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Spatial Patterns of Solar Photovoltaic System Diffusion Kisumu County, Kenya

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Abstract

Purpose: This research aligns with Sustainable Development Goal 7, contributing to the progress outlined in the 2030 Agenda for Sustainable Development and the commitments of the Paris Climate Agreement. Specifically, this study focuses on the spatial analysis of solar photovoltaic (PV) systems, offering valuable insights for academic exploration and informing public policy decisions related to the widespread adoption of this increasingly vital renewable energy technology. The outcomes of this project transcend academic significance, extending to practical applications for energy practitioners, policymakers, academics, and future researchers. The meticulous tracking of solar PV system spatial patterns in Kisumu County yields data that not only benefits its residents but also serves as a valuable resource for the entire nation. This information will be instrumental for current energy practitioners, policymakers, academicians, and prospective researchers seeking to advance the collective knowledge in this field.

Methodology: The study adopted a Quasi-Experimental research design to explore various social phenomena, aiming to identify key facts. Utilizing statistical evidence, we conducted numerical comparisons and statistical inferences to validate or refute the research questions. Locational information on households utilizing small home systems was extracted from a secondary Solar Database. This data underwent georeferencing, enhancing our comprehension of the actual geographical distribution of households and facilitating the achievement of our research objectives. In the process of data analysis, we employed inferential statistics, specifically regression analysis, conducted using ArcGIS PRO powered by ESRI. The utilization of ArcGIS Pro extended to the creation of an empirical model. This model was designed to probe into the factors influencing the observed spatial diffusion patterns, providing a robust analytical framework for our investigation.

Findings: In the initial objective, cluster and outlier analysis unveiled a distinct low-high cluster pattern for solar home systems (SHS). The optimized hotspot analysis consistently identified SHS hotspots and cold spots within the region, particularly aligning with urban areas, notably Kisumu. The second objective exposed factors influencing diffusion, revealing negative correlations with population density, household density, and poverty rate, indicating diminished adoption in densely populated and impoverished areas. Conversely, positive correlations with income, education, and electrification rates signaled heightened adoption in wealthier, educated communities. Despite consistent diffusion trends, an empirical model underscored the substantial impact of income and electricity on SHS diffusion. The third objective disclosed that between 2016-2021, SHS diffusion contributed to the mitigation of 268,581.6 metric tons of carbon emissions.

Unique Contribution to Theory, Practice and Policy: This research makes a distinctive contribution to theory by delving into the impact of solar home systems (SHS) in Kenya, particularly within the context of the country's commitment to reduce greenhouse gas (GHG) emissions. The theoretical foundation lies in addressing the existing gap in understanding the spatial distribution and diffusion patterns of SHS and their role in GHG reduction, aligning with Kenya's focus on renewable energy adoption.

Keywords: *Renewable Energy, Carbon Emissions, Small Home Systems (SHS), Technology Diffusion*

INTRODUCTION

The study of the spatial patterns of solar photovoltaic system diffusion represents a multifaceted exploration of the adoption and distribution of renewable energy technology within a unique geographic and socio-economic context. This research delves into the intricate web of factors influencing the differential uptake of solar PV systems across various regions of Kisumu County, encompassing considerations such as economic disparities, access to infrastructure, government policies, social networks, and cultural dynamics. By examining these spatial patterns, the study not only offers insights into the localized determinants of solar PV adoption but also provides a foundation for designing targeted interventions to promote sustainable energy practices, reduce energy inequalities, and contribute to the broader goal of renewable energy transition in Kenya and beyond.

The heightened attention to significant greenhouse gas emissions resulting from human activities has prompted widespread concern. This phenomenon has led to various environmental impacts, including rising sea levels, elevated ocean temperatures, shifts in rainfall patterns, and the melting of glaciers. Carbon, contributing 80 percent to global warming emissions, is a key focus (IPCC, 2023)

The surge in carbon dioxide emissions over the past two centuries, driven by industrialization and increased electricity demand, accentuates the global challenge (IPCC, 2018). With energy demand projected to triple by 2050, the associated rise in carbon emissions necessitates urgent mitigation (World Economic Forum, 2023) Recent national policies aligned with the United Nations' Sustainable Development Goals (SDGs) underscore the importance of sustainable economic development and emphasize the role of the scientific community in synchronized global monitoring for climate change, renewable energy, food, health, and water.

The exploration of alternative energy sources, stemming from the late 1990s and escalating petroleum prices, underscores the critical importance of transitioning from fossil fuels to renewables (David, 2018). Sub-Saharan Africa faces a significant energy deficit, with 621 million people lacking electricity, representing 32% of the population (Hancock, 2014).In Kenya, the solar market began to flourish in the 1980s, driven by donor-funded large-scale home solar systems and government initiatives, particularly solar home systems (SHS) which comprised three-quarters of the estimated 8 to 10 MWp capacity in 2009.

Renewable energy, particularly solar power, plays a pivotal role in implementing the 2030 Agenda and the SDGs in Africa and Kenya. The widespread adoption of renewables hinges on comprehending diffusion patterns, considering environmental, social, technological, regulatory, and economic factors (IMF/OECD, 2021). This study investigates spatial patterns of photovoltaics (PV) to assess their role in mitigating climate change and advocates for a viable strategy of transitioning from fossil fuels to renewable energy sources.

The statement of the problem highlights the significant contribution of energy-related activities to climate change and health issues, with a need for transformative approaches. While progress has been made toward SDG7, addressing carbon lock-in requires a comprehensive understanding of emission drivers (Benjamin, 2020). This project aims to bridge this knowledge gap by employing geospatial tools to identify and explore spatial patterns of solar PV system adoption, analyze propagation patterns, and quantify greenhouse gases avoided through the widespread adoption of this renewable technology. The conceptual discussion emphasizes the intricate interplay between global environmental concerns, the energy landscape, and the imperative for sustainable solutions.

Problem Statement

Energy constitutes a primary contributor to climate change, responsible for approximately 60% of total greenhouse gas emissions. Additionally, it significantly impacts public health through air pollution resulting from fuel combustion (IPCC, 2018). While strides have been made in achieving Sustainable Development Goal 7 (SDG7) for affordable and clean energy, (Benjamin, 2020) highlights an impediment: an incomplete understanding of the transformations needed to address carbon lock-in. This project endeavours to bridge this gap by utilizing geospatial tools to identify and explore spatial patterns in the adoption of solar photovoltaic (PV) systems. The analysis encompasses examining spatial clusters, and propagation patterns over time and space, and quantifying the reduction in greenhouse gases attributable to the widespread adoption of this renewable energy technology.

