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Optimal Design of Disaster-proof Critical Infrastructure in the Electricity System; A case study of Accra, Ghana

A thesis submitted in fulfillment of the requirements for the award of a PhD degree in Mechanical Engineering (Specialty: Renewable Energy)

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DECLARATION

I declare that the contents of this thesis report are my original work and are as a result of my personal research, except where otherwise indicated. This report has not been submitted anywhere for any academic purposes or otherwise.

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DEDICATION

I dedicate this report to my dear wife Ms. Shamia Atuhaire, who stood with me through the entire PhD journey. Thank you for gracefully withstanding long periods of my absence.

ABSTRACT

Worldwide there are ongoing concerted efforts to expand access to electricity especially in developing countries, with electricity being touted as an important enabler for socioeconomic transformation. Most of the electrification initiatives are geared towards increasing the number of communities or households connected to the grid. However, in many developing countries including in Africa, those who already have an electricity connection often experience electricity outages with consequences for sustainable development. The frequent outages imply weaknesses in the design and operation of the electricity system – a critical infrastructure. This research investigates the extent to which failures in the electricity system cause power outage occurrences in Accra Ghana, the resultant impacts of power outages on households and the predominant coping measures used by households when faced with outages. Moreover, existing literature shows that the distribution of power outages in communities may be influenced by socioeconomic and political factors. Often, it is those who are already socioeconomically disadvantaged who will face more outages and suffer greater impacts due to lack of sufficient coping capacities. This study uses various datasets (2015 outage statistics, census data and survey data), spatial and non-spatial statistical methods and tools to measure the degree of exposure to outages in different Accra communities, identify common outage impacts and response options in households and their drivers. The results show that, in 2015, Accra communities experienced widespread outages which varied significantly across the communities. The distribution of outages was found to be more influenced by demographic factors (household density and presence of large proportions of minorities) and less predicted by economic factors (wealth). Common outage impacts identified include safety/security issues, economic impacts and disrupted access to social services. Being of a low socioeconomic status, characterized by low education level, low income, and informal employment was associated with less likelihood to report being impacted by outages. Having a high exposure to outages, both in terms of frequency and duration, was generally associated with a high likelihood to report household-level impacts of outages. Other household characteristics, such as living in a large family, seem to diminish the possibility of reporting one kind of outage impact while increasing the likelihood of reporting another kind of outage impact. The study also found that selection of outage coping options in households are generally influenced by the household's electricity needs/uses. It also supports the general assumption that household economic characteristics impact greatly on selection of coping choices. Availability of some

natural resources also provides potential coping options that households can utilize during outages. The research results provide vital information which can be used to influence decisions and policies towards all-inclusive and sustainable electrification in Ghana and beyond.

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LIST OF ABBREVIATIONS

IPCC – Intergovernmental Panel for Climate Change

GSS – Ghana Statistical Services

GDP – Gross Domestic Product

UNDESA – United Nations, Department of Economic and Social Affairs

IEA – International Energy Agency

ECG – Electricity Company of Ghana

GIS – Geographic Information System

NES – National Electrification Scheme

GEDAP – Ghana Energy Development and Access Project

VRA – Volta River Authority

USAID – United States Agency for International Development

ISSER – Institute of Statistical, Social and Economic Research

CEPA – Centre for Policy Analysis

GRIDCo – Ghana Grid Company

MW – Mega Watts

NEDCO – Northern Electricity Distribution Company

VALCO – Volta Aluminium Company

kWh – kilo-Watt-hour

GWh – giga-Watt-hour

EPC – Enclave Power Company

WAGP – West African Gas Pipeline

VoLL – Value of Lost Load

WTP – Willingness to Pay

WTA – Willingness to Accept

KTOE – Kiloton of Oil Equivalent

AMA – Accra Metropolitan Area

WC – Water Closet

kV – kilovolts

GH¢ - Ghana Cedis

CSIR-STEPRI – Council for Scientific and Industrial Research, Science and Technology Policy Research Institute

EA – Enumeration Area

HQI – Housing Quality Indicator

USA – United States of America

CA – California

ESRI – Environmental Systems Research Institute

LS_e – Load shedding exposure

LS_f – Average load shedding frequency

LS_d – Average load shedding duration

GSA – Global Spatial Autocorrelation

LISA – Local Indicators of Spatial Association

PCA – Principal Component Analysis

CATPCA – Categorical Principal Component Analysis

OLS – Ordinary Least Squares

SLR – Simple Linear Regression

MLR – Multiple Linear Regression

AICc – corrected Akaike Information Criterion

GWR – Geographically Weighted Regression

BLR – Binary Logistic Regression

SPSS – Statistical Package for the Social Sciences

EED – Electrical Energy Demand

SDGs – Sustainable Development Goals

ITT – Institute for Technology and Resources Management in the Tropics and Subtropics

GIZ – Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH

DAAD – Deutscher Akademischer Austauschdienst

ICT – Information and Communications Technology

1. INTRODUCTION

1.1. Background

Electricity is one of the backbones of a well-functioning society. In developed countries, where access and use of electricity is already universal, electricity supports peoples' economic livelihoods, and powers other critical infrastructure systems such as telecommunication and transport networks, water supply systems, and health care facilities which in turn support the social wellbeing, safety and comfort of people. In developing countries, continued growth in electricity access rates – spurred by initiatives such as Sustainable Development Goals (SDGs) and the Power Africa Initiative – means that people, communities, and businesses in these countries are also increasingly becoming reliant on electricity to support their daily livelihoods.

Most of the electricity used in both developed and developing countries comes from centralized electricity generation plants and is delivered through extensive, interconnected networks of transmission and distribution infrastructure that make up what is commonly referred to as the electric grid. In fact, the electric power system has sometimes been described as the largest man-made interconnected system ever built [1]. The electric grid enables the delivery of electricity to multiple end-users, many of whom are located far away from the generation facilities. However, in the face of changing climatic and environmental factors, the resilience of centralized electricity systems has come into focus over the past years. Today, centralised electricity supply systems are considered to be increasingly vulnerable to disruptive events – both natural and manmade. A disruption in a single component of the electricity system can lead to loss of power to several downstream electricity consumers. Power outages due to failure of electricity delivery systems are, therefore, a concern in many countries including developed nations. The impacts associated with outages in these countries are usually substantial due to high societal reliance on electricity. Even then, concern about power outages in the developed world is low because of their limited scope in terms of frequency, duration and affected area [2].

In many developing countries, however, power outages remain rampant, being mostly associated with poorly developed electricity supply systems which are not able to sustainably meet the growing electricity demand. Most of the outages occur on the low voltage distribution network due to faults associated with aging infrastructure, poor maintenance, illegal connections and adverse weather. Many developing countries also experience another, more serious type of power outages, namely: mandatory rolling blackouts or load shedding. Mandatory load shedding is typically used as a last resort to manage electricity supply shortfalls [3], that are triggered by a supply–demand mismatch due to reduced generation and/or spike in electricity demand. Load shedding sometimes affects large geographic areas (entire regions or countries) and can last for years. Ghana is one of the countries in Africa that has been through several acute, multi-year electricity supply shortages over the past four decades, which have resulted into nation-wide load shedding (also known as "*dumsor*" in the local "*Twi*" language). The most recent mandatory rolling blackouts in Ghana lasted for about four years, from 2013 to 2016. At the peak of the power supply crisis, electricity users experienced up to 16 hours of no power on a daily basis (or 24 hours of power outage for every 12 hours of power) [4] [5].

There are several studies that document the occurrence and characteristics of electricity outages, especially in developed nations, often caused by extreme weather events or other natural hazards [6] [7] [8] [9]. Most of these studies, both by academia and utility managers, are aimed at alleviating power outages by building and operating a resilient power system [10]. This often includes identification of potential points of failure in the power system and preparing the system to remain functional (withstand or recover fast) even when faced with a large array of shocks. However, because threats from both natural and man-made phenomena are constantly evolving, it is nearly impossible to have a perfectly functioning, failure-proof power system. In recognition of this, there is body of literature on power outages which examines outage occurrences, characteristics and interactions with society. This is largely geared towards preparing the society to remain functional in case of interruptions in power supply. This often starts with understanding the relationship between power outages and various social, economic and environmental aspects that may drive outage occurrence, for example, tree cover, season of the year, population density, race/minorities, and proximity to other critical infrastructure [7] [11]. These can influence where (location) and the extent to which (intensity) power outages may occur.

Additionally, other research examines the impacts of and (lack of) resilience to power outages across different aspects of society, for example, economic activity, business performance, households, and critical infrastructure among others [12] [13] [6] [14] [2] [15] [6]. This contributes to the identification of risk posed by electricity outages to the various societal elements and helps to prepare society to better respond or adapt to the threat of power outages. Indeed, whenever electricity supply is interrupted, the consequences for society can be significant. Without electricity, efficient social service delivery is compromised, living environments can deteriorate and human lives and livelihoods are threatened. More often, it is those who are already vulnerable and less resilient – the socially marginalized, those living in poverty, the minorities, and the elderly – who are likely to suffer the most severe consequences of electricity outages [7] [16]. Therefore, understanding where and what causes outages to occur, and their impacts on (and associated resilience of) society is not only a first step towards building/operating a failure-proof electricity system, but is also vital for building an outage-resilient society (rather than a resilient power system) that continues to thrive even when faced with power outages.

1.2 Energy use in urban areas

Urbanization is one of the main demographic shifts that is currently taking place especially in the developing regions of Africa and Asia [17]. Presently, over half of global population resides in urban areas. Although Africa is still the least urbanized world region, an estimated 58.9% of Africa's population will reside in urban areas by 2050, rising from 31.5% in 1990. This makes Africa one of the hotspots of current and future global urbanization. In 2050, Africa's urban population will represent 22% of the projected global urban population [18]. Historically, urbanization has been identified as one of the main drivers of energy consumption [19]. Cities account for between 67% and 76% of the global energy use [20]. In developing countries, urbanization is believed to be an enabler of modern living by facilitating improved access to social/public services including energy (electricity). Energy is required to power the 'modern' lifestyles of urban dwellers. Moreover, urban areas are usually the centre of socioeconomic activity such as trading (commerce), manufacturing and leisure, all of which use energy. The lack of sufficient energy supply has, therefore, been considered a hindrance to social and economic development in some countries. Unfortunately, increased energy consumption due to urbanization has also been associated with the ongoing major global challenges related to climate and environmental change. Cities are said to contribute between 71% and 76% of the global carbon (CO_2) emissions from the energy sector [20].

1.2.1. Urbanization and electrification in Ghana

Ghana is one of the most urbanized countries in Africa. Even when most people on the continent still reside in rural areas, Ghana's urban population has already exceeded its rural population. Ghana's urban population increased form 32.1% in 1984 to 50.9% in 2010 [21]. This is projected to further increase to 63% by 2025 [22]. Ghana's regional urban growth is not uniform. In Ghana, greater Accra region is the most urbanised region with over 90% of the region's population residing in urban centres. Upper West region is the least urbanized region [21]. Urbanization in Ghana has been an important enabler of the country's transformation. Coinciding with the rapid (three-fold) urbanization, Ghana's GDP has also grown rapidly at an average of 5.7% per annum since 1984 while poverty levels have significantly reduced. Improvements in quality of education and overall quality of life (living standards) have been recorded as a result of increased access to social services which comes with urbanization. Conversely, the uncontrolled/unplanned urban expansion in Ghana has resulted into several challenges including congestion, slum development, and limited access housing and other social/public services (World Bank, 2015).

Similar to other countries in sub-Saharan Africa, most of the electrification and electricity consumption in Ghana takes place in urban areas (see ***Figure 1***). In 2018, 93% of Ghana's urban population had access to electricity as compared to 73% of the rural population [23]. Also, historically, the need to establish electricity supply infrastructure in Ghana has been driven by, among other factors, urbanization [22]. It has also been observed that urbanization in Ghana has contributed to growing residential electricity demand possibly related to lifestyle changes and increased use of electrical appliances such as air conditioners, televisions and refrigerators [24] [25]. Indeed, urban households account for 70% of the total electricity consumed in Ghana's residential sector [25]. Other factors such as growth of business enterprises and the manufacturing sector, as well as increasing urban population have also stimulated growth in electricity demand in Ghana's urban areas [22]. Such growing electricity demand, if not matched by increased electricity generation/supply can result into electricity supply shortfalls. Indeed, in Ghana, rapid urbanization has been linked with the perennial electric power crises that have affected the country in the past and the attendant socioeconomic implications [22].

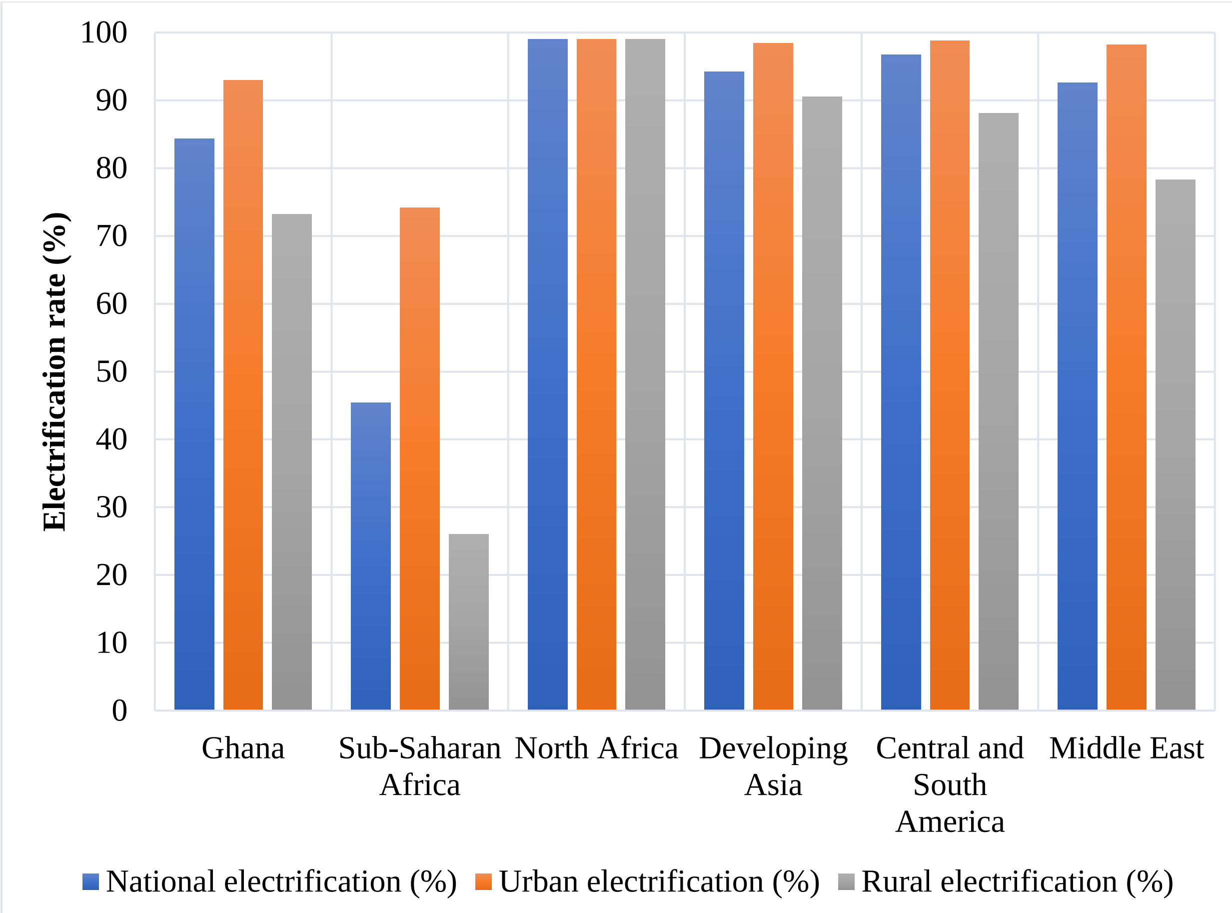
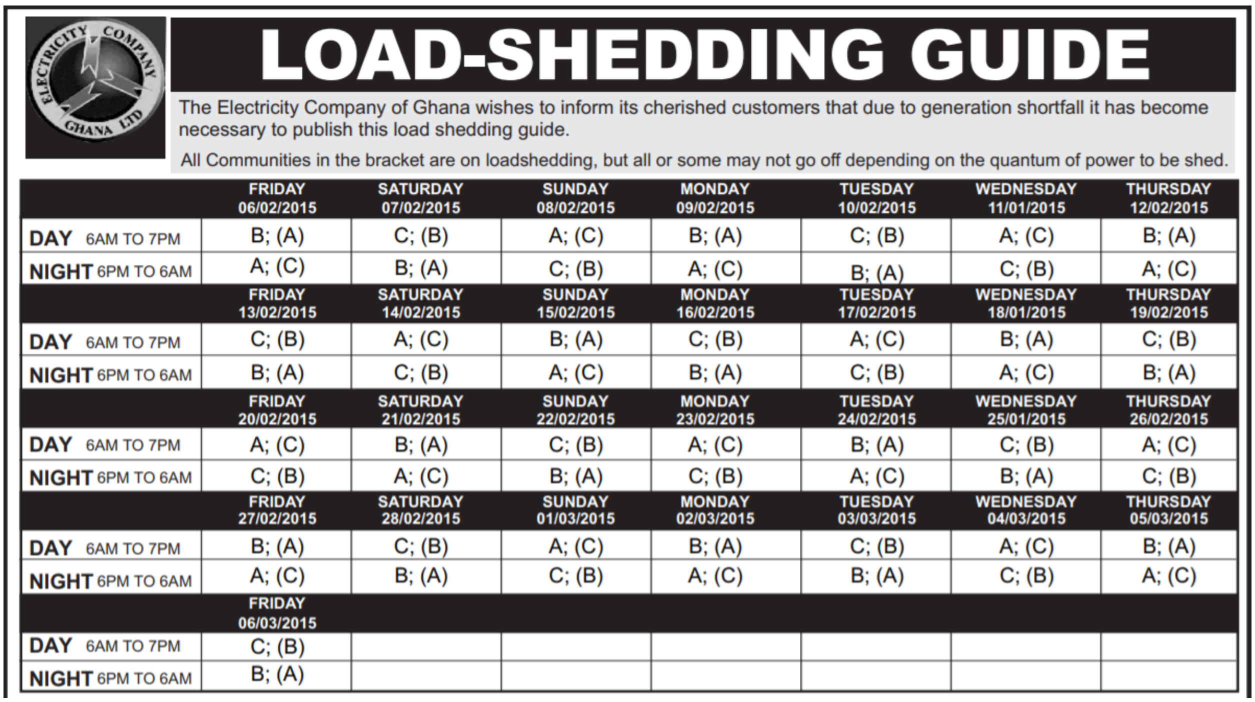


Figure 1: Select electricity access rates worldwide

1.3 Problem statement/motivation

In Ghana, when outages (especially rolling blackouts) occur, the general assumption is that the power outage burden is distributed equally (or at least fairly) to electricity consumers across different communities. To achieve this, the electricity distribution company (ECG) often issues an outage (load shedding) schedule similar to what is shown in ***Figure 2***. However, several reports about the recent power supply crisis show that published load shedding schedules are often not followed and the outage burden is not equally distributed across geographic areas [4] [26]. Furthermore, reports indicate that unequal distribution of power outages often favours particular socioeconomic groups such as the wealthy, and the socially and politically connected who get more power supply while those with a lower ranking in society suffer more outages [4] [27]. The challenges associated with such targeted unequal distribution of outage burden are several. Most importantly, when those who are already socially, economically, or politically disadvantaged experience most outages, it is likely that they will suffer disproportionately high outage-related impacts, since they may not have sufficient capacity to cope with/adapt to the power outages. This will further worsen their precarious conditions and exacerbate the already existing inequalities in society [22]. This study is, therefore, motivated by the need to adequately understand the construction of electricity outage experiences, impacts and resilience across communities in the city of Accra. The overall aim is to contribute to efforts geared towards achieving sustainable and equitable electrification – one which goes beyond a mere connection to the grid – that leads to socioeconomic development for all.


ELECTRICITY COMPANY GHANA LTD

LOAD-SHEDDING GUIDE

The Electricity Company of Ghana wishes to inform its cherished customers that due to generation shortfall it has become necessary to publish this load shedding guide.

All Communities in the bracket are on loadshedding, but all or some may not go off depending on the quantum of power to be shed.

	FRIDAY 06/02/2015	SATURDAY 07/02/2015	SUNDAY 08/02/2015	MONDAY 09/02/2015	TUESDAY 10/02/2015	WEDNESDAY 11/01/2015	THURSDAY 12/02/2015
DAY 6AM TO 7PM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
NIGHT 6PM TO 6AM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
	FRIDAY 13/02/2015	SATURDAY 14/02/2015	SUNDAY 15/02/2015	MONDAY 16/02/2015	TUESDAY 17/02/2015	WEDNESDAY 18/01/2015	THURSDAY 19/02/2015
DAY 6AM TO 7PM	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)
NIGHT 6PM TO 6AM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
	FRIDAY 20/02/2015	SATURDAY 21/02/2015	SUNDAY 22/02/2015	MONDAY 23/02/2015	TUESDAY 24/02/2015	WEDNESDAY 25/01/2015	THURSDAY 26/02/2015
DAY 6AM TO 7PM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
NIGHT 6PM TO 6AM	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)
	FRIDAY 27/02/2015	SATURDAY 28/02/2015	SUNDAY 01/03/2015	MONDAY 02/03/2015	TUESDAY 03/03/2015	WEDNESDAY 04/03/2015	THURSDAY 05/03/2015
DAY 6AM TO 7PM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
NIGHT 6PM TO 6AM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
	FRIDAY 06/03/2015						
DAY 6AM TO 7PM	C; (B)						
NIGHT 6PM TO 6AM	B; (A)						

Figure 2: Sample electricity load shedding schedule published by the Electricity Company of Ghana Ltd *[28]*.

