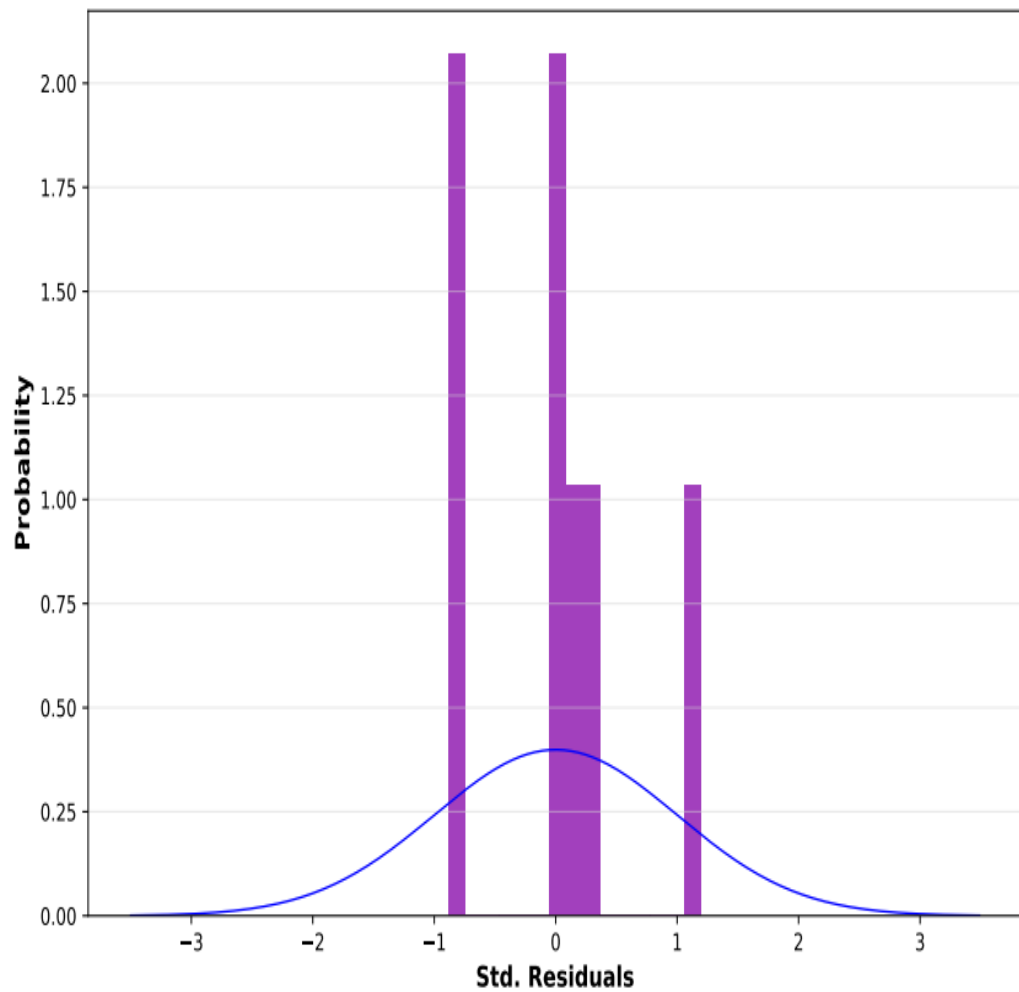
### Appendix I: OLS Results

#### Histogram of Standardized Residuals



Ideally the histogram of your residuals would match the normal curve, indicated above in blue. If the histogram looks very different from the normal curve, you may have a biased model. If this bias is significant it will also be represented by a statistically significant Jarque-Bera p-value (\*).

### Histogram of Standardized Residuals



Ideally the histogram of your residuals would match the normal curve, indicated above in blue. If the histogram looks very different from the normal curve, you may have a biased model. If this bias is significant it will also be represented by a statistically significant Jarque-Bera p-value (\*).

The residuals (over/under predictions) from a correctly specified model were expected to exhibit a random noise pattern, with no clustering of over/under predictions. Additionally, the residuals were supposed to display a normal distribution when plotted on a histogram.