LITERATURE REVIEW

Climate Change and Renewable Energy Protection

The evolving energy landscape is marked by various transformative forces, particularly in the context of the ongoing energy transition, emphasizing environmental considerations. Despite extensive research on renewable energy sources since the 1973 oil crisis (IEA, 2017).Recent findings indicate a significant gap in understanding how renewable energy contributes to climate protection efforts, despite substantial government investments (World Economic Forum, 2023)

Spatial Clusters and Distribution Patterns of Small Home Systems' Diffusion

The IEA defines renewable energy as crucial for sustainable development, holding vast potential with financial benefits tied to reduced greenhouse gas emissions (IPCC, 2023). Yet, little is explored scientifically and politically regarding the spatial distribution of renewable energy. Existing studies, such as (McEachern, 2008) emphasis on bridging community adopters and policymakers, and (Sommerfeld, 2016) Australian study on PV system diffusion influencing demographic variables, provide partial insights. However, a comprehensive understanding of spatial patterns and distribution in the adoption of small home systems remains underexplored.

Examination of the Spatial Patterns in the Diffusion of Small Home Systems

While technology diffusion is a dynamic process with distinctive spatial patterns, literature gaps exist in comprehensively understanding how novel technologies, specifically photovoltaic technology, diffuse over time. Existing viewpoints, like Ha¨gerstrand's traditional distribution models, and the neoclassical perspective on innovation and diffusion (Stafan, 2000), provide valuable insights but fall short of encompassing the socio-cultural and political dimensions that influence the spread of technology. Analyzing the diffusion models presented by Palm (2020) and Rogers (1983) reveals a fragmented understanding that requires further exploration and synthesis. Rogers (2004) emphasizes the importance of including the temporal dimension in diffusion studies, highlighting its strength in understanding innovation distribution and adoption rates all involve a dimension of time. These aspects of Roger's philosophy are outlined below.

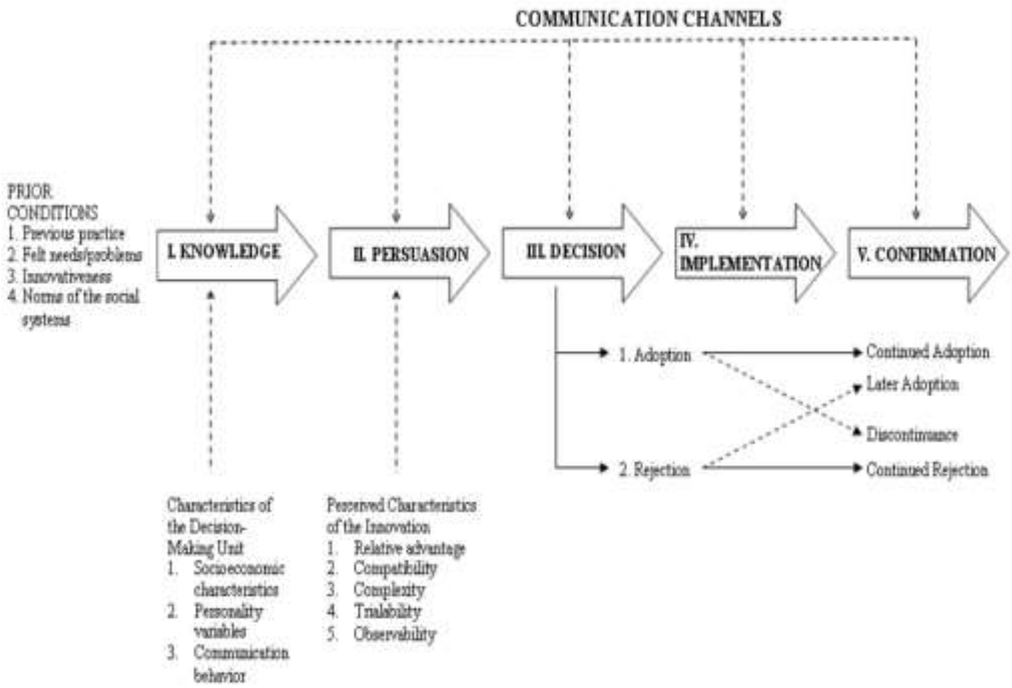

Figure 1: A Model of Five Stages in the Innovation-Decision Process (Rogers, 2004)

(Palm, 2020) Reports that the process of innovation diffusion involves individuals who adopt early and late, indicating that early adopters of photovoltaic technology are primarily motivated by environmental concerns and a love for technology, whereas later adopters are mainly motivated by economic benefits.

David (2018) further adds that the spread of any technology follows not only a socio-technical nature of access but also a socio-cultural and a political dimension, providing insights into the understanding of the diffusion of any technology.

It is therefore evident in the above literature presented, that analysing the diffusion of any technology over time and space is crucial since the two factors play a decisive role in the spread. It's on these theories that this project seeks to build.

Determine the Reduction in Greenhouse Gas Emissions Achieved Through the Utilization of Small Home Systems (SHS)

While human activity has led to a 1°C global warming, the potential to avoid an additional 0.5°C through significant greenhouse gas emission reductions necessitates comprehensive assessments (IPCC, 2023).Although various studies, including (WRI, 2014) and (Russel, 2019), emphasize avoided emissions and evaluate GHG impacts, there is an evident research gap in the precise calculation and evaluation of the reduction in greenhouse gas emissions achieved through the utilization of Small Home Systems (SHS).

The existing literature provides frameworks but lacks a unified, detailed approach to accurately quantify the impact of SHS deployment on emissions reduction. This gap underscores the need for a more thorough investigation into the life cycle assessment (LCA) and GHG emission factor calculations for photovoltaic modules, considering both the product's life cycle and utilization.