**A, B, C represent groups of communities as listed by the utility company.

1.4 Gaps in existing research

Power outages are the topic of this research because not enough attention has been given to this topic especially in developing countries in sub-Sahara Africa where power outages are frequent and electricity unreliability remains a big challenge. Most existing research on energy in sub-Saharan Africa focuses on electrification rates, reliance on traditional fuels, and potential for renewable energy in the region. Little has been documented about the quality of electricity services delivered to consumers especially those who are connected to the power grid. In many African countries, having access to the grid (grid connection) does not automatically translate into access to electricity. Additionally, when power outages have been studied in developing countries, most attention has been directed on examining their economic implications on businesses, industries or the economy. Little research has been carried out on how communities or households experience power outages. Moreover, in Ghana, the known single study on community experiences of power outages [4] employed a limited dataset of outage duration collected from a few volunteer respondents over a short period of time. While useful, such short-term data may not sufficiently characterize outage experiences from electricity supply shortfalls (outages) which sometimes go on for years. The present study attempts to fill these gaps by undertaking a study on community/household level characteristics of power outages using a more comprehensive outage dataset (outage frequency and duration) from the utility company and data from detailed community surveys to determine neighbourhood outage experiences (distribution, impacts and coping mechanisms).

1.5 Research contributions

Results from this research contribute to efforts geared towards addressing electrification challenges in Africa in a holistic way. Specifically, the research contributes to the body of knowledge that seeks to understand electricity unreliability experiences on the continent. Whereas micro-level spatial analyses of power outage experiences have been undertaken in developed countries, these have hardly been done in developing countries. The limiting factor has often been the lack of sufficient, granulated data at a spatial scale of interest. This study proposes and implements a spatial quantification approach to disaggregate available macro (medium) level power outage data and quantitatively estimate community level outage characteristics. The research, therefore, extends the methods used to estimate power outage experiences within communities. Furthermore, the research contributes important community-scale outage information – including outage exposure, impacts, coping mechanisms and their associated socioeconomic factors – to utility-level decision makers to enable better planning of electricity distribution during times of supply shortages.

1.6 Research objectives and questions

The overall objective of this research is to investigate how failure-prone electricity systems drive unequal access to electricity in Ghana and the resultant impacts on society. The research examines the patterns, determinants, impacts, and coping strategies related to electricity outages among communities in the Accra Metropolis.

Specific Objectives

i. To assess the variation in electricity outage levels across different communities in the Accra Metropolis.
ii. To analyze the relationship between local socioeconomic and demographic characteristics and the patterns of electricity outages experienced by communities.
iii. To evaluate the social and economic impacts of electricity outages on households' wellbeing.
iv. To investigate the coping and adaptation strategies adopted by households in response to frequent electricity outages and the factors that explain differences in households' response choices to electricity outages.

Research Questions

The following research questions and sub-questions have been developed as a guide to the research activities.

i. How do levels of electricity outages experienced across communities in Accra Metropolis vary?
    - How can community-level outage experiences be quantified using spatial techniques?
    - What are the spatial characteristics of outage experiences in Accra communities?
    - What communities are considered hotspots or cold spots for electricity outages?
ii. To what extent are local socioeconomic and demographic characteristics related to patterns of electricity outages experienced in Accra communities?
iii. What impacts do electricity outages have on the social and economic wellbeing of the people in Accra, Ghana? What makes people more or less likely to report outage impacts?

- What are the common impacts of outages reported in households in Accra communities?
- How are the reported outage impacts associated with or influenced by household socioeconomic and other factors?

iv. How do people (households) cope with or adapt to frequent electricity outages and what explains their response choices?

- What options do respondents/households use to cope with outages in relation to their electricity needs (uses) and characteristics?
- What are the internal and external drivers/enablers of outage response actions in the communities?

1.7. Study design/thesis lay out

This thesis uses a multiple set of data, both spatial and non-spatial data. Main datasets include power outage statistics collected from the power utility company, household survey data and census data. Using GIS techniques, power outage data is used to calculate electricity outage exposure across communities and analyze its spatial characteristics. Available census data (independent variables) is then modelled together with power outage distribution variable (dependent variable) to determine the community-level factors which influence the observed spatial distribution of power outages. Using other statistical analysis approaches (correlation and regression analysis), the study further examines the relationships between outage impacts and coping mechanisms with several socioeconomic, demographic and other factors.

The first chapter gives a general overview of the research including the background of the research and a brief review of the state-of-the-art. The chapter then describes the research problem that has motivated this study, the existing gaps in literature on the research topic before presenting the research objectives and questions that will guide the study and the research process followed. The specific contributions of this study are also highlighted.

In the second chapter, an overview of Ghana's electricity sector is presented. To this end, trends and progress in electricity supply, demand and consumption trends in Ghana are discussed. Electricity supply challenges in Ghana are also discussed in this chapter.

Chapter three gives a detailed discussion on the state-of-the-art of power outage research specifically in Ghana reviewing various published literature about outage exposure, impacts and coping mechanisms. The research methodology is presented in chapter four, first by describing the study area, identifying the research measures and, finally, describing the analytical strategy to be used.

The results and discussions of the study are presented in chapter five, first by quantifying the level of outages within each community, followed by an analysis of the spatial distribution of the outages and identification of community-level significant drivers of the outage experiences. Furthermore, results from the analysis of outage impacts in households are presented including identification of common impacts and analysis of characteristics that influence the likelihood to report certain outage impacts. The final part of this chapter captures the different measures used by households to cope with outages. Relationships between coping choices and socioeconomic characteristics are also presented. Self-reported drivers of coping choices as well as potential external enablers of coping are highlighted. The thesis concludes with chapters six and seven where conclusions, and recommendations and policy implications respectively are presented.

2. RESEARCH CONTEXT: OVERVIEW OF GHANA'S POWER SECTOR AND ASSOCIATED CHALLENGES

2.1. Introduction

Globally, an estimated 860 million people have no access to electricity. Close to 600 million people without electricity access live in sub-Sahara Africa. A summary of global electricity access rates until 2018 is shown in ***Table 1***. The average electricity access rate in sub-Sahara Africa is 45%, which is about half the global average [23]. While still low, the current electrification rate for sub-Sahara Africa represents a significant improvement from the 24% access rate that was reported at the turn of the century. In sub-Sahara Africa, Ghana is one of the leaders in electricity sector growth and transformation. Significant efforts towards expanding electricity access in Ghana started in 1989 with the launch of the National Electrification Scheme (NES). Operationalized through the National Electrification Master Plan, the target of the scheme was to achieve universal electricity access in Ghana by 2020 [29]. Whereas the intended target has not yet been achieved, the NES has together with other initiatives such as the Ghana Energy Development and Access Project (GEDAP), facilitated a tremendous growth in Ghana's electricity access rates from an estimated 15% in 1990 to 84% in 2018 (see **Figure 3**).

	Proportion of the population with access to electricity (%)						
	National					Urban	Rural
	2000	2005	2010	2015	2018	2018	2018
WORLD	**73**	**77**	**80**	**85**	**89**	**96**	**79**
Africa	**36**	**39**	**43**	**49**	**54**	**79**	**35**
North Africa	91	96	>99	>99	>99	>99	>99
Sub-Saharan Africa	24	28	33	40	45	74	26
Developing Asia	**67**	**74**	**79**	**87**	**94**	**98**	**91**
China	99	>99	>99	>99	>99	>99	>99
India	43	58	68	79	95	>99	92
Other Southeast Asia	65	76	79	85	90	97	83
Other Developing Asia	38	46	57	74	79	89	73
Central and South America	**88**	**91**	**94**	**96**	**97**	**99**	**88**
Middle East	**91**	**90**	**91**	**92**	**93**	**98**	**78**

Table 1: Proportion of population with access to electricity in select regions/countries *[23]*

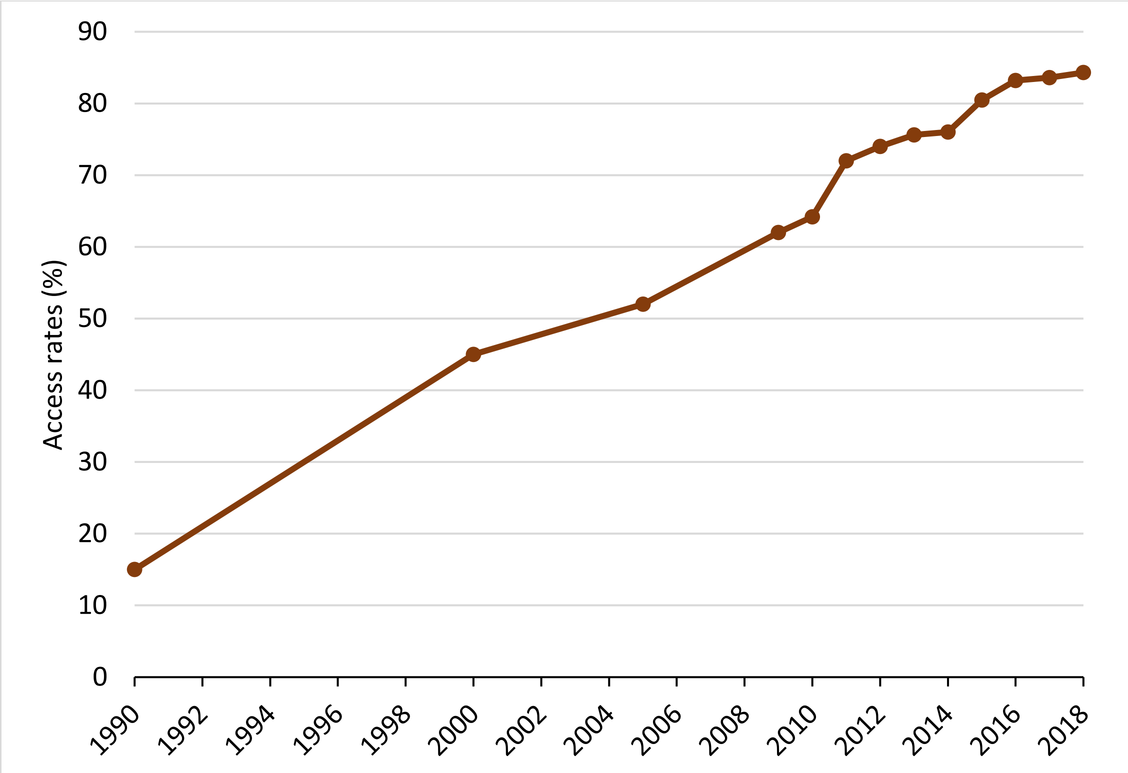


***Figure 3: Trends in electricity access rates in Ghana, 1990 – 2018** [30]**;** [29]**;** [23]*

Expanding access to electricity in Ghana has facilitated a shift from using traditional forms of energy towards modern and sustainable energy use. In 2018, the share of electricity in Ghana's final energy consumption was 15.2% [30]. This is higher than the 9% share reported for 2007 [31]. Petroleum products and biomass resources (mainly wood and charcoal) are the most commonly used energy resources in Ghana. However, the share of biomass in final energy consumption reduced from 43.7% in 2009 to 37.4% in 2018. The contribution of different energy forms to final energy consumption across various sectors in 2018 is shown in ***Table 2***. Most of the final energy consumption in Ghana occurs in the residential sector followed by the transport sector while agriculture & fisheries sector is the least energy consuming. In 2018, residential energy consumption accounted for 43% of Ghana's total final energy consumed. On the other hand, at about 44%, the industrial and commercial sectors have the highest share of electricity in their energy mix [30].

	Electricity	Natural gas	Other petroleum products	Wood	Charcoal	**Total**
Residential	555.0	-	181.6	1321.5	1163.8	**3221.9**
Industry	349.4	64.8	341.8	24.5	6.3	**786.8**
Commercial & Service	228.6	-	16.6	183.5	94.9	**523.6**
Agriculture & Fisheries	0.3	-	94.8	-	-	**95.2**
Transport	0.7	-	2847.2	-	-	**2847.9**
Total	**1133.9**	**64.8**	**3483.7**	**1529.5**	**1265.0**	**7476.9**

Table 2: Final energy consumption in Ghana, 2018 by sector and energy type (KTOE) *[30]*

2.2. Electricity supply in Ghana

Since the early post-independence period, electricity supply in Ghana has been dominated by the government through the Volta River Authority (VRA) [32] [33]. VRA was established in 1961 by an Act of Parliament to lead the new government's electrification efforts, with a mandate to generate, transmit and distribute electricity [33] [22]. Following the commissioning of the first four generation units at Akosombo dam in 1966 [34] [35], VRA became the sole grid electricity supplier in Ghana. Whereas VRA mandate has since changed – with the distribution portfolio allocated to the Electricity Company of Ghana (ECG) and the transmission portfolio occupied by GRIDCo – VRA has remained the leading electricity generation entity in Ghana until today. VRA owns and operates Akosombo hydropower plant, which remains the single largest power plant in Ghana both in terms of installed power capacity and electricity generated, together with other generation facilities including Kpong hydropower plant, VRA Navrongo Solar Plant, and six thermal power plants, giving it a total generation capacity of 2520 MW (2260 MW dependable capacity) [36].

Since the coming online of the Akosombo dam, Ghana has mostly relied on hydropower resources to meet its electricity needs. Until 2014, hydropower plants accounted for over 50% of the total installed power capacity in Ghana. However, intensified investments in natural gas power plants over the last few years has tilted the generation sub-sector towards thermal generation technologies. In 2018, Ghana had at least 20 functional grid-connected electricity generation plants with a total installed capacity of 4888.6 MW (4472.1 MW dependable capacity) (see ***Table 3***).

Thermal power plants accounted for 66.8% of the installed capacity, followed by large hydro plants at 32.3% while other renewable energy resources accounted for less than 1%. The share of electricity generated from thermal power plants, for the first time, exceeded that from hydro sources in 2016 (see ***Figure 4***). Indeed, the share of electricity from hydro power plants in the generation mix has declined from 76% in 2009 to 37% in 2018 while that from thermal power plants exceeded 60% in 2018 [30].

Generation plants	**Installed capacity (MW)**	**Dependable capacity (MW)**	**Electricity generated (GWh)**
Hydro			
Akosombo	1020	900	4273
Kpong	160	140	771
Bui	400	360	974
Total	**1580**	**1400**	**6018**
Thermal			
Takoradi Power Company (TAPCO)	330	300	730
Takoradi International Company (TICO)	340	320	2211
Tema Thermal 1 Power Plant (TT1PP)	110	100	314
Cenit Energy Ltd	110	100	2
Sunon Asogli Power (Ghana) Limited	560	520	1970
Tema Thermal 2 Power Plant (TT2PP)	80	70	3
Kpone Thermal Power Plant	220	200	317
Karpowership	470	450	2556
Ameri Plant	250	230	873
Trojan	44	40	-
Genser	22	18	392
AKSA Energy Limited	370	350	748
Cenpower	360	340	79
Total	**3266**	**3038**	**10195**
Renewables			
Safisana Biogas	0.1	0.1	0.32
VRA Solar	2.5	2	2.5
BXC Solar	20	16	26.6
Mienergy	20	16	3.7
Total	**42.6**	**34.1**	**33.12**
Grand Total	**4888.6**	**4472.1**	**16246.12**

Table 3: Electricity generation plants in Ghana, their capacities and electricity generated, 2018 *[30]*

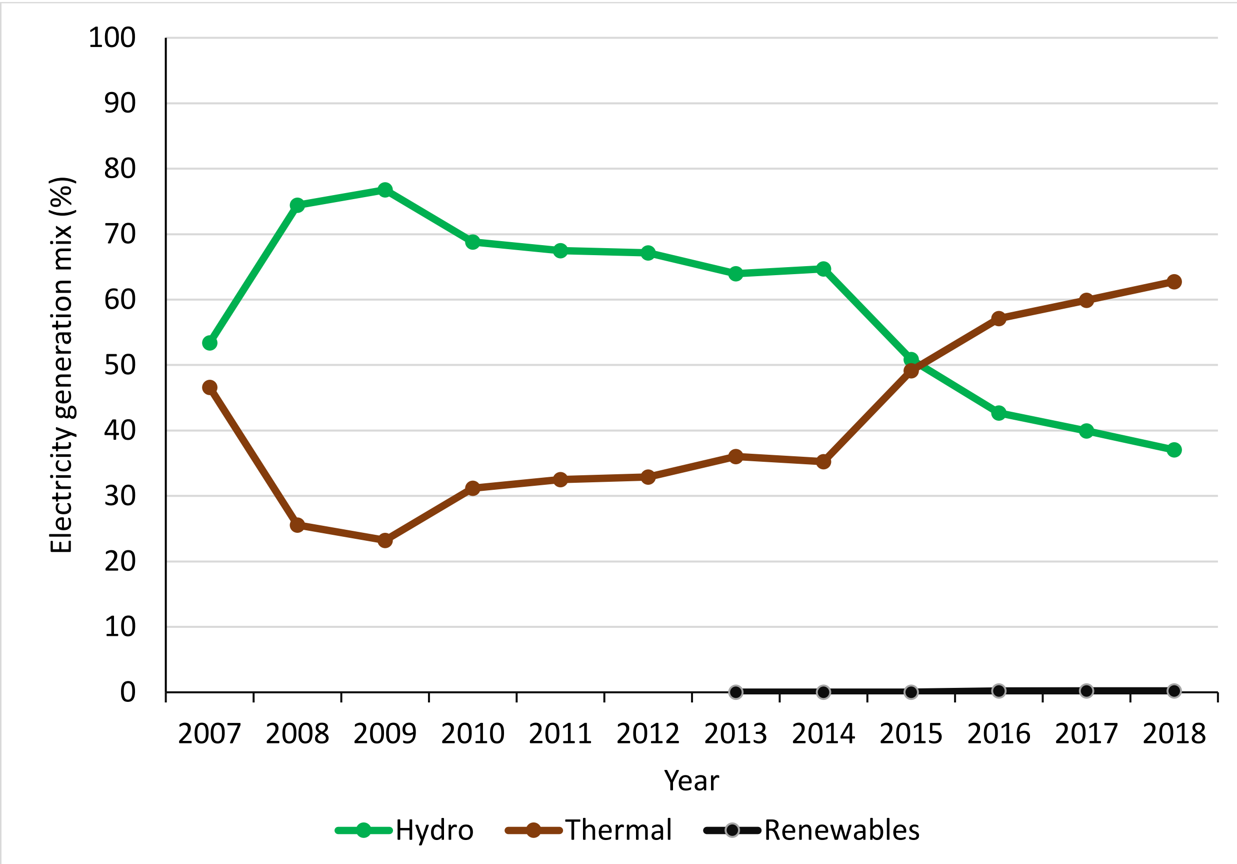


Figure 4: Trends in Ghana's electricity generation mix, 2007 - 2018 *[30]*

2.3. Electricity demand and consumption in Ghana

Expanding access to electricity in Ghana has inevitably led to increased electricity consumption and demand. ***Figure 5*** below shows the growth trends in peak load over a 10-year period. Ghana Load at Peak represents the in-country demand placed on the electricity grid from ECG and NEDCo customers, and from other direct customers of VRA and the mines. The System Peak Load is the overall peak load that includes Ghana Load at Peak and demand from Volta Aluminium Company Ltd (VALCo) and export load. Overall peak demand grew by 77% from 1423 MW in 2009 to 2525 MW in 2018 [30]. This rate is much higher than the 49.8% growth previously reported for the period 2006 – 2016 [29]. As shown in ***Figure 5***, year-to-year peak load has generally been rising since 2009. The only reduction (albeit slight) in peak load relative to the previous year was observed in 2015 at the peak of an electricity supply crisis.