## Appendix II: Distribution of Rresiduals

Input Features:	Point_AggregatePoints	Dependent Variable:	COUNT
Number of Observations:	5	Akaike's information Criterion (AICc) [d]:	148.369684
Multiple R-Squared (d):	0.803310	Adjusted R-Squared [d]:	0.606620
Joint F-Statistic [e]:	4.084148	Prob(>F), (3,3) degrees of freedom	0.196690
Joint Wald Statistic (e):	12.980363	Prob(>chi-squared), (3) degrees of freedom	0.004679*
Koenker (BP) Statistic [f]:	3.062212	Prob(>chi-squared). (3) degrees of freedom	0.382132
<b>Jarque-Bera Statistic (g):</b>	0.776890	Prob(>chi-squared). (2) degrees of freedom	<b>0.678111</b>
Number of Observations :	5	Akaike's Information Criterion (AICC) [d]:	127.428172
Multiple R-Squared [d]:	0.990125	Adjusted R-Squared [d]:	0.980250
Joint F-Statistic [e]:	100.268161	Prob(>F), (3,3) degrees of freedom:	0.009875*
joint Wald Statistic (e):	8906.967766	Prob(>chi-squared), (3) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	4.693493	Prob(>chi-squared), (3) degrees of freedom:	0.195667
Jarque-Bera Statistic [g]:	0.186881	Prob(>chi-squared), (2) degrees of freedom:	<b>0.910792</b>

To assess the normality of the residuals from a regression model, the **Jarque-Bera test** was employed. A statistically non-significant result ( $p > 0.05$ ) indicated that the residuals followed a normal distribution. In our analysis, both Jarque-Bera tests yielded p-values of ( $p \leq 0.67$ ) and ( $p \leq 0.91$ ), and both were non-significant. This suggests that the model was not biased