Knowledge Gaps

A notable drawback in the study conducted by (UN Environment , 2015) is the limited emphasis on quantifying the impact of low-carbon alternatives in addressing climate change, a gap that exists despite advancements in providing such alternatives. Previous studies, including those by (Graziano, 2015) (David, 2018), and (Adwek, 2019), have made strides in exploring low-carbon options, but few have delved into a quantitative assessment of their actual impact. The scarcity of supporting data for the methods proposed in this context, as highlighted by (van der Kam, 2018), contributes to the overall lack of comprehensive information regarding progress toward achieving the 1.5°C targets.

Consequently, there exists a knowledge gap concerning the potential of Small Home Systems as a means of climate change mitigation, emphasizing the critical need to examine the success of already installed systems to gain insights into their greenhouse gas emissions reduction capabilities.

METHODOLOGY

Study Design

Quasi-Experimental study design was used for this study since we were concerned about identifying the facts about the various social phenomena. We employed the use of statistical evidence so that numerical comparisons and statistical inferences could be made to confirm or deny the research questions.

Target Population

The participants in this study made up the population of total number of households in Kisumu East Sub-County which is 61,871. (KNBS, 2019) We were only concerned with the diffusion of the Small home System at the household level.

Sampling Procedure

This study adopted a cluster sampling procedure. This was chosen because the target population was indicative of homogenous characteristics i.e. all had small home systems. This method helped us decide the characteristics of the population.

Sample Size

Therefore, 384 households were the number of households sampled.

The number of households to be sampled (sample size) will be calculated Fishers et al (1998) formula since the number of households in the county is above 10,000.

Hence,

$n = Z^2pq/ d^2$

Where;

n = desired sample

Z = Standard normal deviate at the required confidence level 95% (Usually set at 1.96).

p = the prevalence of diarrhoea disease in under-fives which is unknown hence 0.5 used

q = 1-p (1-0.5=0.5)

d = the degree of accuracy (0.05)

$$= \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2}$$

$$= \frac{0.9604}{0.0025} = 384.16$$

Data Collection Methods

Locational data on households that were using small home systems was sourced from a secondary Solar Database. This data was georeferenced to help us understand the real-world location of the households, as well as enable us to meet our objectives.

Data Analysis

To Identify Spatial Clusters and Patterns of SHS

A geostatistical approach was used. This method was chosen because it was applicable to location-dependent data. Vital to this study, the chosen geostatistical method aimed to identify and quantify the spatial structure of relevant variables. Subsequently, it facilitated estimating variable values by considering their spatial structure in relation to neighboring values.

Two widely used spatial approaches were used: Optimized Getis-Ord Technique (OGO) and Asselins clustering and outlier analysis (COA). Using the two methods helped identify SHS clusters and map them in relation to other spatial factors; they guided the underlying factors influencing diffusion (Getis, 1995)

To Analyse Spatial Clusters of SHS

To analyze spatiotemporal patterns, a space-time cube was created through point aggregation using the fish netting method. This technique facilitated the examination of spatial clusters over time, integrating 2D and 3D visualization for comprehensive spatiotemporal data analysis. Since the data comprised time-stamped point features, spatial aggregation was vital for understanding patterns. The space-time cube by aggregating points tool was employed, employing fish netting to divide study areas into cells of 1km. Cells were highlighted based on adoption numbers, effectively visualizing diffusion patterns by disaggregating the process into smaller, yet meaningful, scales while capturing multiple adoptions in each cell.

Geospatial Modelling (Ordinary Least Squares Regression Test)

An empirical model was built to further model the influence of other explanatory variables on the diffusion of SHS. A geospatial model (OLS) was built. The ordinary least squares regression technique was chosen because it was the starting point for all spatial regression analyses and would help provide a global model of the variables that were in question. It worked by creating a single regression equation to represent the process.

Calculate the GHG avoided using SHS

According to (Power Africa Solar , 2023),an average 3kW solar system has the potential to meet the energy needs of an entire household. Due to the lack of data about the size of each individual solar system in Kisumu, it was assumed that all households had installed a 3kW system and that this system met the basic energy needs of the households.

According to the Kenya National Climate Change Response Strategy (GOK, 2010), the average carbon intensity of Kenya's electricity generation as of 2019 was 0.35kg CO_2 per kWh. This included all sources of electricity generation, including hydroelectric power.

Therefore, to calculate the carbon emissions avoided by using a 3kWh solar panel as opposed to other sources of electricity generation including hydroelectric the following steps were employed:

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

=0.35kg CO_2 per kWh

ii)Determined the energy output for a 3kW panel

=3 kilowatt hours of energy per day

iii)Calculated the emissions avoided for a single panel installed

=3kWh *0.35kg CO_2^e =1.05kg $CO_2{}^e$/day

iv)Calculated emissions avoided in 1 year per Panel.

1.05kg CO_2 *365 days =383.25kg CO_2

v)Calculated emissions avoided in 5 years (2016-2022)

383.25kgCO_2 *1825 days = 699,431.25 kg CO_2^e per household in 5 years.

vi) Calculated total emissions avoided for all households in the area of study

699,431.25*384=268,581,600kg CO_2^e

1kg $CO_2{}^e$ =0.001 metric tonne

Therefore,

268,581,600 CO_2^e =268581.6metric tons CO_2 emissions

Data Analysis

During data analysis, inferential statistics (regression analysis) was computed using ArcGIS Pro powered by ESRI.

An empirical model was designed using ArcGIS Pro to explore the factors that underlined the spatial diffusion patterns observed.

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Data Presentation

Data was presented in maps, tables, and graphs.

RESULTS AND DISCUSSIONS

To Identify Spatial Clusters and Patterns of SHS

For a clearer picture of the location of the PV clusters, two well-known spatial techniques were employed: The optimized Get is-Ord method and Anselin's cluster and outlier analysis.