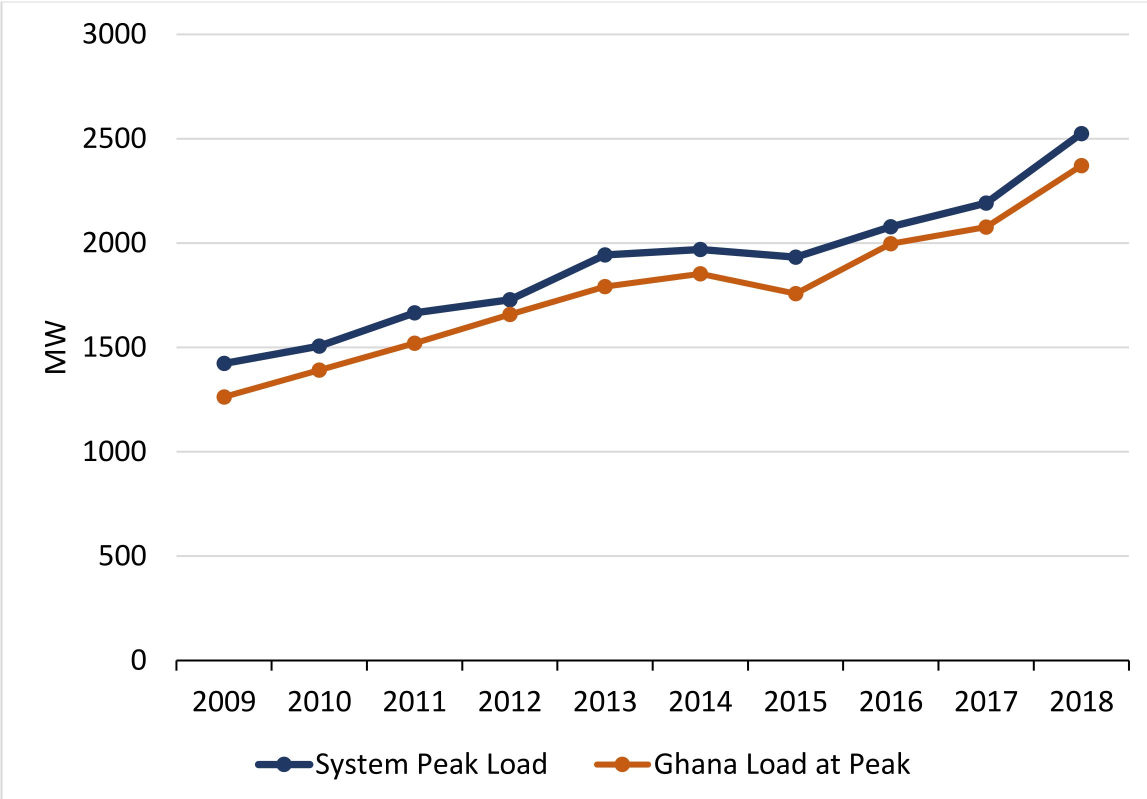


Figure 5: Trends in Ghana's peak load demand, 2009 - 2018 *[30]*

Similarly, grid electricity consumption in Ghana has been growing over the last 12 years. Trends in annual electricity consumption in Ghana from 2007 – 2018 are shown in ***Figure 6***. Overall grid electricity consumption has more than doubled since 2007. On average, electricity consumption has increased in all electricity consumer categories (residential, non-residential, industrial, and street lighting). At 43.3%, special load tariff consumers (mostly large industrial establishments) accounted for the biggest share of the total electricity consumption in 2018, closely followed by residential consumers at 41.4%. Apart from street lighting, which at about 6% was the least electricity consuming category in 2018, residential category posted the highest consumption growth rate of 142%, which is more than the growth rate of special load tariff category (88%) over the 12-year period [30]. Rapid growth in Ghana's residential electricity consumption is attributed to increased grid connections, and growth in per capita income with its associated lifestyle changes such as increased ownership of electrical appliances [32]. The non-residential category, which mostly includes commercial and service sector consumers, exhibited an irregular consumption trend. Between 2007 and 2012, electricity consumption under non-residential category grew by

98% to 1549 GWh. However, from 2012 to 2018, non-residential electricity consumption declined by about 29% to 1103 GWh.

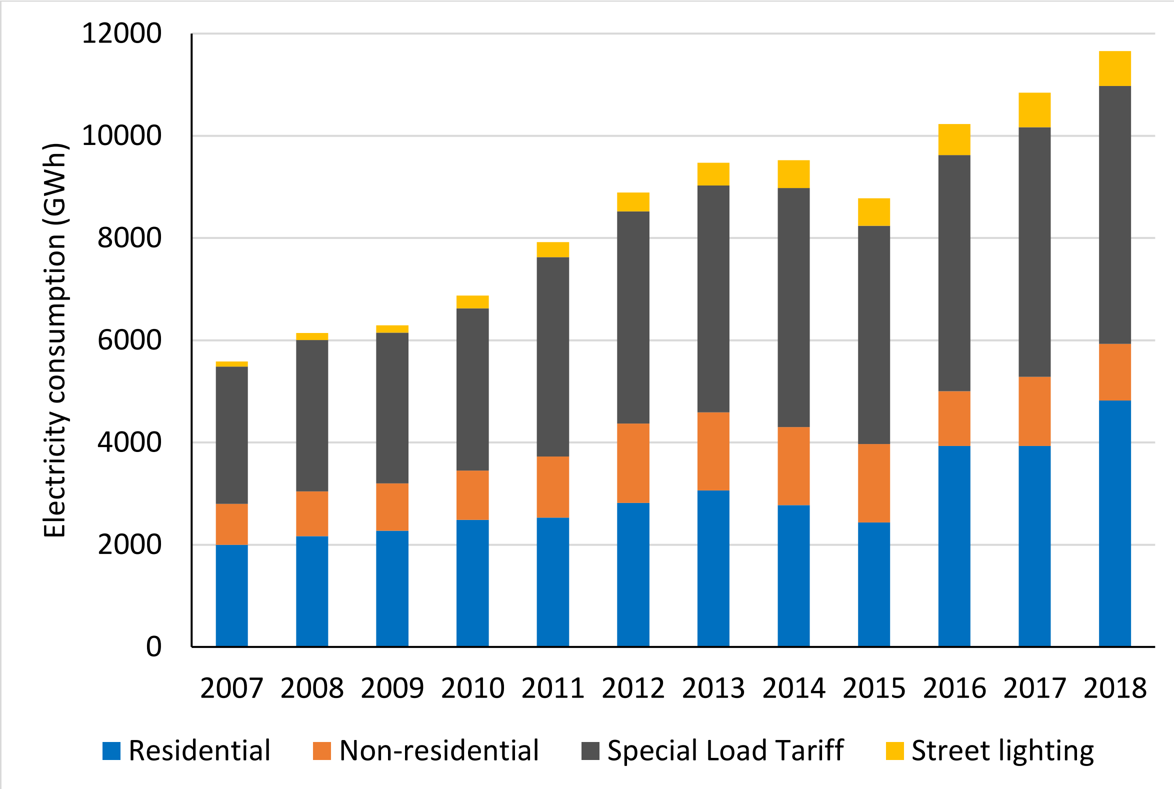


Figure 6: Trends in Ghana's annual electricity consumption by sector, 2007 - 2018 *[30]*

2.3.1. Residential electricity consumption in Ghana

Energy consumption in the residential sector in Ghana is still dominated by traditional biomass resources (particularly charcoal and firewood). However, the share of electricity in residential energy consumption has continued to grow. In 2018, charcoal and firewood together accounted for about 77% of the total consumption while electricity had a 17% share (see ***Figure 7***) [30]. The quantity of electricity, as final energy consumed at a residential level, exceeded that of any other sector (see ***Figure 8***). This is largely because the number of residential electricity customers (that is, connected households) has more than doubled from 1.86 million in 2009 to 3.75 million customers in 2018 [30].

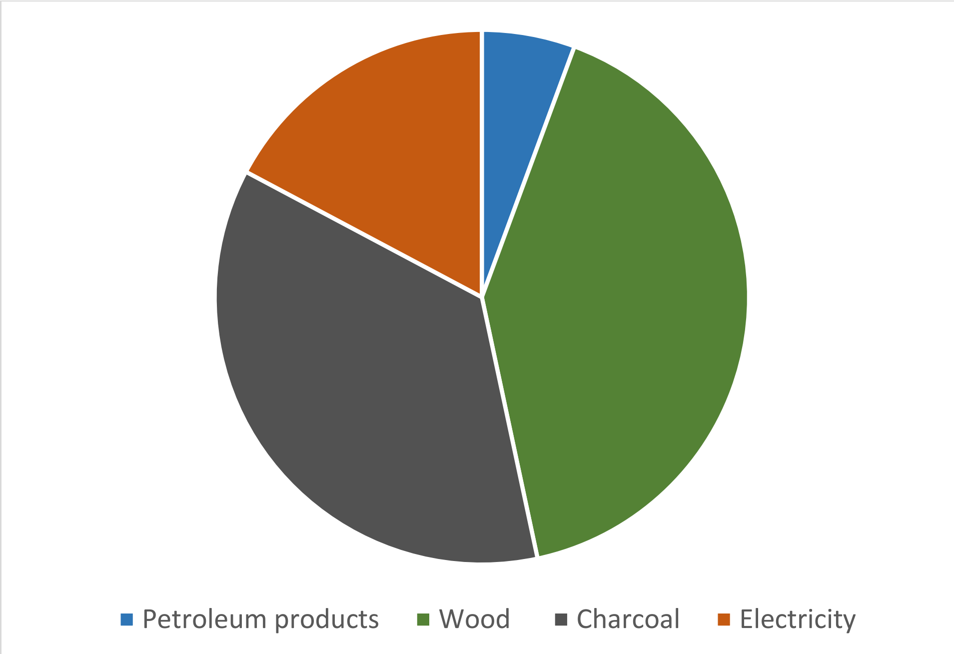


Figure 7: Share of energy resources in Ghana's residential energy consumption, 2018 *[30]*

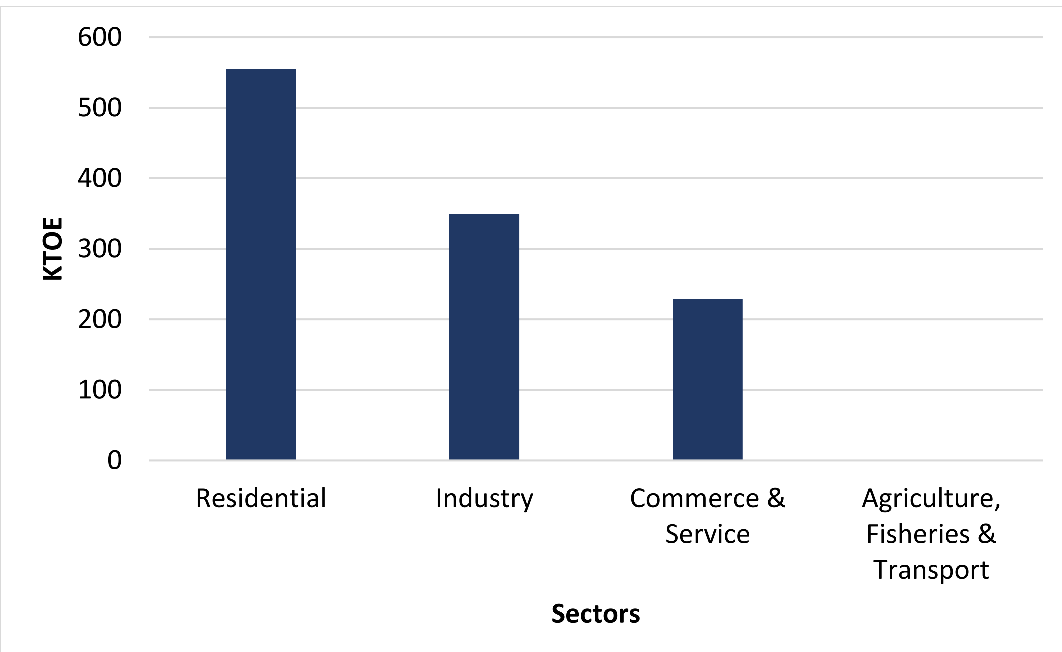


Figure 8: Quantity of electricity in Ghana's final energy consumption by sector, 2018 *[30]*

In most Ghanaian households, electricity is primarily used for lighting. In addition, many households especially in urban centres, where income levels are high, use electricity for refrigeration, information and communication (television, phone), air conditioning, heating and cooking [34]. The average annual electricity consumption for common electrical appliances used in Ghanaian households is shown in ***Figure 9***. For most appliances, electricity consumption is higher for households in Greater Accra Region as compared to other regions and the national average. Nationally, refrigeration (924 kWh) has the highest household electricity consumption annually followed by lighting (262 kWh) and television (146 kWh). Refrigeration accounts for over half (59%) of the annual residential electricity consumption both nationally and in Greater Accra region [37].

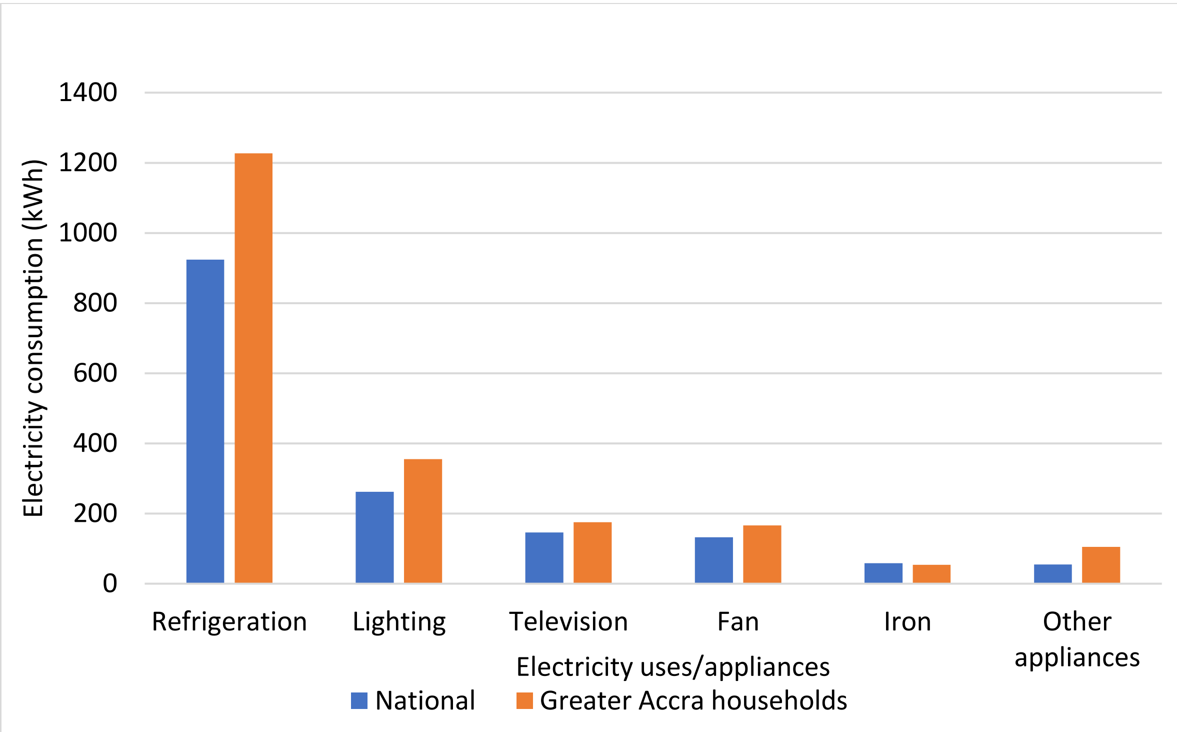


Figure 9: Average annual electricity consumption by use/appliance type per household *[37]*

2.4. Challenges in Ghana' electricity sector

2.4.1. High electricity losses

A significant amount of the total electricity generated in Ghana is lost during the transmission and distribution process. On average, transmission losses accounted for 4.1% of the total electricity transmitted annually from 2009 to 2018 [30]. The share of electricity losses at the distribution level is comparatively higher than the transmission losses. Distribution losses, including commercial losses, are mainly driven by inefficiencies in the distribution system apparatus, non-payment of bills by customers and power theft. There are three power distribution companies in Ghana namely: Electricity Company of Ghana (ECG), National Electricity Distribution Company (NEDCo) and Enclave Power Company (EPC). The annual electricity purchases for each company, given in

Table 4, show that ECG has over 80% of the market share. The distribution losses are also highest for both ECG and NEDCo averaging at 25% between 2011 and 2018. However, as shown in ***Figure 10***, the losses have generally been reducing for ECG but increasing for NEDCo. Enclave power – which is the smallest and newest electricity distribution company – reported the least distribution losses averaging at 4.5% over a four-year period [30]. These electricity losses affect the economic performance of the distribution companies which in turn compromises effective service delivery to the customers.

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
ECG	7944	8479	8370	7544	9316	9783	10901
NEDCo	822	937	998	1013	1140	1224	1318
Enclave Power[1]	-	-	-	102	108	157	161

Table 4: Trends in annual grid electricity purchases (GWh) for electricity distribution companies in Ghana, 2012 – 2018 *[30]*

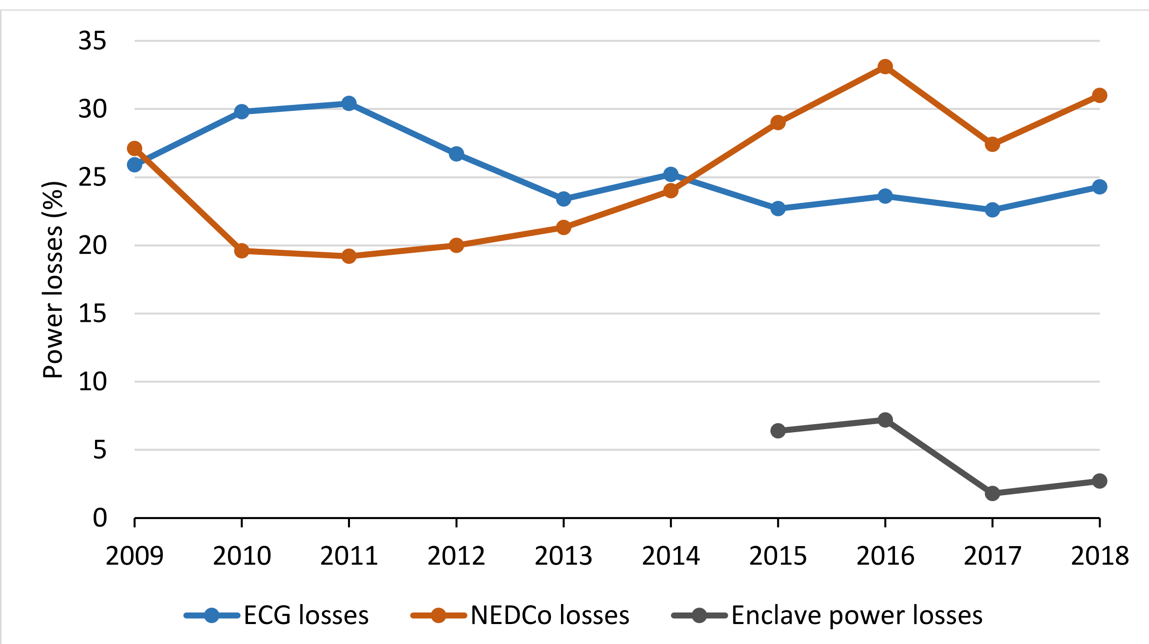


Figure 10: Trends in losses in electricity distribution in Ghana, 2009 - 2018 *[30]*

[1] Data for Enclave Power Company was only available from 2015.

2.4.2. Power supply shortages (outages)

As already mentioned, Ghana has one of the most extensively developed electricity supply systems in sub-Sahara Africa. However, over the past years/decades it has experienced recurrent shortages in electricity supply. The first major electricity crisis in Ghana was recorded in the early 1980s. Between 1981 and 1984, about 67% of Ghana's electricity supply capacity (mainly from the Akosombo hydropower dam) was lost [24]. Subsequent crises in 1997/98, 2002, 2006/07 and 2012 – 2016 also involved major shortfalls in electricity generation which necessitated the implementation of nationwide electricity rationing (rolling blackouts or load shedding) [38]. **Figure 11** shows trends in electricity generation highlighting periods of major generation shortfalls.