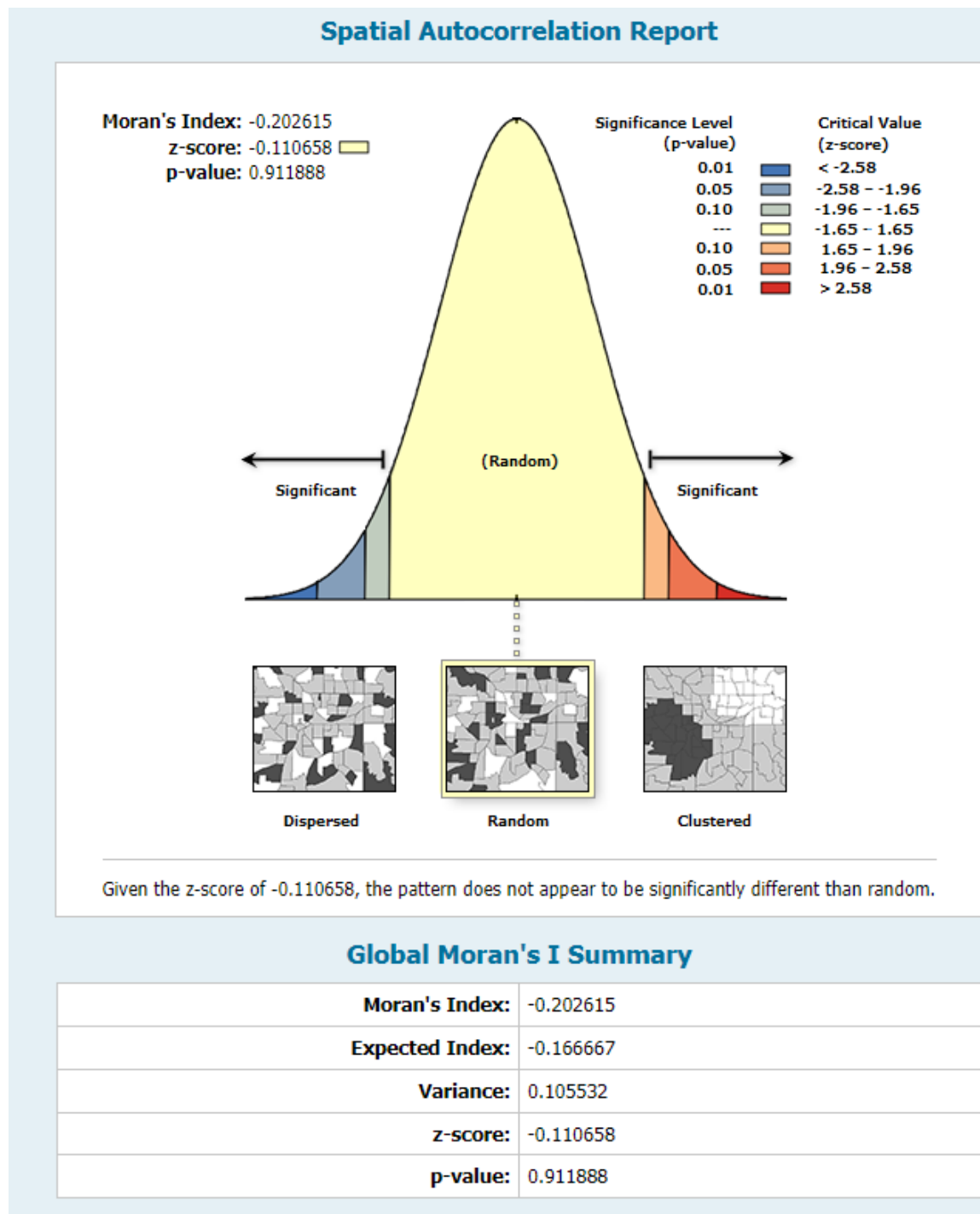
### Appendix III: Model Performance

Input Features:	Point_AggregatePoints_S	Dependent Variable:	COUNT
Number of Observations:	7	Akaike's information Criterion (AICc) [d]:	148.369684
<b>Multiple R-Squared (d):</b>	0.803310	Adjusted R-Squared [d]:	<b>0.606620</b>
Joint F-Statistic [e]:	4.084148	Prob(>F), (3,3) degrees of freedom	0.196690
Joint Wald Statistic (e):	12.980363	Prob(>chi-squared), (3) degrees of freedom	0.004679*
Koenker (BP) Statistic [f]:	3.062212	Prob(>chi-squared). (3) degrees of freedom	0.382132
Jarque-Bera Statistic (g):	0.776890	Prob(>chi-squared). (2) degrees of freedom	0.678111
Number of Observations:	5	Akaike's Information Criterion (AICC) [d]:	<b>127.428172</b>
Multiple R-Squared [d]:	0.990125	Adjusted R-Squared [d]:	<b>0.980250</b>
Joint F-Statistic [e]:	100.268161	Prob(>F), (3,3) degrees of freedom:	0.009875*
joint Wald Statistic (e):	8906.967766	Prob(>chi-squared), (3) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	4.693493	Prob(>chi-squared), (3) degrees of freedom:	0.195667
Jarque-Bera Statistic [g]:	0.186881	Prob(>chi-squared), (2) degrees of freedom:	0.910792

The table displays the corrected **R-squared values for the model**. Both models achieved corrected R-squared values of **0.6 and 0.9, both exceeding 0.5**. This indicated that a substantial portion of the variation in the dependent variable was accounted for by the model.

Furthermore, the AIC value was utilized as a metric to assess model performance. Notably, in this comparison, both candidate models shared the same dependent variable. The second model, with the lowest AIC value of 127.4, emerged as the superior choice in our analysis.

## Appendix IV: Spatial Autocorrelation Report



## Appendix V Research Authorization Graduate School



KENYATTA UNIVERSITY  
GRADUATE SCHOOL

E-mail: [dean-graduate@ku.ac.ke](mailto:dean-graduate@ku.ac.ke)

Website: [www.ku.ac.ke](http://www.ku.ac.ke)

P.O. Box 43844, 00100  
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Tel. 8710901 Ext. 57530

Our Ref: N50/CTY/PT/26322/2018

DATE: 22<sup>nd</sup> February, 2023

Director General,  
National Commission for Science, Technology  
and Innovation  
P.O. Box 30623-00100  
NAIROBI

Dear Sir/Madam,


RE: RESEARCH AUTHORIZATION FOR MWANGI JOYCE WAMBUI – REG. NO. N50/CTY/PT/26322/2018

I write to introduce Mwangi Joyce Wambui who is a Postgraduate Student of this University. The student is registered for M.Env. degree programme in the Department of Agriculture and Environmental Sciences.

Mwangi intends to conduct research for a M.Env. Project Proposal entitled, “Spatial Patterns of Solar Photovoltaic System Diffusion Kisumu County, Kenya.”

Any assistance given will be highly appreciated.

Yours faithfully,

  
PROF. ELISHIBA KIMANI  
EXECUTIVE DEAN, GRADUATE SCHOOL

JO/mo

## Appendix VI: Research License

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  - iv. Result in exploitation of intellectual property rights of communities in Kenya
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15. Relevant Institutional Scientific and Ethical Review Committee shall monitor and evaluate the research periodically, and make a report of its findings to the Commission for necessary action.

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