Cluster and Outlier Analysis (COA)

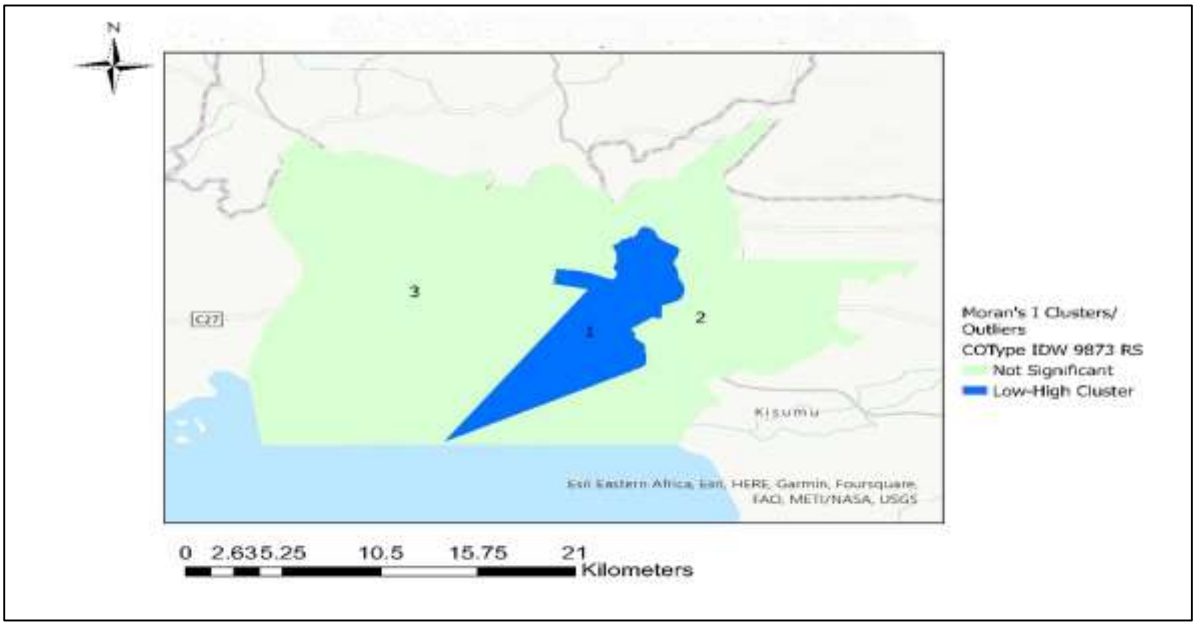

Figure 2: Shows the Cluster and Outlier Analysis Results

The results from the COA above showed that the SHS had a low-high spatial clustering.

Optimised Hotspot Analysis (OGO)

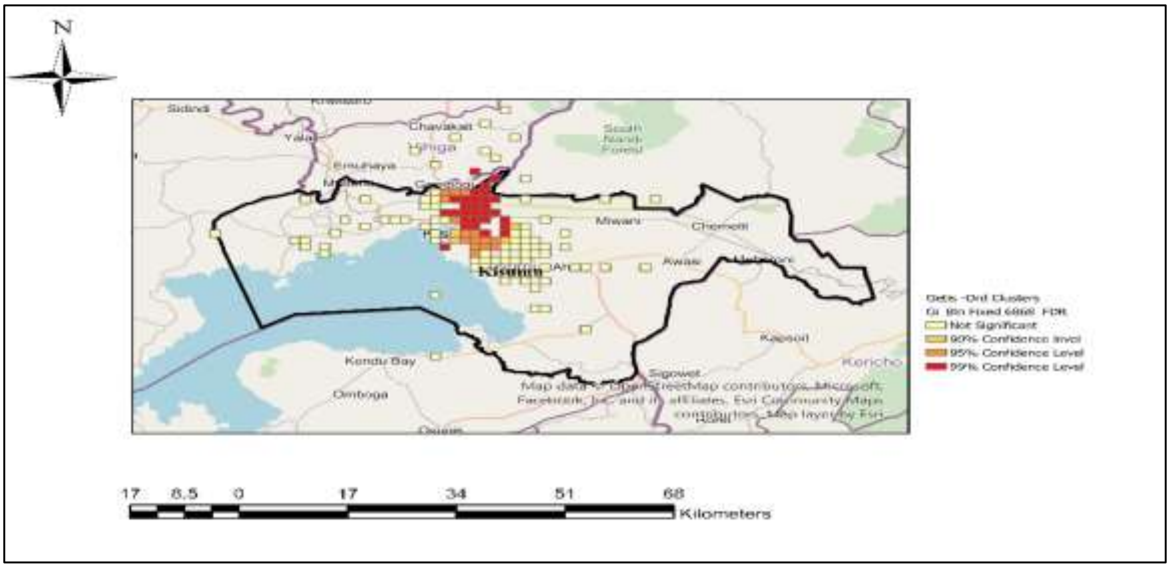

Figure 3: Optimised Hotspot Analysis Results

The optimised hotspot analysis showed that hotspots and cold spots of SHS systems were present in the region and corresponded to the urban areas.

The results were consistent across the two methodologies. The was clustering of SHS in Kisumu.

The finding that diffusion of small home systems (SHS) followed a clustering pattern were consistent with past research by (Graziano, 2015) in Connecticut, where hotspots and cold spots PV systems followed the same pattern and corresponded to the most densely populated urban areas of Connecticut.

These preliminary findings significantly expanded our understanding of the diffusion of Small Home Systems (SHS) and emphasized the intricate connections among population density, households, income, education, electricity, and poverty variables, influencing the pace of SHS adoption.

Previous investigations, as confirmed by (Sommerfeld, 2016), supported this perspective. They highlighted the influence of various variables, emphasizing that demographic factors played a crucial role in the adoption of solar PV technology in households