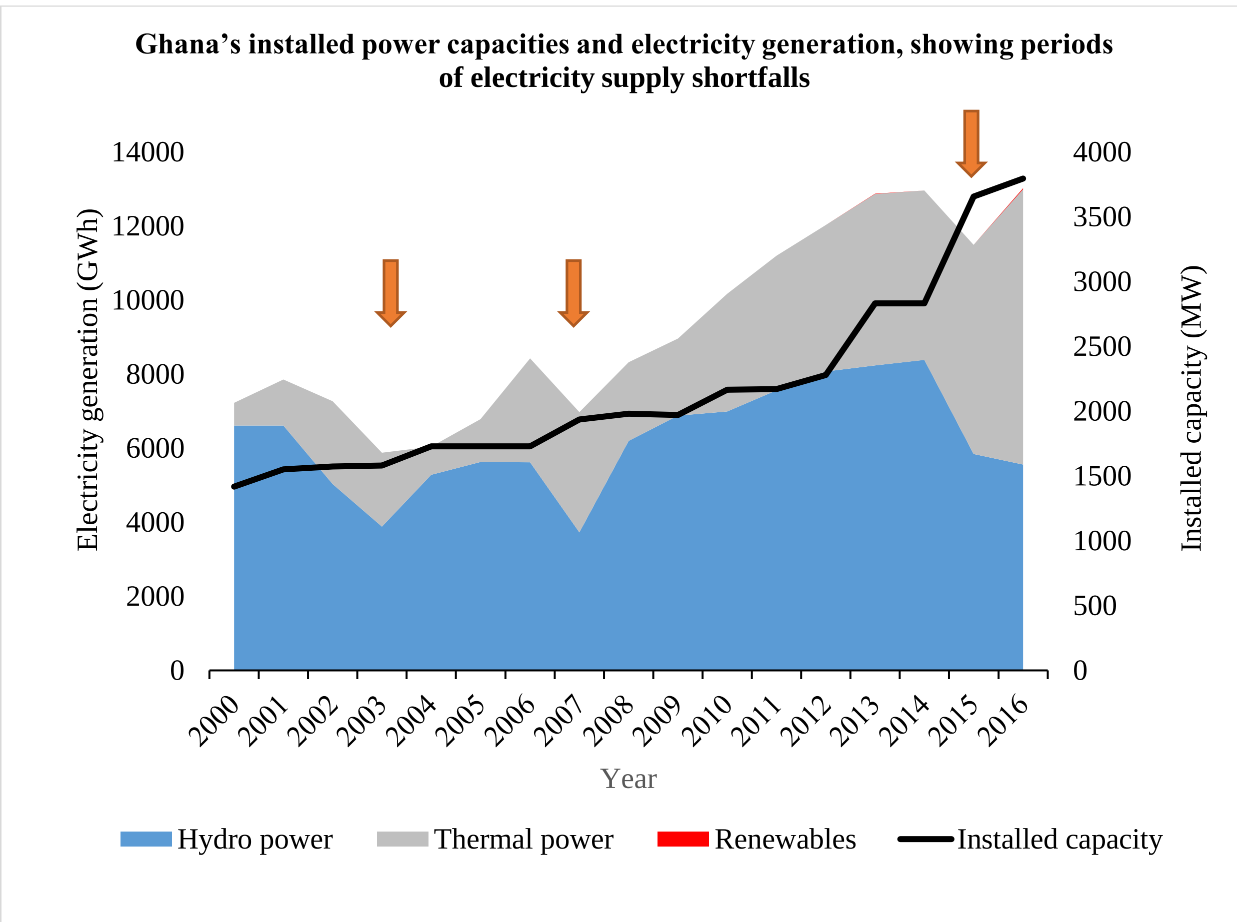


Figure 11: Trends in Ghana's installed power capacity and electricity generated, showing periods of major electricity supply shortfalls

Several factors are blamed for the recurrent electricity supply shortages in Ghana including rapid growth in electricity demand, limited investment in generation facilities/insufficient generation capacity, shortfalls in electricity imports, poor maintenance culture leading to breakdowns, and institutional/governance challenges. Most commonly, however, shortages of water available for electricity generation have been blamed for the power supply shortfalls [32] [35] [3] [38] [39]. For many years, Ghana depended heavily on hydropower plants for its electricity generation. This exposed it to fluctuations in electricity supply due to variations in the amount of water available for electricity generation. Indeed, receding water levels at Akosombo dam during droughts have often coincided with shortfalls in electricity generation and the subsequent power shortages that have rocked Ghana over the years. It is this susceptibility of hydropower plants to severe weather/climatic changes, especially droughts, that has largely influenced Ghana's recent shift from hydro to thermal power generation [32].

With the shift to thermal power generation, Ghana is expected to experience relative stability/reliability in its electricity supply. However, Ghana's thermal power plants – which mostly operate on natural gas – are also faced with several challenges. Even though Ghana is a natural gas producer, it also relies on natural gas imported from Nigeria through the West African Gas Pipeline (WAGP). Challenges including inadequate supply, planned and unplanned supply interruptions as well as non-payment of bills have regularly hindered the continuous and reliable access to natural gas from the WAGP and local suppliers [3] [40]. This affects the operations of the thermal power plants, leaving some of them redundant, operating below capacity or having to rely on more expensive liquid fuels [40] [24]. This further complicates the electricity supply situation in Ghana and sometimes results into electricity supply shortfalls.

3. REVIEWING POWER OUTAGE EXPERIENCES AND RESEARCH IN AFRICA

3.1. Overview of power outage experiences in Africa

In Africa, power outages are known to occur frequently in several countries. In studying power outages in Africa, researchers have often used the sectoral approach to document outage experiences across different sectors. Most existing research on power outage exposure, impacts and resilience on the continent focuses on the economic sector. Analysis of data from the World Bank enterprise surveys shows that between 2010 and 2017, about 78% of business firms in sub-Saharan Africa reported experiencing power outages with the percentages being highest in Central and West Africa and lowest in North and Southern Africa. Firms in Central and West Africa regions, reported experiencing more power outages in a month as compared to the other regions (see **Figure 12**).

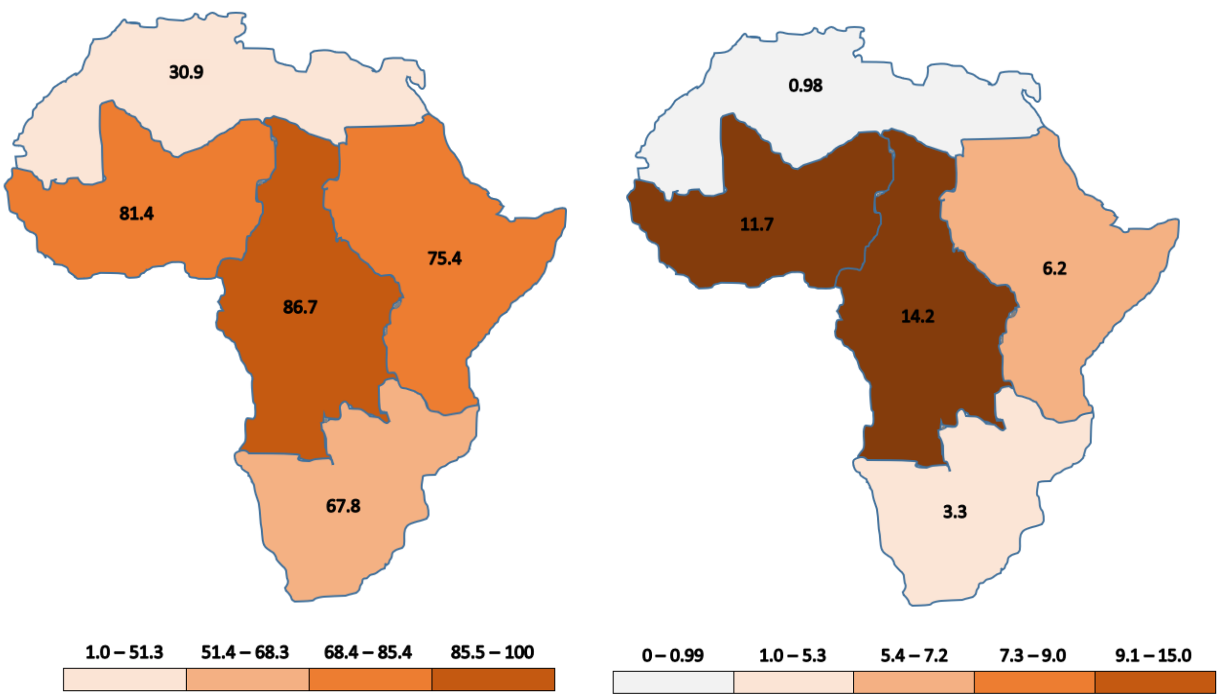


Figure 12: Percentage of firms experiencing power outages (left), and average number of outages experienced by firms in a month (right)

Frequent exposure to power outages in African business firms is also evidenced by their impacts on firm sales and high ownership/use of backup generators. Most firms reported a loss of at least 5% of their sales due to power outages, with firms in Central Africa reporting the highest sales loss of 11%. Furthermore, over 50% of business firms in East, Central and West Africa regions reported owning or sharing a generator (see **Figure 13**). Considering that the capital and operating costs of generators are high, high ownership/use of generators by African firms points to the extreme measures to which firms are willing to go avoid the impacts of frequent power outages. Firms which cannot afford to use generators are often forced to operate for fewer hours, change production time, or change production processes/products [41].

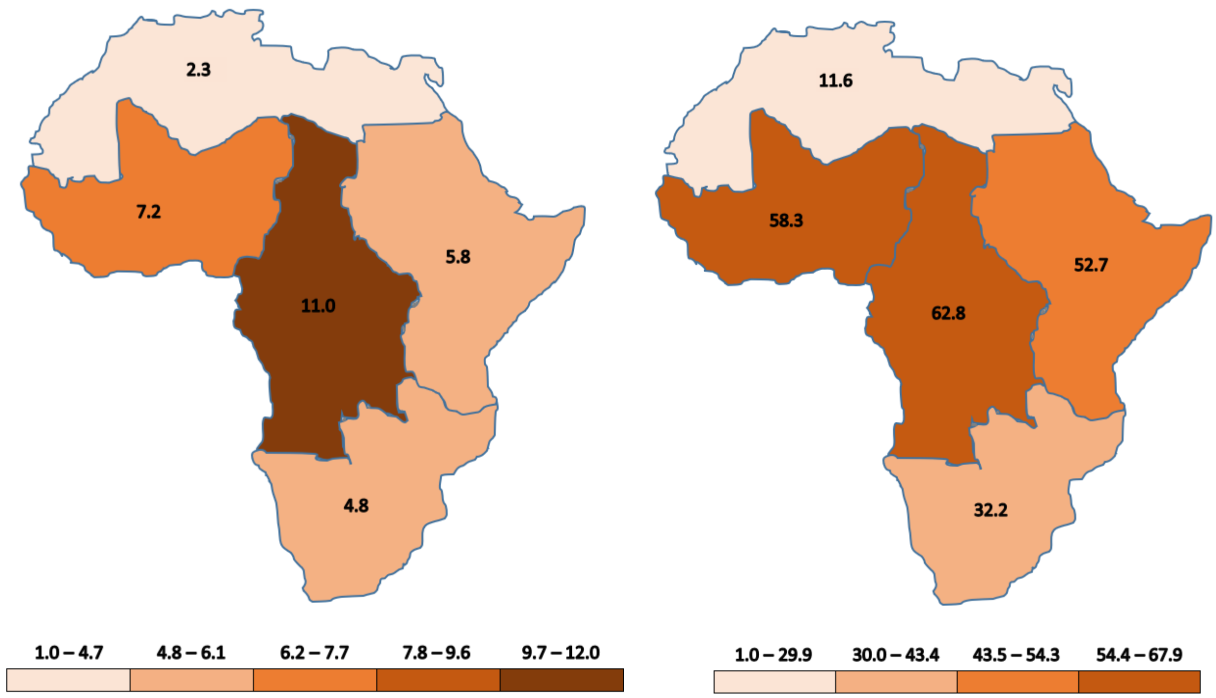


Figure 13: Percentage loss of sales by firms due to outages (left), and percentage of firms owning/using a generator (right)

Apart from the economic sector, residential electricity consumers in Africa are also frequently exposed to power outages. A 2016 report by Afrobarometer shows that 31% of grid-connected households in Africa experience unreliable power supply – one that doesn't work most or all of the time. As shown in ***Table 5***, household power supply unreliability situation in Africa varies greatly across countries, whereby countries in North Africa such as Algeria and Egypt – which traditionally have high electricity access rates – have high electricity reliability (few electricity outage experiences). Several countries in West Africa including Guinea and Nigeria, have some of the lowest electricity reliability rates (most electricity outage occurrences) in Africa. In Ghana, only 42% of the grid-connected households reported having reliable power supply and erratic electricity supply was identified among the top five problems affecting the country in 2016 [42].

Country	Electricity access rate (%)	Level of electricity supply reliability in households (%)
Algeria	>99	89
Egypt	>99	89
South Africa	95	81
Senegal	69	80
Kenya	75	77
Mozambique	29	61
Zambia	37	58
Tanzania	37	54
Ghana	84	42
Uganda	23	36
Nigeria	60	18
Guinea	27	12

Table 5: Electricity access and reliability rates in select African countries *[23] [42]*

3.2. Distribution of outages in urban communities

In Africa, including Ghana, experiences with power outages are often most pronounced among urban dwellers since cities often have high electricity access and consumption rates being driven by high population, emergency of small and medium enterprises, shift to more electricity-intensive sectors and high energy-consuming buildings [22]. But even within a city, electricity (un)reliability can significantly vary from one locality to another. Several studies have examined the distribution of electricity outages within cities/communities, albeit mostly in developed nations. Some of these studies have also identified the factors that influence the distribution of power outages across small communities within a city [10] [11]. For example, during times of limited electricity supply, high priority facilities such as hospitals may continue to receive uninterrupted power due to the criticality of the services that they provide [11]. This may indirectly benefit local communities within the vicinity of such critical facilities. Sometimes, areas with industrial and large commercial establishments also maintain a continuous supply of electricity (even during times of shortages) due their perceived importance to the national economy [43]. Additionally, in the case of Ghana, the distribution of electricity during the recent power crisis was said to have had political and wealth leanings. A study by Min [27] showed that improvements in electricity service quality after the recent power crisis were more noticeable in communities with high support for the ruling elite. Aidoo and Briggs [4] also found a relationship between duration of outages and wealth in Accra, Ghana, where residents in ‘poor communities’ were more likely to experience longer power outages than those in ‘wealthier ones.’

3.3. Impacts of power outages in Africa

Frequent and prolonged electricity outages have significant negative consequences in the affected countries. The impacts cut across the social, economic and environmental aspects of society [22] [38]. Across several African countries, power outages have been found to have a substantial drag effect on economic growth [12]. Power outages are negatively correlated with the performance of firms, measured as firm sales [13], firm productivity [44] and also cause significant monetary losses related to equipment damage and damage to raw materials [45]. Power outages also have negative implications for social and sustainability issues such as health, employment, education, population growth and poverty eradication. The use of back-up diesel generators to mitigate power outage impacts often drives up consumer expenditure on electricity and also reduces air quality due to increased local emissions [46]. Power outages also discourage entrepreneurship and reduce demand for labor thereby limiting the chances of finding employment [47]. In Ghana, up to US$ 3 billion of economic activity and thousands of jobs are reported to have been lost during the recent electricity crisis [48]. These outages were also linked to increased tax evasion by firms [49] and non-payment of utility bills by household-level consumers [50]. Outage-induced increased risk of in-facility mortality has also been reported especially for healthcare facilities situated in Ghana's urban centers [51]. *Dumsor*-themed public demonstrations were also held in the leading cities of Accra and Kumasi to protest the government's failure to deal with the power crisis [52].

3.3.1. Outage impacts in households

As explained above, most of the studies on impacts of power outages in Africa have analysed the economic aspects, especially for business firms and the economy. On the other hand, outages also have significant negative economic effects on households. There are some studies, particularly in developed countries, which have examined the economic (monetary) value of outage impacts within households. By quantifying measures such as value of lost load (VoLL) [53] [54] [55], willingness to pay (WTP) and willingness to accept (WTA) [56], these studies have shown that the economic impact of outages in households is substantial and in some instances may exceed that of business enterprises [57]. However, quantifying the economic value of home-based, non-material benefits of electricity such as welfare, leisure, comfort and general social wellbeing is a difficult and subjective task since the real economic value of such intangible benefits is not well known and can vary greatly. To avoid any potential bias from subjective approaches, more direct economic measures of impacts of outages on households have sometimes been used. For example, power outages have been shown to have a direct impact on household earnings [41] [58]. In a study carried out in India, access to electricity was found to confer a 9.6% increase in household income while access to reliable electricity (with fewer outages) was associated with a higher income increase of 17% [59]. This can be attributed to the fact that the benefits which accrue from access to electricity such as increased opportunities for home production, extended time for business operations, and electricity-induced job creation may be eroded if the electricity supply is unreliable. Another direct economic measure of outage impacts on households is outage-related expenditure. Sometimes, household expenditure on outage coping/adaptation measures (e.g., purchasing and operating backup electricity supply system) may be high and exceed regular expenditure on electricity. This can also impact negatively on the overall economic situation of the household.

Disruption in electricity supply can also have a negative effect on the delivery of critical social services to households and communities. Vital infrastructures such as water supply systems, hospitals, education institutions and telecommunication systems all require a reliable electricity supply to operate optimally. Power outages have been shown to hinder the provision and access to quality health services in several countries including India and Ghana [15] [51]. Power outages may render medical devices unusable, and compromise the quality of life-saving medicines such as vaccines. Electricity access is also positively associated with education attainment including reduction in illiteracy levels and increasing years of schooling [60]. With household access to electricity, more school-going children participate in academic activities including school enrolment and attendance, use of enhanced-learning gadgets and personal study at home [61]. But if the electricity supply is unreliable, it may lead to the deterioration of the learning environment by limiting opportunities for learning. For example, because of power outages, electrically-powered learning aids may not be used in class and personal study time may be reduced considerably. This has a consequence of compromising the delivery of quality education, and affects the morale and academic performance of students [62]. Extended power interruptions can also disrupt the supply of water to households since all the aspects of a modern water supply system (extraction, treatment, transmission and distribution) require electricity. In highly populated areas, including many cities in developing countries, loss of water supply may have attendant negative consequences for public health including high risk for disease outbreaks such as cholera. Communication services (phones, radios, televisions) are also disrupted by outages, complicating access to information and home-based leisure activities. Outages can also accelerate food spoilage/losses in homes by impeding refrigerated storage [63].

In addition, power outages have been associated with increased crime [22]. In 1977, a blackout which lasted for 25 hours, set off a "crime rampage" in the city of New York with shops being looted, properties vandalized and stores set on fire. The resulting havoc also left two people dead and many law enforcement personnel injured [63]. While this may be considered as one example of an extreme case, power outages in both developed and developing countries are still associated with increased criminal activity. The safety risks associated with power outages include physical assault, robbery/looting and burglary (house break-in). During the recent emergency power outages in the state of California, USA, there were reports of burglary in some areas even after local police had imposed a curfew [64]. Incidences of burglary, theft and exploitation during power outages have also been reported in Brazil, Chile, and South Africa [65]. In Ghana, there was heightened public concern about the increased threat of physical assault, house break-in and theft during the recent electricity supply crisis [38] [62]. Indeed, the sustained power outages prompted Ghana National Police to announce measures to curtail a potential rise in crime [66]. Besides, personal safety concerns related with power outages are not limited to criminal activity. Erratic power supply is also said to be among the leading causes of fire outbreaks in Ghana [22] [67]. These fires which mostly occur within households have been attributed to the use of unsafe alternative energy sources (e.g., open fires) during outages as well as high voltage surges when power is reconnected.

Frequent power outages are also said to be responsible for direct damage to electrical appliances including refrigerators, television sets and other appliances [69]. Moreover, the lack of reliable electricity also renders electrical appliances redundant and unable to fulfil their intended purpose. For example, due to outages, refrigerators cannot consistently offer cold storage for food stuffs which accelerates food spoilage/losses in homes [63].

3.3.2. Determinants of outage impacts in households

In developing countries such as Ghana, electricity is mainly used in households to power appliances including refrigerators, lighting systems, television, ceiling fan and iron. These offer important services to support food preparation and preservation, home-based academic activities, safety and security, communication and access to information, as well as air conditioning, comfort and leisure. In some cases, electricity is used to provide medical services in homes, operate lifts to ease movement, and to charge of electric vehicles. When power outages occur, all these services can be disrupted. The impacts that result from loss of electricity supply will therefore differ for individual households depending on their electricity needs (uses), capacities and preferences [53]. Higher electricity-consuming households are most likely to suffer a greater cost/impact from power outages than less electricity-consuming households [68]. Households which use electricity for critical/specialized purposes such as powering medical devices used for providing home-based healthcare services may suffer even greater outage impact.

There are several studies in literature that have attempted to examine the impact of electricity supply disruptions/power outages in the residential sector [69]. Most of these existing studies employ the stated preference approaches (contingent evaluation or choice experiment) to estimate the willingness to pay (WTP) for improved electricity supply (that is, to avoid power outages) or willingness to accept (WTA) an outage (or compensation) and forego the benefits of uninterrupted electricity supply [70] [71] [72] [73]. WTP and WTA analyses show the value that is placed on electricity in households and, therefore, indirectly indicate the potential impact that households suffer whenever electricity supply is disrupted. Respondents or households that have a higher willingness to pay (or are more willing to pay) for improved electricity reliability (to avoid outages) attach more value to electricity and are likely more impacted by power outages. The reverse is also true.

In the residential sector, several respondent/household characteristics have been shown to be associated with outage impacts, measured as WTP or WTA. These include age, gender, marital status, education, employment, income, home ownership, family size and outage duration among others. Respondent's age has been associated with loss (impact) arising from very frequent outages, with older people being less likely to suffer loss of utility (possibly because they are more experienced at coping) as compared to younger people [71]. Older persons, and the unemployed have been found to be less willing to pay for improved electricity reliability while larger households were more willing to pay for improved electricity reliability than others [74]. A study of Italian households identified education as a significant determinant of willingness to accept an outage, whereby more educated people – who have a high school diploma or more – are less willing to accept an outage than less educated ones [75]. A study in Kenya found that the gender of a household head has a negative and significant relationship with WTP for improved electricity reliability, with female-headed households having lower WTP values than male-headed households [76]. In South Korea, the level of income showed a significant association with WTP, whereby high-income households are more likely to be willing to pay to avoid the "inconvenience cost" of outages when compared to low-income households [77].

Similarly, studies carried out in Ghana have identified significant relationships between WTP for improved electricity services and several household-level factors, including gender, marital status, household size, monthly income, level of education and outage duration. In the Greater Accra Region of Ghana, males/male-headed households have been found to have significantly higher willingness to pay for improved electricity reliability than females/female-headed households. Household size is also positive and significantly associated, whereby large households have a higher probability of paying more for improved electricity services than small-sized households [78] [79]. In studies conducted in both the Greater Accra Region and the Cape Coast Metropolitan Area in Ghana, being married was positive and significantly associated with WTP for improved electricity reliability. Income is also positive and significantly related to WTP, whereby high-income households have a higher probability of paying more for improved electricity services than low-income households. Level of education of the household head was also shown to be significantly related with WTP whereby respondents with a higher level of education are more likely to pay for improved electricity reliability as compared to less educated ones. Duration of previous outages was also found to be positively and significantly associated with willingness to pay for improved electricity reliability while trust in the government has a negative and statistically significant relationship with WTP [79] [73]. However, there are other studies which have found that age, house ownership and monthly electricity expenditure do not have a significant relationship with WTP to avoid power disruptions [73]. This, therefore, indicates a lack of consensus on which factors are associated with household-level power outage impacts as one moves from one study context to another. This further cements the need to study power outage impacts and their drivers, specific to Accra's highly urbanized communities, which may offer different insights from those obtained for the larger Greater Accra Region or the entire country of Ghana.

4. RESEARCH METHODOLOGY

4.1. Study area

General description: Accra Metropolis, also known as, Accra Metropolitan Area (AMA) or simply, Accra is one of the districts in the Greater Accra Region and is located in southern Ghana along the Atlantic coastline. **Figure 14** below shows the map and location of Accra in Ghana. Accra has a total surface area of approximately 200 km^2. It is one of the fast-growing cities in Africa [80]. In 2010, Accra Metropolis had a population of 1,665,086 people but the population was projected to be in excess of 2 million people in 2020 [81]. Most of the ongoing population growth in Accra is driven by migrants coming from other parts of the country. Many of the new migrants live in informal unplanned settlements or slums [80].

Economy: Accra is the socioeconomic and political capital of Ghana. Households in Accra have an estimated mean annual income of GH¢ 63,027 while the mean annual per capita income is GH¢ 23,532. This is much higher than the national average. However, despite the high mean per capita income, about 24.2% of the people who are unemployed in Ghana live in the Accra area [82]. Of those who are employed in Accra, 90.3% are employed in the private sector and 23.8% are involved in the informal sector. 56.4% of households in Accra operate a business.

Access to social services: Accra has the highest level of access to social services in Ghana. 82.2% of all households in greater Accra have access to piped water for general use while 79.5% use sachet water, which is considered safe water for drinking. With 96.5% of households connected to the national electric power grid, Accra also has the highest electrification rate in Ghana. Gas (51.2%) and charcoal (39.5%) are the main fuels used for cooking in Accra households. 65.4% of the households in Accra have access to rubbish (solid waste) collection services while 36% use water closet (WC) toilets [82].

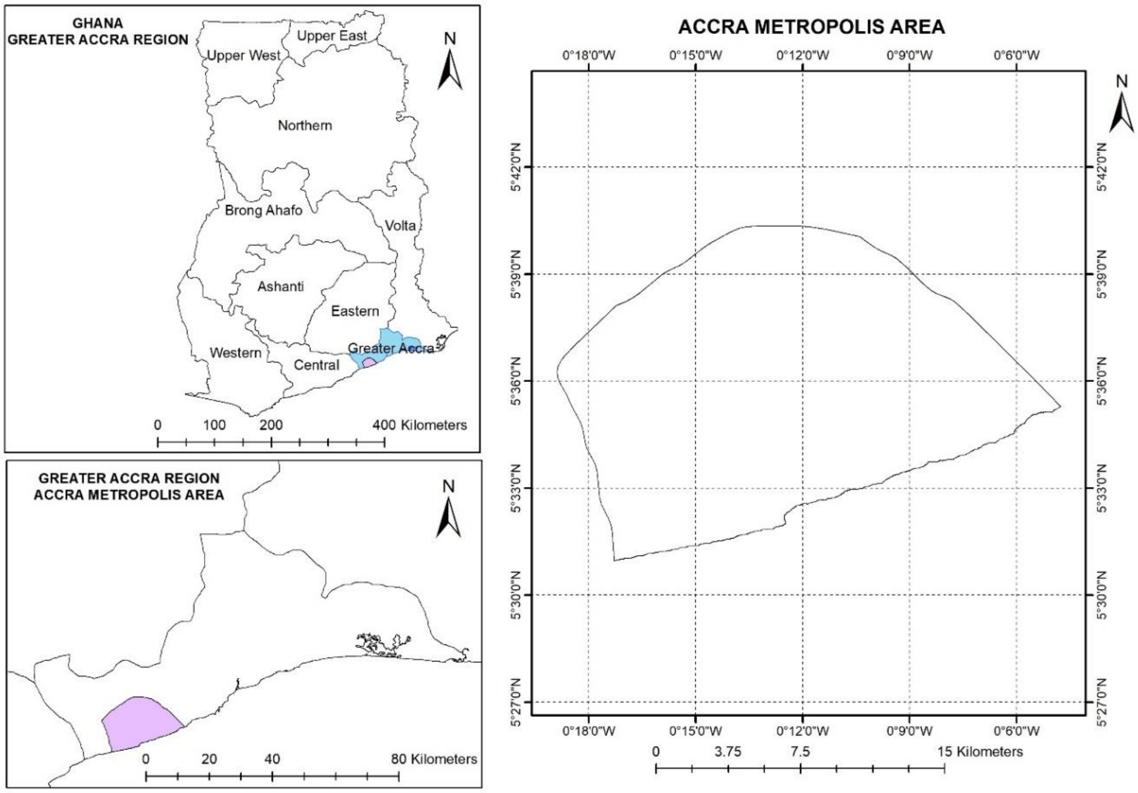


Figure 14: Map of Ghana showing Accra Metropolis

4.2. Data and data sources

4.2.1. Technical and statistical data

Together with the neighborhood map, this study utilized several datasets, including: electricity network (feeder) drawing, electricity outage statistics, and socio-demographic data. Socio-demographic data, particularly census data, was obtained from Ghana Statistical Services (GSS) and Engstrom et al. [83]. Extra primary data was also collected through a household survey. The electricity network drawing (in AutoCAD format) was obtained from the electricity utility company together with the electricity outage statistics. The electricity network drawing was first converted into shapefile format in ArcGIS and georeferenced. Only the 11 kV feeder network was used in this study because electricity load shedding was mostly carried out at the 11 kV feeder level. The electricity outage statistics obtained from the electricity utility company consist of information about different outage types, including planned, unplanned, national load shedding and emergency outages. For most outage segments, information about the start date and time of the outage, end date and time of the outage, the duration of outage, the name and voltage of the affected 11 kV feeder, and the number of affected customers was recorded. For this study, the national load shedding statistics recorded over the year 2015 were used. The 2015 load shedding statistics are one of the most comprehensive outage statistics collected by the utility in the study area. Over 10,000 load shedding segments were recorded in that year at the peak of an acute electricity supply crisis. This represented about 70% of the total outages reported within the utility service area over a four-year period, 2013–2016.

4.2.2. Survey data

In order to select households for the survey, the study employed a systematic random sampling approach similar to what was used by [84]. Survey questionnaires were administered to household respondents from September to November 2018. The questionnaire included questions necessary to identify household socioeconomic, demographic and electricity usage/outage characteristics including but not limited to age and marital status of the respondent, occupancy status, number of rooms and number of household occupants, household income, employment status and level of education of the respondent, uses of electricity within the household, household expenditure on electricity, experiences with electricity outages (frequency and duration). In addition, questions related to household-level outage impacts and coping measures/choices, access to outage-related information and natural resources were also included.

The questionnaires were administered with the help of research assistants from the CSIR-STEPRI under the supervision of the researcher. The research assistants were first trained on the questionnaire for two days and one community trial run of the questionnaire was also conducted with them. The survey questions were administered by the assistants through face-to-face interviews with the household respondents. The questionnaire was paper-based and written in the English language. In some cases, the research assistants would orally translate the questions to one of the local languages (especially Ga and Twi) for respondents who did not understand the English language. The survey interviews were mostly administered in the evening hours when most people in Accra have returned to their homes. The questionnaires were administered to household heads or any other adult persons who could answer on behalf of the households. The survey targeted at least twelve households in each neighborhood, bringing the total number of surveyed households to 564. **Figure 15** is a summary of all the datasets used in this research.

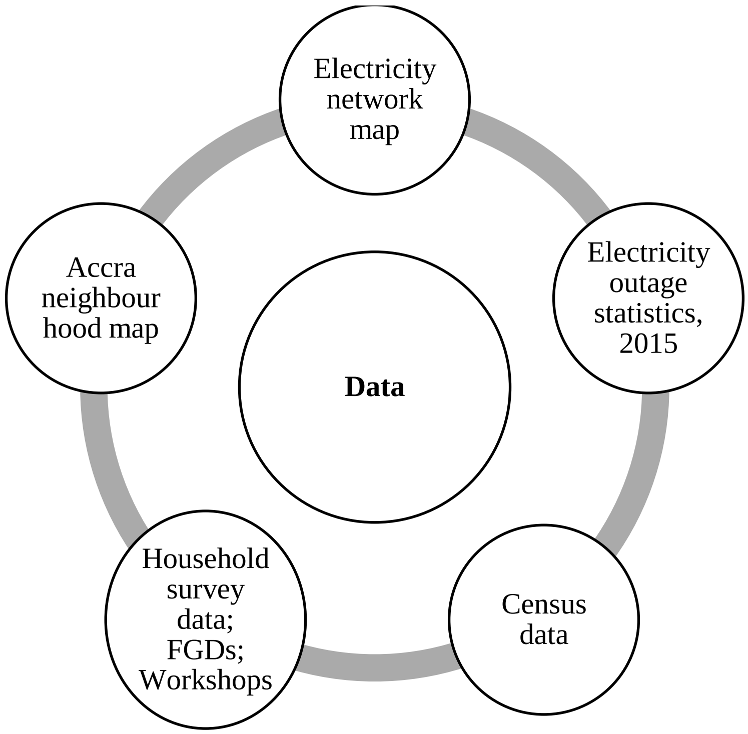


Figure 15: Summary of datasets used

4.3. Measures

4.3.1. Units of analysis

To assess community exposure to power outages, this study uses a neighborhood as the spatial unit of analysis. The Accra metropolitan area is divided into several sub-metropolitan areas, including: Okaikoi, Ashiedu Keteke, Ayawaso, Kpeshie, Osu Klotey and Ablekuma. Within the sub-metropolitan areas, there are several smaller communities whose informal boundaries mainly follow natural barriers, such as roads and drainage channels. These communities are herein referred to as neighborhoods. A neighborhood has been defined as "a geographic unit of limited size, with relative homogeneity in housing and population, as well as some level of social interaction and symbolic significance to residents" [83]. This definition presents a neighborhood both as a social entity—with similar characteristics and a sense of cohesion—and as a physical/geographical area of known boundaries. The boundaries of the Accra neighborhoods have been delineated in the Accra neighborhood map. The map was developed by first georeferencing a local tourist map—containing local vernacular names of the communities—onto an enumeration area map. Each enumeration area (EA) was then 'dissolved' into an associated neighborhood such that no EA was shared by two neighborhoods. The resultant neighborhood map was validated by local residents as well as by public officials [83].

For this research, the study area covers 47 neighborhoods in the western part of the Accra metropolitan area as shown in **Figure 16**. The neighborhoods were selected because they are served by a single electricity utility branch, which availed relevant data useful to the study. The selected neighborhoods cover 31% of the total area of Accra metropolis but are home to about 56% of the city's total population. The average population density of the neighborhoods is 19,930 people per square kilometer. The average size of the selected neighborhoods is 1.48 km^2, ranging from 0.26–5.12 km^2 and a standard deviation of 0.95. The average population in the neighborhoods is 24,505 people, ranging from 2,050–58,120 people. Dansoman estate is the neighborhood with the largest population and surface area, covering about 7% of the total area of the selected neighborhoods. Awudome estate is the neighborhood with the least population and surface area. At 65,838 people per square kilometer, Sabon Zongo has the highest population density among all the selected neighborhoods, while Victoriaborg has the lowest population density [83].

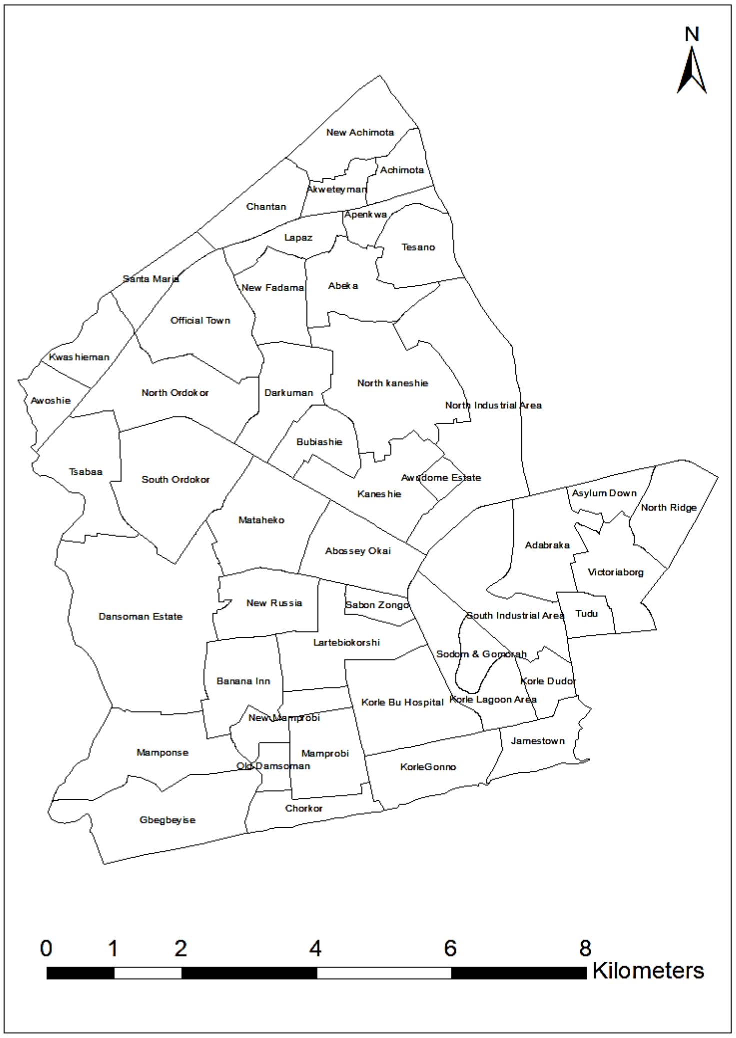


Figure 16: Map of the study area showing neighborhoods

Households: This study also uses a household as a unit of analysis for analyzing outage impacts and coping mechanisms. A household is considered the smallest unit of society from which most of the common socioeconomic and demographic characteristics of a society are measured [82]. Also, as already indicated, households are some of the main centers of electricity consumption in Ghana. They are, therefore, significantly impacted whenever power outages occur. Understanding how and why households in Accra are impacted by outages and the mechanisms used to cope with the outages can provide important information for building an outage-resilient society.

4.3.2. Dependent variables

In this research, several dependent variables are used to answer different research questions. Load shedding exposure is the dependent variable used to assess drivers of outage distribution in Accra communities. To analyze impacts of outages on households and their drivers, outage impacts are the dependent variables. In the survey questionnaire, household respondents were asked to indicate whether or not they had suffered a particular impact from a list of twenty-one possible outage impacts identified through literature review. Therefore, the respondents' outage impact responses were binary in nature (yes or no answers). Selected outage impacts (impacts identified by at least ten percent of the respondents) were then considered for further statistical analysis using correlation and regression approaches. The coding of the selected outage impacts was done as shown in ***Table 6***.

Dependent variable	Description of dependent variable	Response (code)
Y1	Increased instances of or concern about physical assault/injury	Yes (1), No (0)
Y2	Increased instances of or concern about burglary or house break-in	Yes (1), No (0)
Y3	Increased instances of or concern about disruption in water supply	Yes (1), No (0)
Y4	Increased instances of or concern about disruption in communication services	Yes (1), No (0)
Y5	Increased instances of or concern about disruption of academic activities	Yes (1), No (0)
Y6	Increased instances of or concern about reduction in household earnings	Yes (1), No (0)
Y7	Increased instances of or concern about high expenditure on alternative energy sources	Yes (1), No (0)

Table 6: Select impacts of outages in Accra households

4.3.3. Independent variables

For purposes of examining drivers of outage exposure in communities, a number of socioeconomic factors were considered as potential explanatory variables. Housing Quality Indicator (HQI) and percent of vegetation cover were used as proxies for neighborhood wealth/socioeconomic status. In Ghana, vegetation cover has been associated with level of income, where high income neighborhoods are said to have high percent of vegetation cover while low-income areas tend to have a low percent of vegetation cover [85] [86]. The neighborhood demographic characteristics are represented by household density and percent of minority groups. Other factors considered in the analysis are shown in ***Table 7***. All variables used were numerical in nature.

Measure	Indicator variable	Units
Wealth/ Socio-economic status	Housing Quality Indicator (HQI)	-
Traditional energy use	Level of charcoal use	%
Public or environmental health rating	Level of use of modern sewerage services	%
Wealth/Socio-economic status	Percent of vegetation cover	%
Demographics	Household density	Number of households/km^2
Access to social services	Access to piped water	%
Public or environmental health	Use of formal rubbish collection services	%
Minorities	Percentage of minorities	%

Table 7: Potential explanatory variables associated with outage distribution in Accra neighborhoods

The potential explanatory variables considered in modelling drivers of outage impacts and coping measures in Accra households can be categorized into demographic factors (age, sex, marital status); housing characteristics (family occupancy, home ownership, number of occupants); socioeconomic characteristics (annual income, level of education, employment status); and electricity outage characteristics (outage frequency, outage duration). These variables were identified through literature review as presented in section 3.3.2. The potential explanatory variables were treated as binary categorical variables and coded (see ***Table 22***).

4.4. Analytical strategy

The analytical steps followed in this research are described under this section. **Figure 17** shows a summary of the analytical strategy.

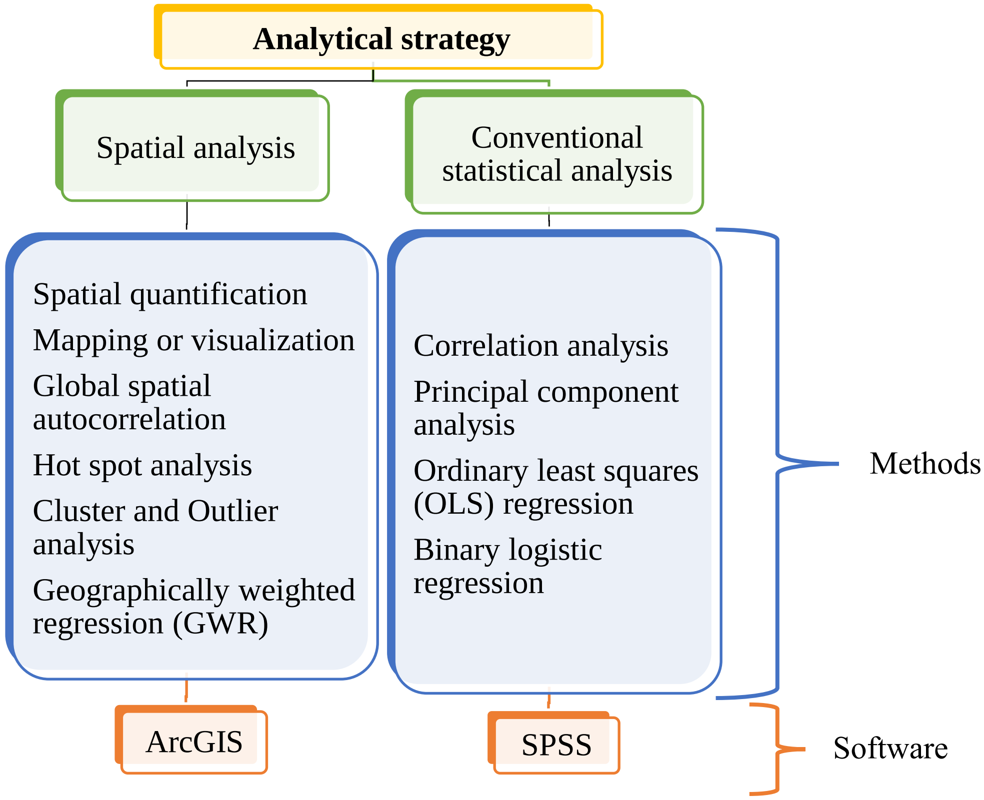
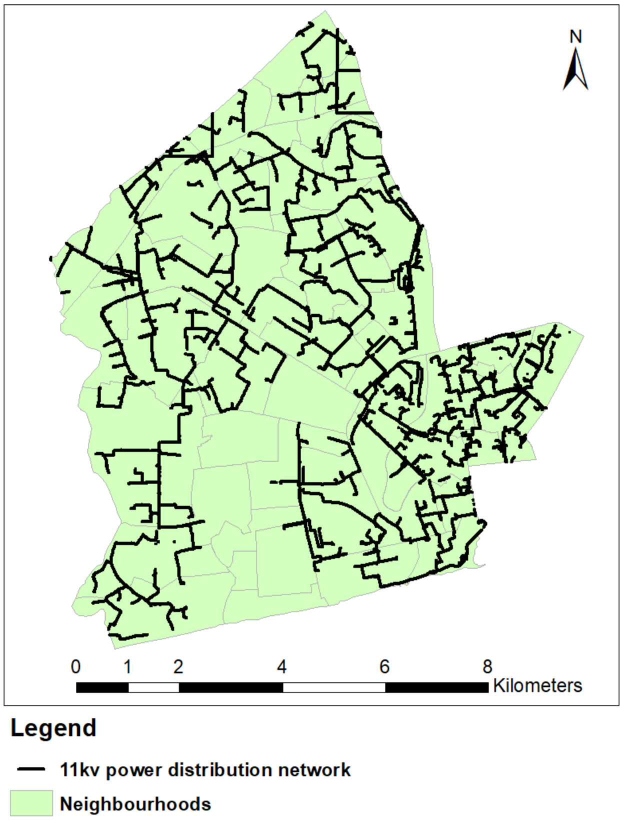


Figure 17: Summary of the analytical strategy

4.4.1. Spatial quantification

4.4.1.1. Mapping Neighborhood Load Shedding Outage Experiences

In order to assess the load shedding experience of each neighborhood, the georeferenced 11 kV electricity network drawing was overlaid onto the neighborhood map within ArcGIS Desktop software (Release 10.5.1, ESRI, Redlands, CA, USA) as shown in **Figure 18**. Each neighborhood in the study area was associated with one or more 11 kV electricity network feeders that intersected it. A feeder that crosses a neighborhood potentially supplies electricity to that neighborhood and therefore contributes to its load shedding experience. However, it is also possible that a feeder might pass through a neighborhood without necessarily supplying electricity to it (going to another place). Therefore, in determining whether a feeder contributed to the load shedding experience of any given neighborhood, we only considered feeders that were connected to 11 kV stepdown distribution transformers located in that neighborhood (see **Figure 18**). Knowing which feeder(s) supply electricity to a neighborhood is essential for accurately tagging load shedding outage statistics to corresponding neighborhoods.