Analyse Spatial Clusters and Patterns of SHS, Over Time and Space

Temporal Analysis

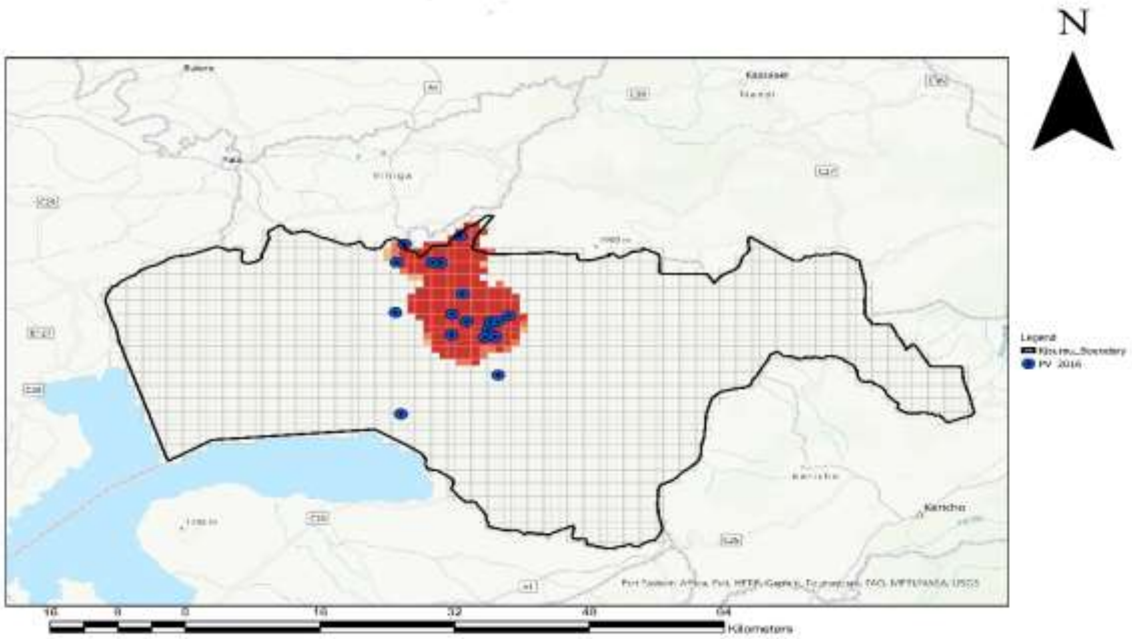

Figure 4: Spatial Distribution of SHS Diffusion as of 2016

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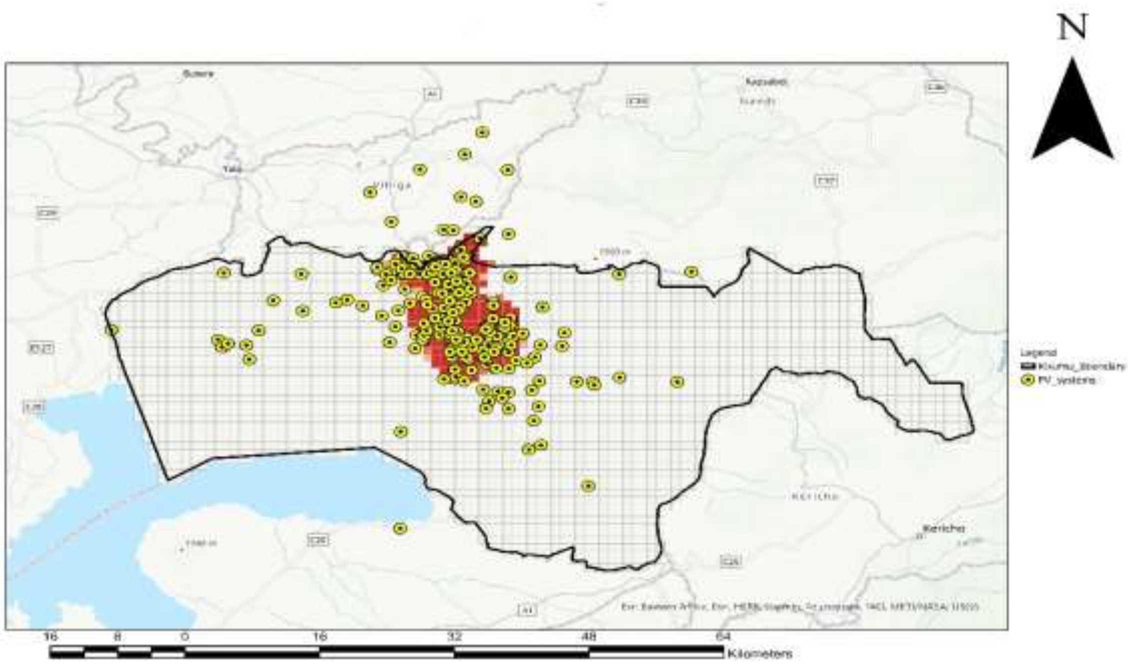

Figure 5: Spatial Distribution of SHS Diffusion as of 2021

The result was a fishnet (Mitchell, 2005) . The findings indicated that the diffusion exhibited a wave-like pattern originating from a larger population center, as illustrated in Figures (4) and (5) above, before subsequently spreading to other areas.

These findings were consistent with the classic diffusion models that suggested that new technologies were adopted in a wave-like pattern starting from larger population centres (Ha¨gerstrand, 1952).

Drawing upon research by (Hongying, 2021) utilizing the Bass model and an extension model in the introduction, his paper formulated a diffusion model for the leading technology in the new energy industry and examined its diffusion mechanism. The identified mechanism revealed that under imperfect market and policy conditions, the dissemination of the new energy industry's leading technology was predominantly shaped by the "expected utility" among innovators and the "actual utility" among imitators. These assertions were substantiated through simulation analysis.

The results, similarly, aligned with the research by (Riss, 2023), which also observed parallels in the evolution of social actions across various domains, pinpointing a consistent wave-like pattern in their development. Riss (2023) study underscored that any multiagent social action inherently incorporates the acceptance of innovation. Due to the wave-like nature of this process, social actions similarly unfold in a wave-like manner.

This result was further corroborated by (Sommerfeld, 2016) who reaffirmed the significance of socio-economic explanatory variables in solar PV uptake.

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Trend Analysis

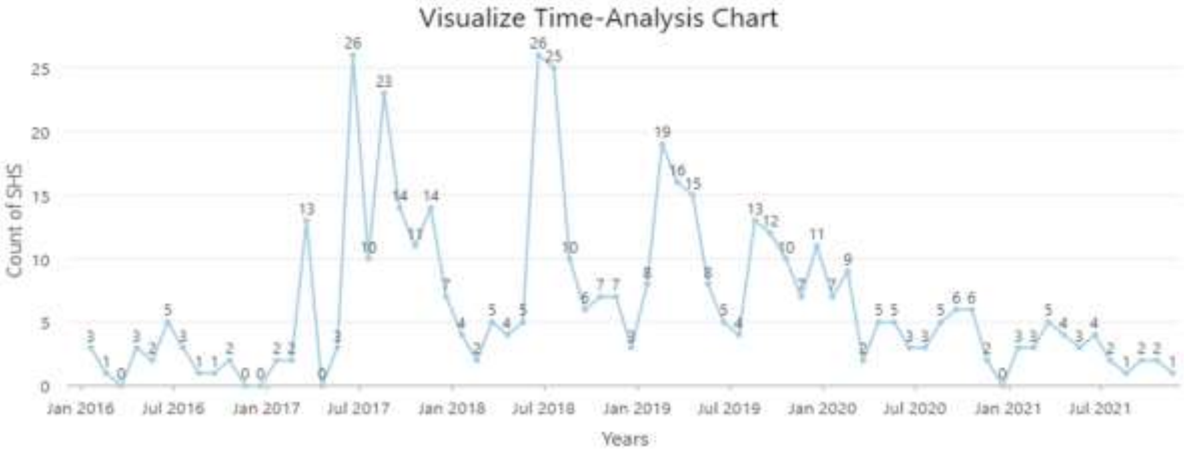

Figure 6: Spatial Diffusion Counts of SHS over Time for the Period (2016-2021)

The results showed that the diffusion of SHS had a diminishing effect over time.