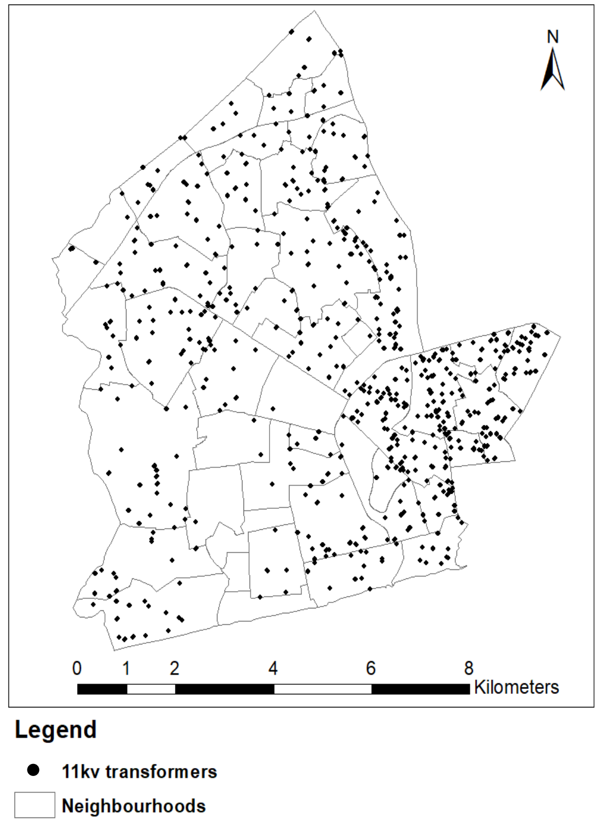


Figure 18: Map of neighborhoods overlaid with an 11 kV power distribution network (left), and 11 kV distribution transformers (right)

From **Figure 18** above, it can be seen that some neighborhoods were not intersected by any 11 kV electricity feeder. A case in point is Chorkor and Old Dansoman in the south of the study area. This—according to utility officials—was a case of missing data and did not imply that those particular neighborhoods are not supplied by an 11 kV electricity network. This was also verified by the researcher who physically visited the neighborhoods and found that there was a functional electricity distribution network. During the validation process of the overlaid network map, the electricity feeders that serve these neighborhoods were identified basing on the knowledge of technical personnel from the electricity utility company. As such, all the neighborhoods are included in the subsequent calculations and analyses.

4.4.1.2. Calculating Neighbourhood Load Shedding Exposure and Normalization

In order to determine load shedding experiences across the neighborhoods in the study area, a variable called load shedding exposure (also known as outage exposure), was used. Load shedding exposure is defined here as the cumulative number of load shedding outage hours (or minutes) experienced on any single electricity feeder serving a given neighborhood in the study area. The load-shedding exposure variable is a standardized variable and is therefore suitable for avoiding potential bias of comparing total neighborhood outage hours—since neighborhoods are served by a different number of electricity feeders. Load shedding exposure, LS_e, for each neighborhood was calculated according to the following equation:

$$LS_e = LS_f \times LS_d, \qquad (1)$$

where LS_f is the average load shedding frequency; LS_d is the average load shedding duration.

Average load shedding frequency, LS_f, refers to the number of times that a single electricity feeder serving a given neighborhood was under load shedding (experienced load shedding outages). Average load shedding duration, LS_d, is the average length of time that a single load shedding outage, experienced on a single feeder serving a given neighborhood, lasted. LS_f and LS_d are calculated according to the following equations.

$$LS_f = \frac{T_f}{N}, \qquad (2)$$

$$LS_d = \frac{T_d}{T_f}, \qquad (3)$$

where T_f is the total number of load shedding outages experienced on all feeders serving a neighborhood, T_d is the sum of the duration of all load shedding outages experienced in a neighborhood, and N is the total number of electricity feeders serving the neighborhood.

The load-shedding exposure values obtained using Equation (1) show which neighborhood is exposed to more (or less) load shedding hours than others. But the load-shedding exposure variable does not tell the external factors that often influence the observed load shedding distribution patterns. Electricity distribution decisions especially under conditions of limited supply can be influenced by societal factors such as socio-economic, demographic and political factors [4] [27]. In order to fully understand load shedding distribution dynamics in Accra communities, these factors need to be taken into account. Through normalization, the load-shedding exposure values can be adjusted to integrate societal/community characteristics. Therefore, as a further step in exploring load shedding experiences in Accra communities, load-shedding exposure values were transformed using surface area, population and population density of the neighborhoods. A list of the variables involved in this step is given in ***Table 8***. Hereafter, we focus our attention on analyzing the spatial patterns of the four load-shedding exposure variables (LS_e, $LS_e/area$, $LS_e/population$, and $LS_e/population\ density$).

Variable	Unit of Measurement
Neighborhood surface area	km^2
Neighborhood population	number of people
Neighborhood population density	number of people per square kilometer
Load shedding exposure, LS_e	H
$LS_e/area$	h/km^2
$LS_e/population$	min/capita
$LS_e/population\ density$	$min/(capita/km^2)$

Table 8: Normalizing and transformed variables for assessing neighborhood load shedding experiences

4.4.2. Spatial Analysis

In this sub-section, a two-step spatial analytical process is presented. Firstly, visualization of the load-shedding exposure values and their transformations is undertaken within the Accra neighborhood map. Secondly, spatial statistical tools are utilized to assess for global and local patterns of spatial association in the load-shedding exposure variables.

4.4.2.1. Visualization

Data visualization is a useful way for easily identifying patterns in a given dataset. When visualization is done using a map, it helps to identify how certain attributes vary across space. In this study, the load-shedding exposure variable and its transformations are visualized in order to generate an initial picture of their spatial distribution in Accra neighborhoods. However, data visualization alone cannot be relied upon to make spatial inference [87]. As a step towards making complete spatial inference, this study further undertakes spatial statistics analysis of the visualized variables. In particular, the study examines the presence of significant global spatial autocorrelation, and the presence/location of hot/cold spots, clusters and outliers. The visualization and statistical analysis were carried out using ArcGIS Desktop software (Release 10.5.1, ESRI, Redlands, CA, USA).

4.4.2.2. Global index of Spatial Autocorrelation

Autocorrelation is the measure of the similarity of one value relative to other values surrounding it. In most traditional (nonspatial) statistical analysis, autocorrelation in a dataset is undesirable because it violates the principle of independence/stationarity of data. However, in spatial analysis, significant spatial autocorrelation points to the presence of spatial structuring in a dataset, and is a basic indicator that some underlying spatial processes could be influencing the patterns, thus necessitating further examination. In this study, the global Moran's I statistic is used to evaluate the global spatial autocorrelation (GSA) of load-shedding exposure. Moran's I statistic is related to the Pearson's Correlation Coefficient [88] and is represented by the following equation [89]:

$$\mathrm{I} = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (4)$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \overline{X})$; $w_{i,j}$ is the spatial weight between feature i and j; n is the total number of features; and S_O is the aggregate of all the spatial weights:

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \quad (5)$$

The z_{I}-score for Moran's I statistic is calculated as:

$$z_{\mathrm{I}} = \frac{\mathrm{I} - E[\mathrm{I}]}{\sqrt{V[\mathrm{I}]}}, \quad (6)$$

$$\text{where: } E[\mathrm{I}] = -1/(n-1), \text{ and} \quad (7)$$

$$V[\mathrm{I}] = E[\mathrm{I}^2] - E[\mathrm{I}]^2 \quad (8)$$

From the analysis, a positive and statistically significant Moran's I (z-score > 1.65, p-value < 0.10) indicates spatial clustering in a dataset while a negative and statistically significant Moran's I (z-score <-1.65, p-value < 0.10) indicates spatial dispersion. A positive or negative Moran's I value that is not statistically significant (z-score between -1.65 and 1.65, p-value > 0.10) implies spatial randomness [89]. While global Moran's I statistic is important for examining the presence of spatial patterns within a dataset, it does not tell specifically where the patterning occurs. To investigate the locations of spatial patterns in the load-shedding exposure variables, local indicators of spatial association were used.

4.4.2.3. Local Indicators of Spatial Autocorrelation

Local indicators of spatial association (LISA) are important for pinpointing the locations of spatial hot spots, cold spots, clusters and outliers [88] [89]. The two most common local indicators, namely Getis-Ord G_i^* statistic and Anselin Local Moran's I statistic were used in this study.

Briefly, the Getis-Ord G_i^* statistic was used for identifying statistically significant hot spots and cold spots from a set of weighted features. The Getis-Ord G_i^* statistic is a *z*-score and is calculated according to Equation (9) [90]. Features with high/low values can only be hot/cold spots if they are surrounded by other features with similarly high/low values in a statistically significant way. For a given set of features and variables, the G_i^* statistic tool generates a set of *z*-scores and *p*-values for each feature. The limits of the *z*-scores and *p*-values necessary for identifying statistically significant hot/cold spots are described in ***Table 9***.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}, \tag{9}$$

where x_j is the attribute value for feature j; $w_{i,j}$ is the spatial weight between feature i and j; $\bar{X}$ is the mean of the corresponding attribute; S is the standard deviation of the corresponding attribute; and n is the total number of features.

z*-score		***p*-value****	**Meaning**
Hot Spot	**Cold Spot**		
>2.58	<−2.58	0.01	Statistically significant hot/cold spot at 99% confidence level
1.96 to 2.58	−2.58 to −1.96	0.05	Statistically significant hot/cold spot at 95% confidence level
1.65 to 1.96	−1.96 to −1.65	0.1	Statistically significant hot/cold spot at 90% confidence level

Table 9: Hot/cold spot classification

* z-scores are standard deviations. Positive and negative z-scores correspond to hot spots and cold spots respectively. ** p-values are probabilities.

Anselin Local Moran's I statistic is used to identify spatial clusters and outliers among the features and their corresponding variables. Akin to hot/cold spots, clusters are neighborhoods that are surrounded by other neighborhoods with similarly high or low load-shedding exposure values. Outliers are neighborhoods that are surrounded by other neighborhoods with dissimilar load-shedding exposure values. The possible combinations of cluster/outlier neighborhoods are given in ***Table 10***. The calculation for Anselin Local Moran's I statistic is based on the following Equation 10 [91]:

$$\mathrm{I}_i = \frac{x_i - \bar{X}}{S^2} \sum_{j=1, j \neq i}^{n} w_{i,j}\left(x_j - \bar{X}\right), \tag{10}$$

where x_i is an attribute for feature i; $\bar{X}$ is the mean of the corresponding attribute; S is the standard deviation of the corresponding attribute; and $w_{i,j}$ is the spatial weight between the feature i and j.

Cluster/Outlier Type	**Explanation**
High-High Cluster	Statistically significant* cluster with surrounding neighborhoods having similarly high outage values
High-Low Outlier	Statistically significant* spatial outlier with a high load-shedding exposure value surrounded primarily by neighborhoods with low load-shedding exposure values
Low-High Outlier	Statistically significant* spatial outlier with a low load-shedding exposure value surrounded primarily by neighborhoods with high load-shedding exposure values
Low-Low Cluster	Statistically significant* cluster with surrounding neighborhoods having similarly low outage values

Table 10: Cluster and outlier classification

* Statistical significance is interpreted from the z-scores and pseudo p-values which are calculated together with the Local Moran's I statistic.

4.4.2.4. Conceptualization of Spatial Relationships

To better analyze the spatial associations amongst the load shedding exposure variables, it is necessary to first conceptualize how the neighborhoods interact within space. Various methodological options for defining spatial relationships among features exist within ArcGIS platform. Selecting an appropriate approach depends on the perceived spatial associations among the features under analysis. In this study, the polygon contiguity method, particularly the first-order contiguity edges and corners (Queen's case) spatial weights matrix was used. The Queen's case has been shown to better represent the spatial interaction of irregularly shaped and sized polygons than distance-based methods [92]. For this reason, it arguably represents better the interaction among Accra neighborhoods in the study. Subsequent to the use of the first-order queen's case, the study also utilizes the row standardization option—where applicable—to minimize bias due to effects of aggregation and sampling that could result in neighborhoods having different numbers of neighbors.

4.4.3. Correlation analysis: Pearson chi-square test

Correlation analysis is oftentimes the first approach used to examine the relationship between a pair of variables. Common correlation analysis methods such as Pearson correlation, Kendall rank correlation and Spearman correlation require that the data under analysis be quantitative (numerical) in nature. For categorical/non-numerical data, such as respondents' gender or marital status, crosstabulation of different variable response groups is done first before correlation analysis. Crosstabulation of variables helps to determine the frequency (and proportion) of responses for intersecting variable subcategories. From the crosstabs, a Chi-Square test is then carried out to determine whether or not there is a statistically significant association between any two categorical variables under analysis. In general, a Chi-Square test of association is based on the null hypothesis that there is no significant association between two categorical variables under consideration. In the case of a Pearson Chi-Square test, the analysis returns a Pearson Chi-Square statistic, X^2. Large values of X^2 together with small values of significance ($p < 0.05$) imply that the null hypothesis of no association can be rejected, indicating presence of significant association. The reverse is also true for small X^2 values and large p-values which support the null hypothesis. The Pearson Chi-square statistic is calculated according to Equation 11 below.

$$X^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}, \quad (11)$$

Where X^2 is the Pearson Chi-Square statistic; O_i is the observed frequency for cell i, E_i is the expected frequency for cell i, and n is the number of cells in the table.

In this study, the Pearson Chi-Square test was used first to examine the relationships between dependent and explanatory variables. In addition, the Chi-Square test was also used to test for existing associations between pairs of explanatory variables which could indicate the presence of multicollinearity. Multicollinearity is an undesirable characteristic in statistical modelling because strongly correlated (multicollinear) explanatory variables will potentially explain the same variance in a statistical model. Using collinear explanatory variables in modelling returns an improperly specified and unstable model equation.

4.4.4. Dimension reduction: Categorical Principal Component Analysis for determinant factors

Principal component analysis (PCA) is one of the most common approaches used for dealing with multicollinearity in explanatory variables. The purpose of principal component analysis is to reduce the number of correlated variables into a few uncorrelated principal components that account for most of the variance in the correlated variables. Ordinary PCA is suitable for continuous/numerical variables which have a linear relationship. On the other hand, categorical principal component analysis (CATPCA), which is a type of PCA, is particularly useful for countering multicollinearity issues in categorical (nominal and ordinal) variables which may not have a linear relationship. CATPCA uses optimal scaling to transform the categorical values into numerical data. CATPCA was used in this study since the explanatory variables are categorical in nature.

4.4.5. Modelling: Regression analysis

Regression analysis is a common statistical modelling approach used to evaluate causal relationships between dependent and independent variables. Regression analyses are different from correlational analyses in that they show the extent to which changes in some variable(s) can cause variation in another (dependent) variable. In a regression equation, the dependent variable is a function of independent variable(s). In this study, several regression approaches have been applied to answer some of the research questions.

4.4.5.1. Ordinary least squares: Ordinary least squares (OLS) regression was used to assess the strength and direction of the relationship between load shedding exposure and several neighborhood characteristics (potential drivers of load shedding exposure). OLS is one of the most commonly used regression techniques. OLS is a global linear regression technique that produces a single regression equation to represent the relationship between the dependent variable and one or more explanatory variables. A typical OLS regression equation is shown in Equation 12 below:

$$Y = b_0 + b_1X_1 + b_2X_2 + \cdots b_nX_n + \varepsilon \,, \tag{12}$$

where Y is the dependent variable, b_n is the coefficient, X_n is the explanatory variable, and ε is the error term (residuals).

An OLS regression model between a dependent variable and one independent variable is known as a simple linear regression (SLR) model while that between a dependent variable and two or more independent variables is a multiple linear regression (MLR) model. In this study, both SLR and MLR were employed.

OLS Model fit and diagnostics: OLS regression model diagnostics are important for proving the validity and accuracy of the model equation. Regression model results can have several violations that can put into question the accuracy of the model. For OLS model results to be valid, they should satisfy several assumptions. OLS regression model diagnostics are used to check whether these assumptions are met and ensure proper interpretation and/or troubleshooting of the model results. ***Table 11*** summarises some of the common OLS model violations, the diagnostic tests used and potential solutions in case violations are identified.

Potential OLS model violation	Diagnostic test	Solution
Nonlinear relationship	Use scatter plot matrix graph to explore relationships between dependent variable and all independent variables	Exclusion of explanatory variables with a nonlinear relationship with the dependent variable from the analysis

Data outliers	Use scatter plot matrix graphs and histograms to check for any extreme data values	Exclusion of any extreme data values from the analysis
Nonstationarity of variables	Use Koenker (BP) Statistic test. A probability of less than 0.05 associated with Koenker (BP) statistic test indicates inconsistent relationships between the dependent and explanatory variables across the study area (regional variation).	For small probabilities (less than 0.05) associated with the Koenker (BP) statistic test, robust probabilities are used to determine if an explanatory variable is statistically significant or not.
Inconsistent variance in residuals	Same approach as with nonstationarity of variables	Same approach as with nonstationarity of variables
Spatially autocorrelated residuals	Carry out spatial autocorrelation of model residuals using global Moran's I test to ensure that they do not exhibit statistically significant spatial clustering. Statistically significant spatial autocorrelation is almost always a symptom of model misspecification.	Remodelling should be done using other suitable variables
Normal distribution bias associated with model residuals	Use Jarque-Bera statistic. A significant Jarque-Bera statistic indicates a mis-specified or non-linear model.	Remodelling should be done using other suitable variables

Table 11: Potential OLS model violations and diagnostic tests

In addition to the above model diagnostic tests, multiple R^2 and corrected Akaike Information Criterion (AICc) are used to measure the extent to which the OLS equation fits the model data. Keeping other factors constant, a model with the maximum R^2 and a minimum AICc is the best fitted model.

4.4.5.2. Geographically weighted regression: Geographically weighted regression (GWR) is a type of linear regression that is used to model the relationship between spatially varying predictor variable(s) and a particular outcome variable. GWR develops a local OLS model equation for each feature by taking into consideration other surrounding features within a specified bandwidth from the feature under consideration. A GWR model shows the extent to which independent variables have varying associations with the dependent variable across geographic space.

The GWR model is generally represented as shown in Equation 13:

$$y_i = \beta_{i0} + \sum_{k=1}^{p-1} \beta_{ik} x_{ik} + \varepsilon_i \,, \tag{13}$$

Where, y_i is the value of the dependent variable for feature i, x_{ik} is the value of the kth covariate for feature i, β_{i0} is the intercept, β_{ik} is the regression coefficient for the kth covariate, p is the number of regression terms, ε_i and is the random error for feature i [93].

Both OLS and GWR were carried out within ArcGIS platform.

4.4.5.3. Binary Logistic regression

Binary Logistic Regression (BLR) is another modelling approach that was used in this study. It was specifically used to model the relationships between the outage impacts and potential explanatory factors. Binary Logistic Regression is a type of generalized linear model used when the binary response variable (in this case, outage impacts) and the independent variables are categorical in nature. Here, the odds of the response variable returning a particular value are modelled as a linear combination of the values of the explanatory variables. A multivariate binary logistic regression model, as used in this study, can be represented by Equation 14 below. Binary Logistic regression analysis was carried out in IBM SPSS software version 25.

$$P(Y) = \frac{e^{b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n}}{1 + e^{b_0 + b_1 x_i + b_2 x_2 + \cdots + b_n x_n}} \,, \tag{14}$$

Where $P(Y)$ is the probability of Y occurring; e is the natural logarithm base, b_0 is the intercept on the y-axis; x_n is the predictor variable, b_n is the regression coefficient of x_n.

BLR Model fit and diagnostics: Several diagnostic/model fit measures are used in binary logistic regression. One of the commonly used measures is –2 log likelihood. –2 log likelihood represents how much of the variation in the dependent variable is not accounted for by the model, and whether or not the model is missing other important explanatory variables. –2 log likelihood is mostly used for comparing two models of the same dependent variable but varying explanatory variables. Other BLR diagnostic/model fit measures used in this study include Nagelkerke R Square, Hosmer and Lemeshow Test and the Overall predictive capacity. Nagelkerke R Square is a Pseudo R Square measure similar to the R square used in ordinary linear regression. However, pseudo–R Square does not represent the proportion of variance accounted.

5. RESULTS AND DISCUSSION

5.1. Community distribution to outages, its spatial characteristics and drivers

5.1.1. Spatial quantification and analysis of load shedding distribution

5.1.1.1. Calculating, Normalizing and Visualizing Load Shedding Exposure

The calculated neighborhood-level load shedding exposure, LS_e, values are shown in **Figure 19**. The values range from 1117 to 3244 hours. The descriptive statistics of load shedding exposure, LS_e together with those for the normalized variables are given in ***Table 12***. From the LS_e results, it can be seen that exposure to power outages varies markedly across communities in Accra. In general, neighborhoods in the North, Central and Western parts of the study area had higher load shedding exposure, LS_e than those in the South and Eastern parts. New Russia had the highest load shedding exposure value while North Kaneshie had the lowest load shedding exposure value. Eleven neighborhoods have load-shedding exposure values in the highest classification range (2919 to 3244 h), two more than those in the lowest classification range (1117 to 1760 h). Each of the neighborhoods in the highest classification range, apart from Korle Dudor, shares a physical boundary with at least one of the other neighborhoods with which it occupies the same classification range. This indicates the potential clustering of neighborhoods with similarly high values. The same can be said for the neighborhoods with values classified under lower classification ranges.

Variable	Mean	Standard Deviation	Minimum	Maximum
Area (km^2)	1.48	0.96	0.26	5.12
Neighborhood population	24,505	14,860	2050	58,120
Neighborhood population density	19,930	13142	2443	65,838
Load shedding exposure, LS_e (h)	2497.40	549.81	1117	3244
$LS_e/area$ (h/km^2)	2632.17	2105.18	362	11,151
$LS_e/population$ (min./capita)	11.11	13.66	1.54	84.59
$LS_e/population\ density$ (min/capita/km^2)	11.96	10.56	2.60	64.79

Table 12: Descriptive statistics of the study variables

Through normalization of the load shedding exposure variable, factors of surface area, population and population density were introduced to control for size and compositional differences among the neighborhoods. The spatial distribution of normalization factors is given in Figures 20–22, while the resultant normalized load-shedding exposure values are visualized in Figures 23–25. From the maps, it is evident that the spatial distribution of load shedding exposure is markedly altered by the normalization. For all normalized load-shedding exposure variables, most of their values fall within the two lowest classification ranges. For example, for $LS_e/population$, only six neighborhoods have values in the two highest classification ranges combined (17.43 to 84.59 min/capita). Because of this, there is therefore a high likelihood of finding significant spatial clustering of neighborhoods with low values. From **Figure 23**, normalization with surface area confers higher values to neighborhoods with smaller surface areas. For both $LS_e/population$ and $LS_e/population\ density$, only one neighborhood Awudome estate and Victoriaborg, respectively has a very high value, classified under the highest classification range. The fact that there are a few, scattered neighborhoods with high normalized load shedding exposure surrounded by low exposure neighborhoods also hints at the potential presence of spatial outliers.

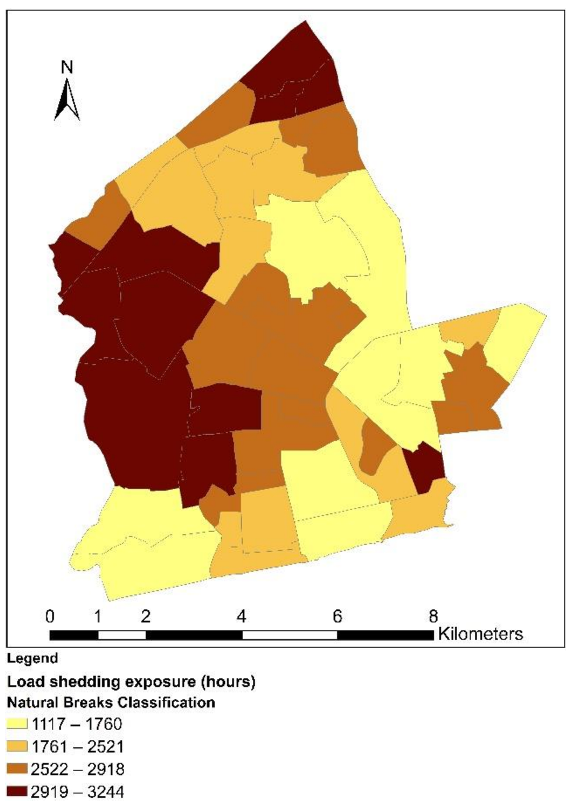


Figure 19: Neighborhood exposure to electricity load shedding

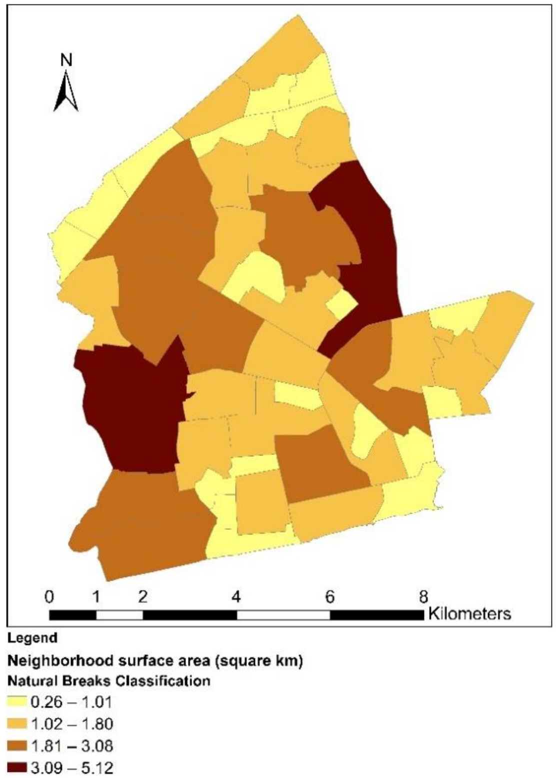


Figure 20: Distribution of neighborhood surface area

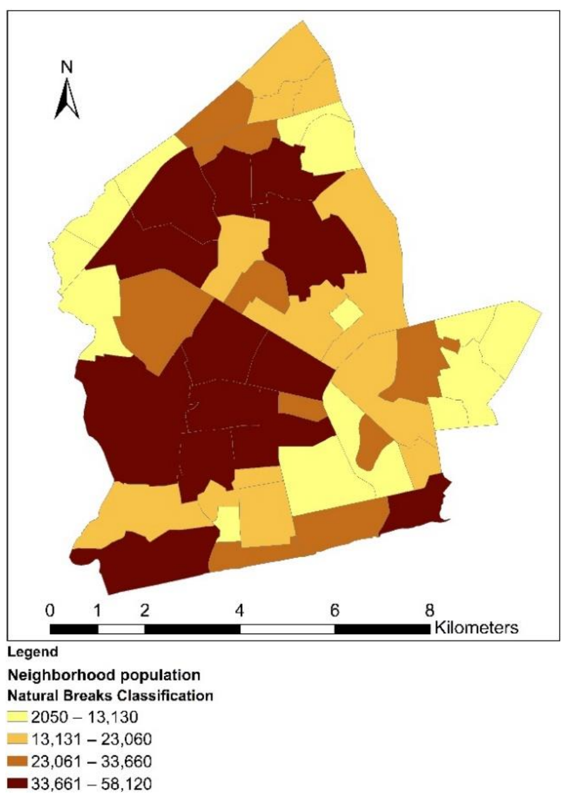
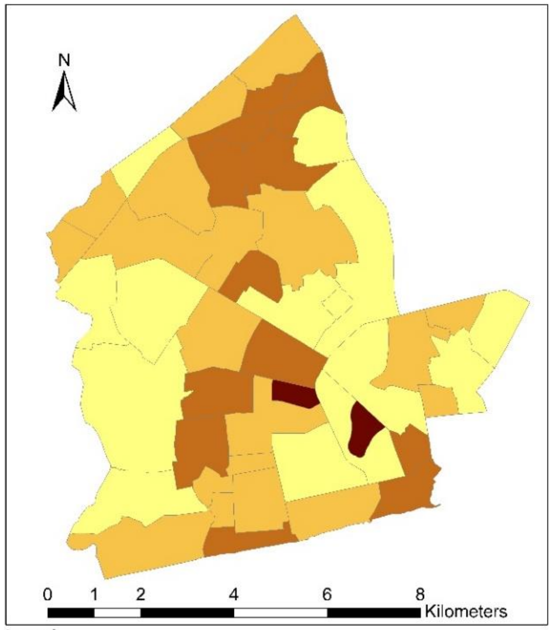
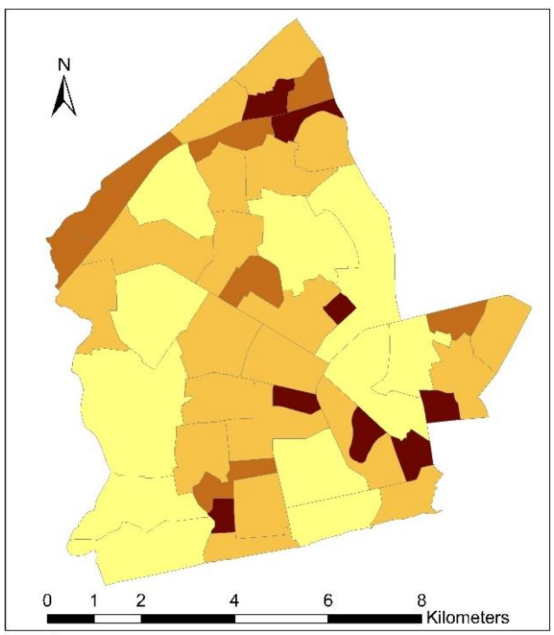


Figure 21: Distribution of neighborhood population



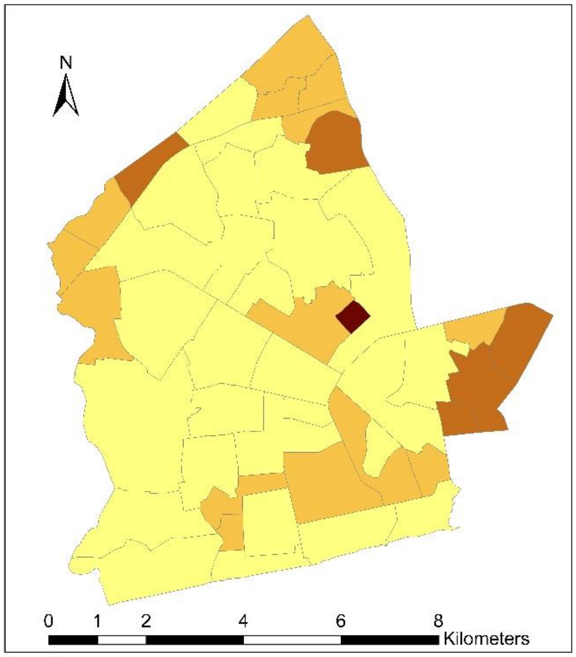
Legend
Neighborhood population density (per square km)
Natural Breaks Classification
2443 – 11,636
11,637 – 23,970
23,971 – 42,215
42,216 – 65,838

Figure 22: Distribution of neighborhood population density



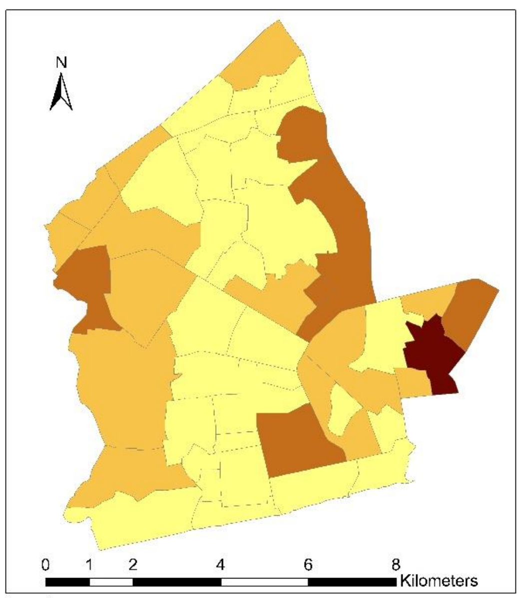
Legend
Ratio of load shedding exposure to surface area (hours per square km)
Natural Breaks Classification
362 – 1135
1136 – 2555
2556 – 4611
4612 – 11,151

Figure 23: Neighborhood exposure to electricity load shedding per unit area



Legend
Ratio of load shedding exposure to population (minutes/capita)
Natural Breaks Classification
1.54 – 6.92
6.93 – 17.42
17.43 – 44.21
44.22 – 84.59

Figure 24: Neighborhood ratio of load shedding exposure to population



Legend
Ratio of load shedding exposure to population density (minutes/capita/square km)
Natural Breaks Classification
2.60 – 9.23
9.24 – 18.95
18.96 – 31.11
31.12 – 64.79

Figure 25: Neighborhood ratio of load shedding exposure to population density

5.1.1.2. Global Spatial Autocorrelation of Load Shedding Exposure

The results from the analysis of global spatial association for the load-shedding exposure variables are summarized in ***Table 13***. As already explained, the global Moran's index is useful for investigating the (non-)existence of global spatial patterns. Load shedding exposure, LS_e and $LS_e/population\ density$ values exhibited statistically significant Moran's I results (p < 0.05), while the Moran's I results for $LS_e/area$ and $LS_e/population$ values were not significant (p > 0.1). Statistically significant Moran's I values indicate the presence of global spatial autocorrelation.

Variable	Moran's I	*z*-score	*p*-value
Load shedding outage exposure, LS_e	0.332901	3.841752	0.000122**
$LS_e/area$	−0.086759	−0.745002	0.456270
$LS_e/population$	0.092946	1.598783	0.109869
$LS_e/population\ density$	0.181642	2.573218	0.010076*

Table 13: Global Moran's I result for load shedding exposure variables

***** indicates statistical significance at p < 0.05; ****** indicates statistical significance at p < 0.01.

The statistical significance of the global Moran's I results for load shedding exposure, LS_e and $LS_e/population\ density$ is at 99% and 95% confidence levels, respectively. This implies that the likelihood of the spatial distribution of their values in the study area being as a result of random chance is 1% and 5%, respectively. Furthermore, the positive z-score results of 3.84 and 2.57 obtained for LS_e and $LS_e/population\ density$, respectively, confirm the spatial patterns as clustering of similar values. What this means is that, for both variables, neighborhoods with similar values tend to be located more closely together than would be expected by random chance. Consequently, the null hypothesis of complete spatial randomness is rejected for both variables. Therefore, it can be concluded that spatial processes, other than random chance, influence the distribution of both load shedding exposure, LS_e and $LS_e/population\ density$ in the study area.

The z-scores of all the transformed load-shedding exposure variables are smaller in magnitude compared to the unnormalized variable. This indicates that normalization has had a diminishing effect on the intensity of spatial patterning of load shedding exposure. Precisely, normalization with population density weakens but retains a statistically significant level of spatial clustering (z-

score = 2.57; $p < 0.05$) of load shedding exposure. Normalization with population also reduces the clustering intensity of load shedding exposure (z-score = 1.60), but to a level where the clustering pattern is no longer statistically significant ($p > 0.1$). On the other hand, the negative z-score (−0.745) obtained for the $LS_e/area$ variable indicates spatial dispersion rather than clustering. However, the pattern is also not statistically significant.

5.1.1.3. Hot Spot Analysis

Figures 26–29 show the results from the hot spot analysis for the load-shedding exposure variables. Across all the variables, 16 different neighborhoods were identified as hot spots, and 10 neighborhoods as cold spots. Hot spots were identified in three of the four variables while cold spots were found in only two variables. Some neighborhoods were identified as hot spots in more than one variable while in another instance, a neighborhood classified as a hot spot in one variable was identified as a cold spot in another variable. A summary of the cross-cutting hot/cold spot neighborhoods is given in ***Table 14***.

Hot Spot Analysis (Getis-Ord G_i^* Statistic)		**Cold Spots**	**Hot Spots**
		$\boldsymbol{LS_e/area}$	$\boldsymbol{LS_e/population\ density}$
Cold Spots	LS_e	-	Adabraka
Hot Spots	LS_e	South Ordokor	-
	$LS_e/population$	-	Asylum Down North Ridge Victoriaborg

Table 14: Intersecting hot/cold spot neighborhoods for different load shedding exposure variables

For the unnormalized load shedding exposure, LS_e, (**Figure 26**), a total of 18 out of the 47 neighborhoods were identified as either hot spots or cold spots at different confidence levels. Ten neighborhoods are classified as hot spots while eight neighborhoods are cold spots. Two neighborhoods—Tsaabaa (a hot spot) and Korle Gonno (a cold spot)—are spots at the highest confidence level of 99%. Ten neighborhoods are hot/cold spots at the 95% confidence level. With regard to the normalized load-shedding exposure variables (Figures 27–29), not many hot/cold spots were identified. Darkuman and South Ordokor are the only significant (cold) spots—at a

90% confidence level—for $LS_e/area$. For $LS_e/population$ and $LS_e/population\ density$, four and five hot spot neighborhoods, respectively, have been identified, being mostly located in the eastern tip of the study area. No cold spot neighborhoods were returned for these two variables. Awudome estate is a highly significant (99% confidence level) hot spot for $LS_e/population$. Both Adabraka and Tudu are moderately significant (95% confidence level) hot spots for $LS_e/population\ density$.

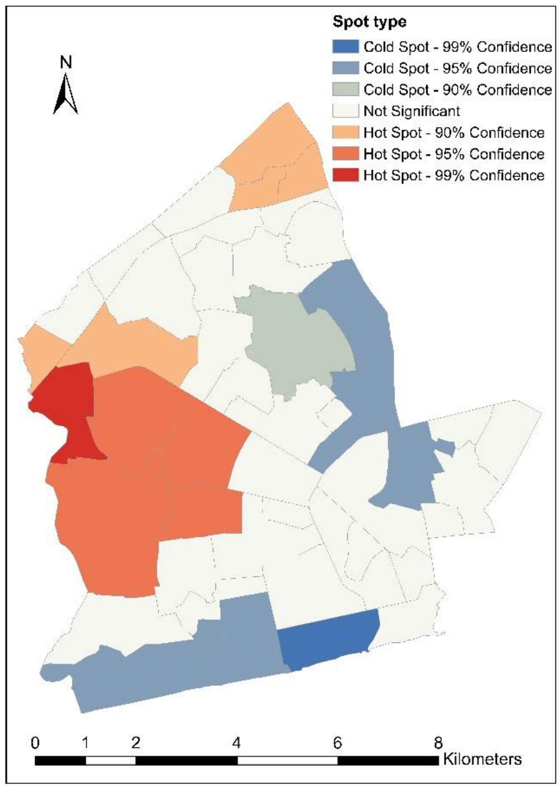


Figure 26: Hot/cold spot neighborhoods for load shedding exposure

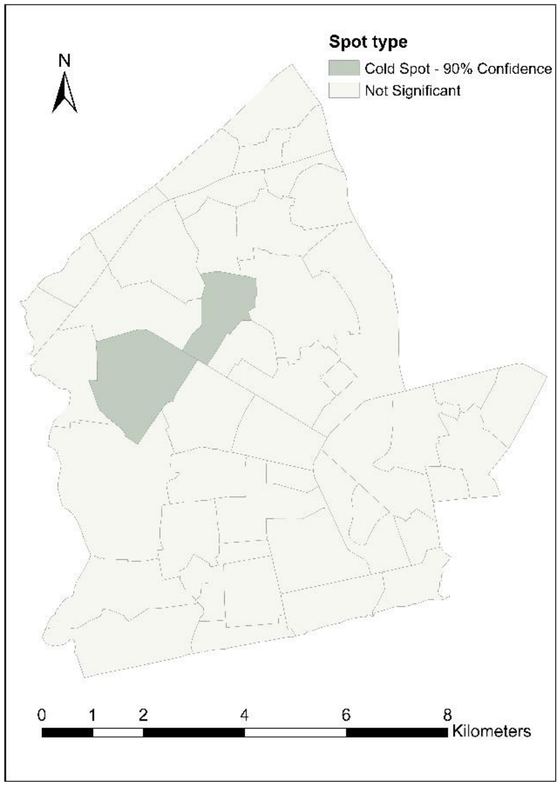


Figure 27: Cold spot neighborhoods for load shedding exposure per unit area

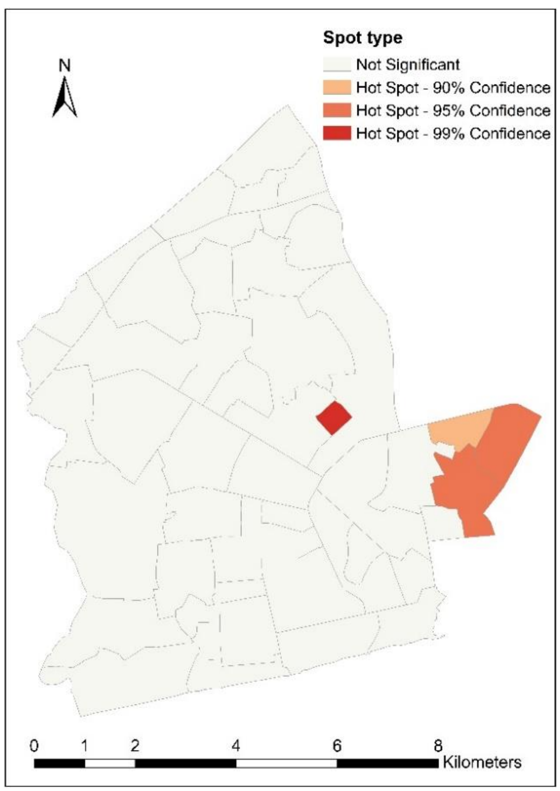


Figure 28: Hot spot neighborhoods for ratio of load shedding exposure to population