The SHS diffusion counts dropped towards the end date (July 2021).

SHS diffusion did not have a significant increase or decrease over time.

Geospatial Modelling (Ordinary Least Squares Regression Test)

Since there was not a statistically significant increase or decrease in SHS points over time. Other explanatory variables were tested in order to understand the relationships between solar home system diffusion and relevant factors like population density, income levels, education level, housing density, poverty rate, and electricity access. Modelling of these variables helped explain the spatial-temporal patterns observed.

Table 1: Ordinary Least Squares Results for the Explanatory Variables of Population Density, Households and Income Were Examined

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-257.893209	157.894551	-1.633326	0.195235	146.305040	-1.762709	0.171057	--------
POP_DENSITY	-0.116282	0.166666	-0.697698	0.530854	0.148899	-0.780948	0.487039	1.048732
HOUSEHOLDS	-0.000410	0.000468	-0.876674	0.440272	0.000383	-1.071678	0.356885	1.008953
INCOME	45.367415	13.387772	3.388720	0.037028*	12.947677	3.503904	0.031765*	1.039770

Input Features:	Point_AggregatePoints_S	Dependent Variable:	COUNT
Number of Observations:	7	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
Jarque-Bera Statistic [g]:	0.776890	Prob(>chi-squared), (2) degrees of freedom:	0.678111

Notes on Interpretation

*An asterisk next to a number (robust_Pr[b]) indicates a statistically significant p-value ($p<0.01$)

In Table 1, the findings indicated that population density (-0.11628) and households (-0.0004) exhibited negative correlation coefficients with SHS diffusion counts. This signified that as SHS counts increased, both population density and households decreased. Conversely, SHS counts demonstrated a positive correlation with income levels, meaning an increase in income levels corresponded to an increase in SHS diffusion counts.

The model further indicated that income (0.0317*) held significant importance in the overall model. This implies that the patterns of SHS diffusion counts could be explained by variations in this variable.

The negative relationship of SHS diffusion with population and households was consistent with the study by (Graziano, 2015) where he found that diffusions decreased with housing density. He further stated that the diffusion of any new technology did not simply follow population density as well and that these two variables were less important for the diffusion of SHS. Small and midsized centres of housing density and population density were just as important as the larger centres when it came to the diffusion of PV systems.

Income had a positive relationship. This meant that as the SHS diffusion increased, with an increase in income levels. This finding was consistent with the study by (Yibeltal, 2020) and

(Caiquan, 2020) where the researchers found out that the wealthy or more prosperous individuals were more likely to adopt SHS technology sooner than the less prosperous ones.

Table 2: Ordinary Least Squares Results for the Explanatory Variables of Education, Electricity and Poverty Were Examined

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-85.258049	33.207668	-2.567421	0.082109	34.538094	-2.468522	0.089300	--------
EDUCATION	0.110754	0.304686	0.363501	0.734654	0.221569	0.499860	0.646352	1.300104
ELECTRICITY	0.012586	0.000749	16.797066	0.000000*	0.000467	26.953655	0.000000*	1.067230
POVERTY_RATE	-0.464056	0.735039	-0.631336	0.567844	0.490646	-0.945806	0.408903	1.256730

OLS Diagnostics

Input Features:	Point_AggregatePoints_S	Dependent Variable:	COUNT
Number of Observations:	7	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:	0.910792

Notes on interpretation

(*An asterisk next to a number (robust_Pr[b]) indicates a statistically significant p-value ($p<0.01$)

The results from Table 2 revealed a positive correlation between education and electricity with SHS diffusion counts. This implied that an increase in electrification rates and education levels corresponded to an increase in SHS diffusion.

Notably, the electrification rate variable (0.000*) carried an asterisk, signifying its significant contribution to the overall model. This suggested that the SHS diffusion counts were notably influenced by electrification rates.

A positive relationship between SHS diffusion and education variable could be attributed to the awareness of the benefits of using renewable energy. A study by (Moorthy, 2019) reported that if benefits were known to the villagers, then the education had the ability to drive the diffusion of off-grid solar energy. (Moorthy, 2019)

The finding that electricity access had a positive relationship with SHS diffusion was consistent with the study by (McEachern, 2008) where a string of unfulfilled grid promises translated into villagers losing faith in politicians' assurances and hence opting for SHS adoption. (Walters,

2018) in addition, reported that the rapidly increasing retail electricity rates further stimulated the demand for residential solar PV.

Poverty rate on the other hand, had a negative relationship (-0.4641) with the SHS diffusion counts. Diffusion counts went down with the increase in poverty rates. This was an expected result because the model had earlier shown that income played a key role in SHS diffusion counts.

This finding was consistent with a study by (Joshua, 2020) in Ethiopia where he reported the main problem in the sustainable development of off-grid solar systems was the financial constraint whereby the energy users were unable to pay. He further added that resolving such challenges was inevitable to move towards universal power access.

Reduction in Carbon Emissions due to Solar Panel Installation

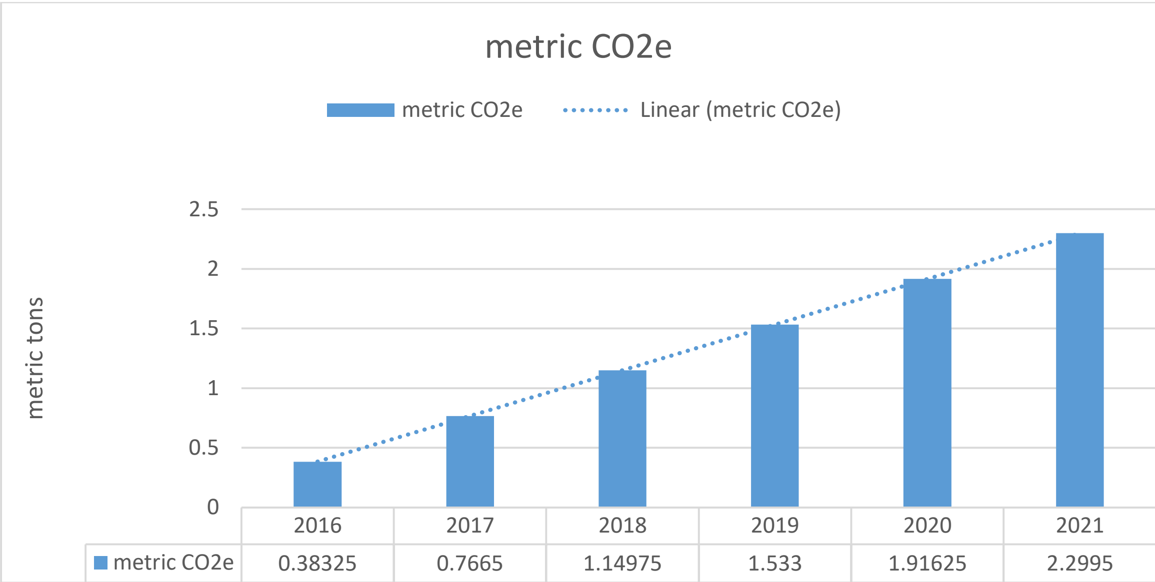

Figure 7: Total Emissions Avoided for the Period 2016-2021

Of the 61,871(target population) households in Kisumu East,384(0.006%) had installed small home systems. A mean of 268581.6 metric tons of carbon emissions had been avoided due to the installation of these solar systems for the period 2016-2021.

The fact that only 0.006% of all Kisumu east households had installed SHS was a barrier. An important factor to consider is the high poverty rates and low-income levels that makes it impossible for households to consider green energy technologies. (Adenle, 2020)

The government, therefore, should facilitate implementation by stepping up awareness. In general, more environmentally conscious communities (those who are more concerned about climate change) are more likely to install solar power than the average community (Arif, 2013)

Shahsavari (2018) further substantiated the results in this report by adding that solar energy was an attractive climate change mitigation option and an appropriate low-carbon development. He concluded by stating that renewable energy technologies mainly solar energy could bring long-term economic and environmental benefits.

The use of renewable energy sources is necessary for sustainable development and must be implemented by all possible means. This is necessary not only for the current generation but also for the next generation

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CONCLUSIONS AND RECOMMENDATIONS

Conclusion

The following conclusions were made according to the objectives of the study.

The first objective on the identification of spatial clusters and patterns of SHS diffusion, the results showed that the observed spatial patterns were concluded to be too unusual to be the result of random chance. Statistically significant spatial clusters of high values(hotspots) and low values (cold spots) were found. There was clustering of SHS in Kisumu and it was evident that a pattern existed.

The second objective was to analyse the spatial clusters and patterns of the SHS diffusion. The results showed that SHS diffusion did not have a significant increase or decrease over time. The geospatial analysis revealed that the pattern of SHS diffusion did not simply follow patterns of housing density or population density. The patterns found indicated that the primary determinants of the patterns of diffusion of SHS in Kisumu were socioeconomic and demographic variables. Electricity access and income levels played a major role in influencing diffusion.

The third objective was to calculate the amount of GHG avoided because of SHS diffusion in Kisumu. The results showed that SHS diffusion for the period 2016-2021, had abated 268581.6 metric tons of carbon emissions. It was evident that SHS had the potential to significantly reduce carbon emissions, with easier access to solar technology. SHS had the potential to contribute to a dramatic reduction in greenhouse gas emissions and help reduce climate change.

Policy Recommendations

The unique diffusion of SHS in Kisumu appeared too structured for random chance, with additional explanatory variables playing a pivotal role in elucidating patterns and clusters. Beyond contributing new insights into the diffusion process of this vital renewable energy technology, the findings hold significant policy and marketing implications. Business strategies recommend solar companies target grid-less villages near the grid, especially those with promises from visiting politicians. The government could enhance SHS diffusion by directing solar companies' marketing efforts to villages with frequent requests for government-funded initiatives. Policies easing regulatory barriers for community-based solar may facilitate broader diffusion of PV systems in denser and less affluent communities.

Limitations and Further Research

The study's major limitation stemmed from numerous assumptions made due to limited available data, essential for the validity of the results. The assumption that all residential solar systems in Kisumu were identical and catered to entire household electricity needs, while valid, would have been more precise with specific data on system sizes and home energy consumption. Additional research on installed solar system sizes is imperative.

Data mining and transformations, especially concerning explanatory variables datasets, consumed significant time. The study was constrained by the scarcity of available, usable, and free data on crucial explanatory variables. It also overlooked energy generation for commercial purposes, suggesting further research for renewable energy in the commercial sector.

The findings underscore the government's need to enhance solar technology accessibility for curbing greenhouse gas emissions in the residential energy sector

REFERENCES

Abbasi, T. (2010). Renewable energy sources: Their impact on global warming and pollution. *PHI Learning*.

Adenle, A. A. (2020). Assessment of solar energy technologies in Africa-opportunities and challenges in meeting the 2030 agenda and sustainable development goals. *Energy Policy*, 111180.

Adwek, G. (2019). The solar energy access in Kenya: a review focusing on Pay-As-You-Go solar home system. *Environment,Development and Sustainability*.

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 93-115.

Arif, M. S. (2013). Residential Solar Panels and Their Impact on the Reduction of Carbon Emissions. *Spring* , 1-18.

Benjamin, G. (2020). The carbon footprint of household energy use in theUnited States. *PNAS*, 19122 - 19130.

Caiquan, (2020). Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions? *Journal of Environmental Management*.

David. (2018). The uptake and diffusion of solar power in Africa: Socio-cultural and political insights on a rapidly emerging socio-technical transition. *Energy Research & Social Science* .

Getis. (1995). Local Spatial Autocorrelation Statistics :Distributional Issues and An Application. *Geographical Analysis*.

Gillingham, M. G. (2014). Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. *Journal of Economic Geography* , 1-25.

GOK. (2010). *National-Climate-Change-Response-Strategy.*

Graziano, M. (2015). Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environmentz. *Journal of Economic Geography*, 815-839.

Ha¨gerstrand, T. (1952). The propogatoin of innovation waves Lund Studies in Geography. *Geography*.

Hancock, K. J. (2014). The expanding horizon of renewable energy in sub-Saharan Africa: Leading research in the social sciences. *Energy Research & Social Science jou*.

Handoh, I. a. (2003). Periodic mid-Cretaceous oceanic anoxic events linked by oscillations of the phosphorus and oxygen biogeochemical cycles. *Global Biogeochemical Cycles*, 17.

Hughes. (2000). Biological consequences of global warming: is the signal already apparent? *Trends in ecology & evolution*, 56–61.

IEA. (2017). *World Energy Outlook.* France: International Energy Agency.

IMF/OECD. (2021). *Tax Policy and Climate Change: IMF/OECD Report for the G20 Finance Ministers and Central Bank.* Italy: OECD.

IPCC. (2018). *Global warming of 1.5 C* . Intergovernmental Panel of climate change .

IPCC. (2023). *Climate Change 2023.* Geneva, Switzerland: IPCC.

IRENA. (2015). *Renewable Energy In The Water,Energy and Food Nexus* . IRENA.

Keizer, D. (2017). Renewable Electricity in Kenya. 1-70.

KNBS. (2019). *2019 Kenya Population And Housing Census.* Nairobi: KNBS.

Lashof, D. (1990). Relative contributions of greenhouse gas emissions to global warming. . *Nature*, 344, 529-531.

McEachern, M. (2008). Socio-geographic perception in the diffusion of innovation: Solar energy technology in Sri Lanka. *Energy Policy*, 2578-2590.

Menzie McEachern, S. H. (2008). Socio-geographic perception in the diffusion of innovation: Solar energy technology in Sri Lanka. *Energy Policy*, 2578–2590 .

Mitchell. (2005). *The ESRI Guide To Analysis ,Volume 2.* ESRI PRESS.

Moorthy, K. P. (2019). Breaking barriers in deployment of renewable energy. *Heliyon*.

Müller, S. (2013). The adoption of photovoltaic systems in Wiesbaden, Germany. *Economics of Innovation and New Technology*, 519-535.

Ondraczek, J. (2013). The sun rises in the east (of Africa): A comparison of the development and status of solar energy markets in Kenya and Tanzania. *Energy Policy*, 407-417.

Owusu, P. A. (2016). A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Engineering*.

Pailman, W. L. (2015). Mobile payment innovation for sustainable energy access. *Proceedings of the 23rd Conference on the Domestic Use of Energy, DUE 2015.*

Palm. (2020). Early adopters and their motives: Differences between earlier and later adopters of residential solar photovoltaics. *Renewable and sustainable energy reviews*.

Power Africa Solar . (2023). *What You Can Power With a 2 KW (2 KVA) OFF GRID Solar System in Kenya.* Nairobi: powerafricasolar.

Ramirez Camargo, L. (2018). Spatiotemporal modelling for integrated spatial and energy planning. *Energy, Sustainability and Society*, 1-29.

Rogers. (2004). A Prospective and Retrospective Look at the Diffusion Model. *Journal of Health Communication*, 13-19.

Rogers, E. M. (1983). Diffusion of Innovations. *The Turkish Online Journal of Educational Technology*.

Russel, S. (2019). *Estimating and Reporting the comoparative emmision impacts of Products.* Washington: World Resources Institute.

Russell, S. (2019). Estimating and reporting the comparative emissions impacts of products. *World Resources Institute Working Paper*, 26.

Saxenian, A. (1994). *Culture and competition in Silocon Valley and route 128.* Cambridge ,Massachusetts and London ,England.: Harvard University Press.

Sommerfeld, J. (2016). Influence of demographic variables on uptake of domestic solar photovoltaic technology. *Renewable and Sustainable Energy Reviews*, 1364-0321.

Stafan. (2000). The Diffusion of Renewable Energy Technology. *Energy Policy*, 625-640.

Statistics, K. N. (2019). *National Census.* Nairobi: KNBS.

Tian, X. (2021). Energy and Environmental Sustainability Assessment of Photovoltaics Transition toward Perovskite–Perovskite Tandems from the Attributional and Consequential Perspectives. *ACS Sustainable Chemistry & Engineering* , 11247-11257.

UN Environment . (2015). *ENSURING ACCESS TO AFFORDABLE, RELIABLE, SUSTAINABLE AND MODERN ENERGY FOR ALL Environmental dimension of SDG 7.*

UN-Habitat. (2011). *CITIES AND CLIMATE CHANGE.* London • Washington, DC: Earthscan.

van der Kam, M. J. (2018). Diffusion of solar photovoltaic systems and electric vehicles among Dutch consumers: Implications for the energy transition. *Energy Research and Social Science* , 68-85.

Venkatesh Bala, S. G. (1998). Learning From Neighbours. *Review of Economic Studies*, 595-621.

Walters, J. (2018). A systems analysis of factors influencing household solar PV adoption in Santiago, Chile. *Sustainability (Switzerland)*, 1-17.

Wang, S. (2010). Spatial Modelling of Renewable Energy. 138.

WBCSD. (2013). Addressing the Avoided Emissions Challenge. Guidelines from the chemical industry for accounting for and reporting greenhouse gas (GHG) emissions along the value chain based on comparative studies. 44.

Wilby, R. &. (1997). Downscaling general circulation model output: a review of methods and limitations. *Progress in Physical Geography*, 530-548.

World Economic Forum. (2023). *Fostering Effective Energy Transition.*

(2000). *World Energy Outlook* . FRANCE: IEA Publications.

WRI. (2014). *Standard On Quantifying Avoided Emissions:Summary of Online Survey Results.Greenhouse Gas Protocol.* World Resources Institute.

WRI. (2019). *Estimating and reporting the comparative emissions impacts of products.*

Young, H. P. (2009). Innovation Diffusion in Heterogeneous Populations:. *The American Economic Review* , 1899-1924.