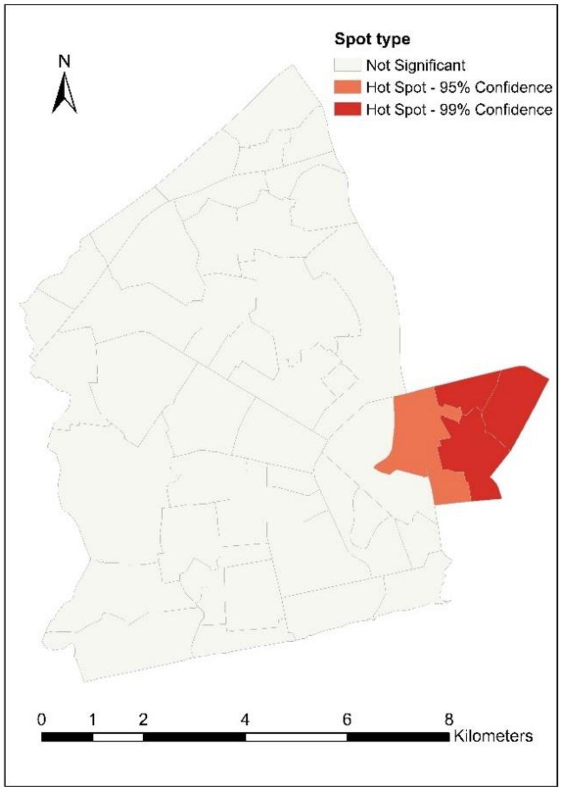


Figure 29: Hot spots for ratio of load shedding exposure to population density

5.1.1.4. Cluster and Outlier Analysis

Cluster and outlier analysis was carried out to complement the results from the hot spot analysis. Beyond this, however, cluster and outlier analysis is important for identifying outlier neighborhoods whose load-shedding exposure values significantly differ from those of their surrounding neighborhoods. Across all variables, a total of eight (08) different neighborhoods were identified as high-high clusters, ten (10) as low-low clusters, two (02) as high-low outliers and three (03) as low-high outliers. Each variable returned at least two low-low clusters while high-high cluster neighborhoods were identified in all variables except $LS_e/area$. Neighborhoods that were identified as clusters in more than one variable are given in ***Table 15***.

Cluster and Outlier Analysis (Local Moran's I Statistic)		Low-Low Cluster		High-High Cluster	
		$LS_e/population$	$LS_e/population\ density$	LS_e	$LS_e/population$
Low-Low Cluster	LS_e	-	Chorkor	-	-
	$LS_e/area$	Darkuman	-	South Ordokor	-
	$LS_e/population$	-	New Fadama	Mataheko New Russia	-

High-High Cluster	$LS_e/population\ density$	-	-	-	North Ridge

Table 15: Neighborhoods showing more than one clustering tendency for different load shedding exposure variables

From **Figure 30**, the unnormalized load shedding exposure, LS_e, has the highest number of clusters—both high-high (07) and low-low (05) clusters. However, no significant outlier was identified for this variable. With regard to the $LS_e/area$, two neighborhoods—Darkuman and South Ordokor—were identified as low-low clusters and Bubiashie as a high-low outlier (see **Figure 31**). In **Figure 32**, four neighborhoods, including Darkuman, Mataheko, New Fadama and New Russia, are low-low clusters for $LS_e/population$, while the Korle Lagoon area is a high-low outlier. The clusters for $LS_e/population\ density$ are Chorkor, Lapaz and New Fadama (all low-low clusters), while Adabraka, Asylum Down and Tudu are low-high outliers (see **Figure 33**). North Ridge is a high-high cluster for both $LS_e/population$ and $LS_e/population\ density$.

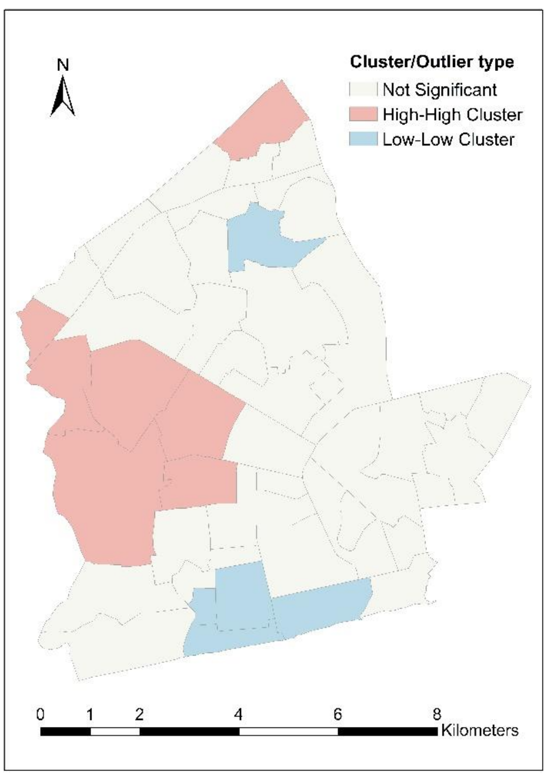


Figure 30: Cluster neighborhoods for load shedding exposure

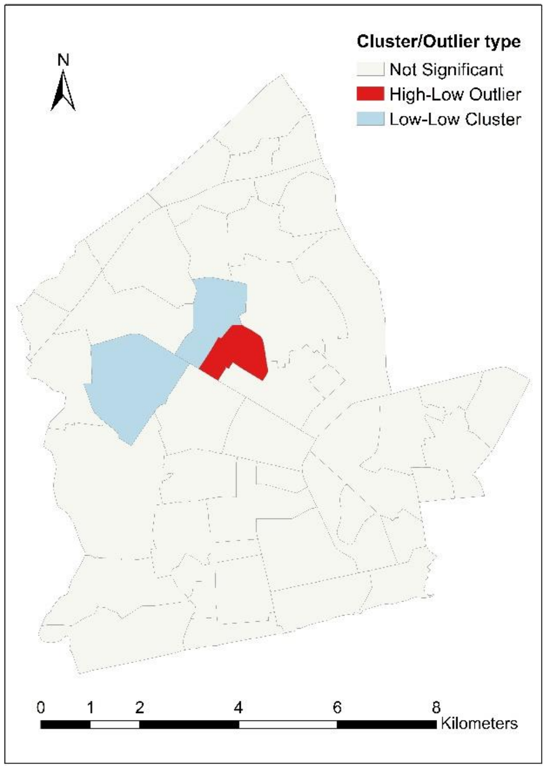


Figure 31: Cluster and outlier neighborhoods for load shedding exposure per unit area

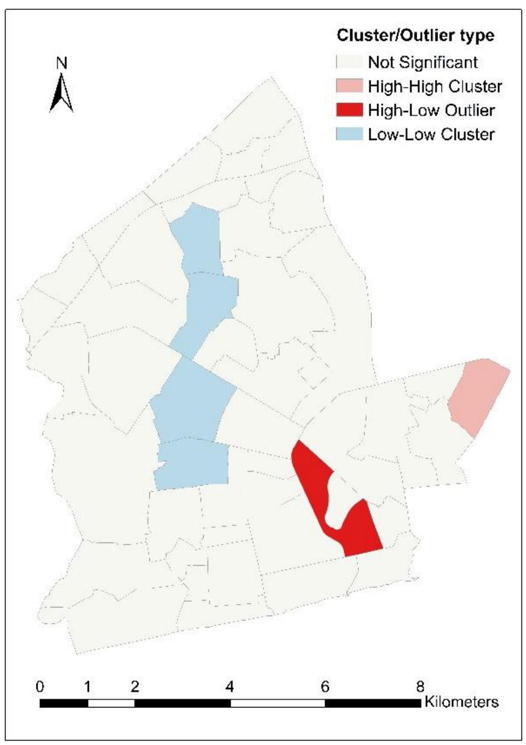


Figure 32: Cluster and outlier neighborhoods for ratio of load shedding exposure to population

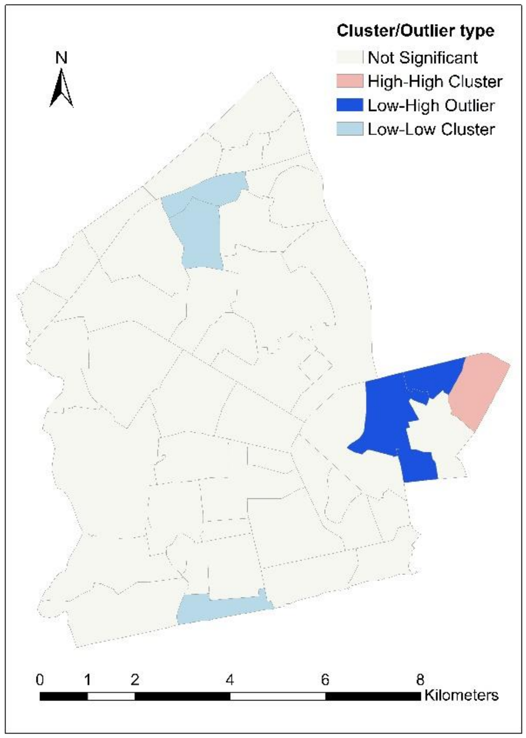


Figure 33: Cluster and outlier neighborhoods for ratio of load shedding exposure to population density

5.1.1.5. Comparing Results from Local Indicators of Spatial Association (LISA) Analyses

Table 16 is a comparative presentation of results from both hot spot analysis and cluster and outlier analysis. Several neighborhoods that intersect as spots and clusters/outliers are identified. There are eight (08) neighborhoods categorized both as hot spots and high-high clusters. Seven of these were identified under load shedding exposure, LS_e. The other neighborhood categorized both as a hot spot and a high-high cluster is North Ridge under both $LS_e/population$ and $LS_e/population\ density$. Several neighborhoods that were identified as hot spots fall under outlier category when using cluster and outlier analysis. Particularly, Adabraka, Asylum Down and Tudu, which are hot spot neighborhoods for $LS_e/population\ density$, are identified as low-high outliers under the same variable. Other hot spot neighborhoods under LS_e, $LS_e/population$ and $LS_e/population\ density$ are categorized as "insignificant" when using cluster and outlier analysis.

Several neighborhoods identified as cold spots also turned out as low-low clusters. Six (06) neighborhoods under LS_e and $LS_e/area$ fall within this category. For LS_e, four (04) neighbourhoods, which are cold spots, are categorized as "insignificant" when using cluster and outlier analysis. Under all variables, some neighborhoods that were categorized as "insignificant" under hot spot analysis were found to be significant clusters/outliers and vice versa. However, in general, most of the neighborhoods remained “insignificant” when using both hot spot analysis, and cluster and outlier analysis.

Hot Spot analysis (G_i^* statistic).		Cluster and Outlier Analysis (Local Moran’s I Statistic)				
		Load shedding exposure, LS_e				
		High-High Cluster	Low-Low Cluster	High-Low Outlier	Low-High Outlier	Insignificant
Load shedding exposure, LS_e	Hot Spot	Awoshie Dansoman Estate Mataheko New Achimota New Russia South Ordokor Tsabaa	-	-	-	Achimota Akweteyman North Ordokor
	Cold Spot	-	Chorkor KorleGonno Mamprobi Old Dansoman	-	-	Adabraka Gbegbeyise North Kaneshie North Industrial Area
	Insignificant	-	Abeka	-	-	All the remaining neighbourhoods (28)
		$\boldsymbol{LS_e/area}$				
$LS_e/area$	Hot Spot	-	-	-	-	-
	Cold Spot	-	Darkuman South Ordokor	-	-	-
	Insignificant	-	-	Bubiashie	-	All the remaining neighbourhoods (44)
		$\boldsymbol{LS_e/population}$				
$LS_e/population$	Hot Spot	North Ridge	-	-	-	North Ridge Victoriaborg Asylum Down Awudome Estate
	Cold Spot	-	-	-	-	-
	Insignificant	-	New Russia Mataheko Darkuman New Fadama	Korle Lagoon Area	-	All the remaining neighbourhoods (38)
		$\boldsymbol{LS_e/population\ density}$				
$LS_e/population\ density$	Hot Spot	North Ridge	-	-	Tudu Adabraka Asylum Down	Victoriaborg
	Cold Spot	-	-	-	-	-
	Insignificant	-	Chorkor Lapaz New Fadama	-	-	All the remaining neighbourhoods (39)

Table 16: Neighborhoods at the intersection of different spot and cluster/outlier types

5.1.2. Drivers of community distribution of electricity outages

For this analysis, the standardized load shedding exposure variable: load shedding exposure per unit area (LSe/Area), hereafter referred to simply as load shedding exposure, was used as the dependent variable. Additionally, one neighborhood (Awudome estate) which was an outlier, with very high value of load shedding exposure per unit area, was excluded from the analysis of outage distribution drivers.

5.1.2.1. Variable descriptive statistics and correlation results

The descriptive statistics for potential predictor variables of load shedding exposure are given in ***Table 17***. The analyzed potential predictors include neighborhood-level socioeconomic and demographic characteristics.

Measure	Indicator variable	Units	Minimum	Maximum	Mean	Std. Deviation	Correlation coefficient with LSe/area
Wealth/ Socio-economic status	Housing Quality Indicator	-	0.70	1.69	1.16	0.22	**-0.345****
Traditional energy use	Level of charcoal use	%	26.07	82.71	58.79	13.66	0.289
Public health measure	Level of use of modern sewerage services	%	0.44	70.61	16.87	15.61	-0.228
Wealth/Socio-economic status	Percent of vegetation cover	%	0.014	0.631	0.210	0.145	**-0.414*****
Demographics	Household density	Number of households/km^2	784	21141	6483	4180	**0.555*****
Access to social services	Access to piped water	%	87.58	97.50	93.51	2.03	-0.125
Public health measure	Use of formal rubbish collection services	%	0.89	86.83	27.43	23.15	-0.213
Minority groups	Percentage of minorities	%	1.31	68.48	11.68	12.22	**0.444*****

Table 17: Descriptive statistics for select potential explanatory variables of outage distribution

** and *** indicates that correlation is significant at 0.05 and 0.01 respectively.

The nature of relationships between neighborhood load shedding exposure (dependent variable) and potential predictor variables was first analyzed using bivariate correlation analysis. The Pearson correlation coefficients from the analysis are also given in ***Table 17*** (significant correlations are highlighted in bold) while **Figure 34** is a graphical representation of the relationships between load shedding exposure and the significantly correlated variables. The correlation coefficient (r = 0.555) between neighborhood load shedding exposure and neighborhood household density was highest, followed by r = 0.444 with percent of minorities, r = -0.414 with level of vegetation cover, and r = -0.345 with housing quality indicator (HQI). Other potential explanatory factors including level of charcoal use, access to piped water, and access to modern sewerage services had a small and statistically insignificant correlation with neighborhood load shedding exposure.

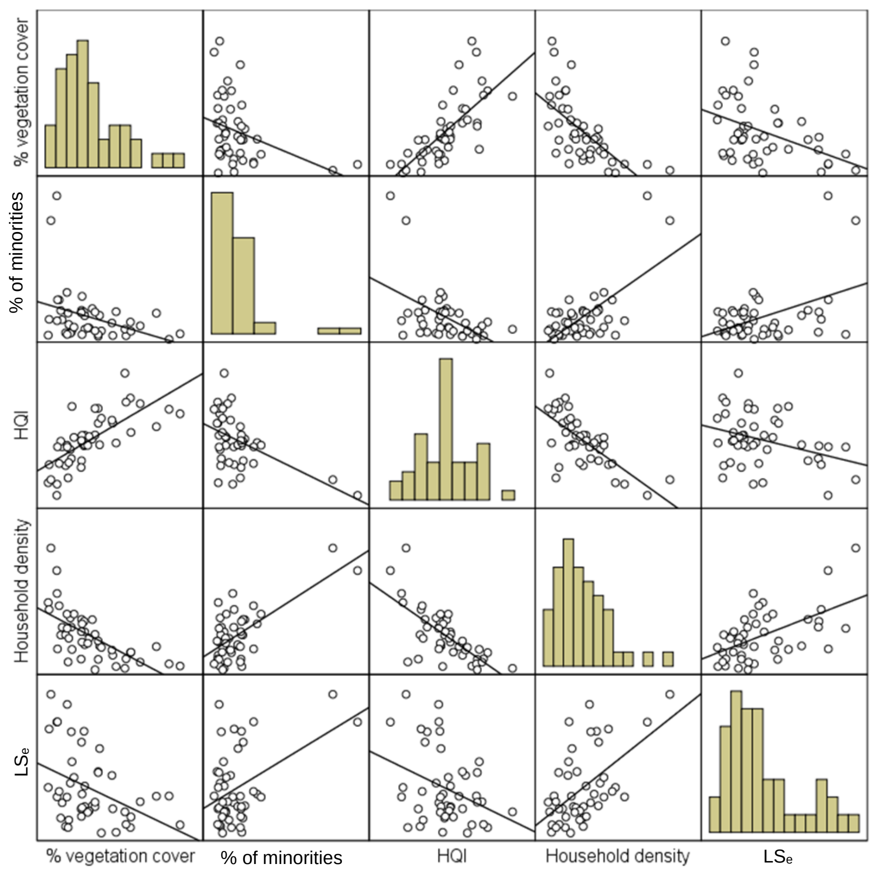


Figure 34: Dependent variable bivariate correlations with significantly correlated explanatory variables

5.1.2.2. Predictor variables of load shedding distribution: ordinary least squares (OLS) and GWR results

Table 18 presents results of a simple linear regression which examines the extent to which a set of select explanatory variables predict the level of neighbourhood exposure to load shedding. Specifically, regression was carried out using predictor variables that are significantly correlated with load shedding exposure per unit area (dependent variable). All the four OLS models are statistically significant. Household density emerged as the most important predictor variable accounting for 31% of the variation in load shedding exposure. A positive regression model coefficient also implies that load shedding exposure increases with increasing household density and vice versa. Additionally, the coefficient of determination between load shedding exposure and household density is 0.22. This indicates that holding all other factors constant, the load shedding exposure per unit area increases by 0.22 hours for every one unit increase in household density. Percent of minorities emerged as the second most important predictor variable, accounting for about 20% of the variation in the neighbourhood load shedding exposure. Percent of minorities is also positively related with load shedding exposure, such that an increase in neighbourhood percent of minorities increases load shedding exposure. Specifically, a unit increase in percent of minorities leads to an increase in load shedding exposure by 60.96 hours. The percent of vegetation cover of the neighbourhood has a negative association with load shedding exposure, whereby increasing vegetation cover is associated with reducing load shedding exposure. Specifically, a unit increase in the percent of vegetation cover decreases the load shedding exposure per unit area of 4784.39 hours. This variable explains about 17% of the overall variance in the load shedding exposure variable. With regard to housing quality indicator (HQI), the analysis also found a negative and significant association with load shedding exposure. This implies that as housing quality indicator increases, load shedding exposure decreases. Specifically, a unit increase in housing quality indicator results into a reduction in load shedding exposure per unit area of 2844.16 hours. HQI accounts for only 12% of the variation in neighbourhood load shedding exposure.

LSe/Area (n = 46)	Coefficient	Standard Error (SE)	T-Statistic	Probability (Pr)	Robust SE	Robust T	Robust Pr	R^2	AICc	Joint F-Statistic	Joint Wald Statistic	Koenker (BP) Statistic	Jarque-Bera Statistic
Intercept	1735.18	313.74	5.53	0.00*	289.32	6.00	0.00*						
Percent of minorities	60.96	18.56	3.28	0.00*	14.23	4.28	0.00*	0.20	810.23	10.79*	18.34*	0.11	6.99
Intercept	3449.86	404.37	8.53	0.00*	458.66	7.52	0.00*						
Percent of vegetation cover	-4784.39	1585.24	-3.01	0.00*	1427.27	-3.35	0.00*	0.17	811.66	9.11*	11.24*	7.51*	3.52
Intercept	5716.16	1363.64	4.19	0.00*	1453.30	3.93	0.00*						
HQI	-2844.16	1168.20	-2.43	0.02*	1149.12	-2.48	0.02*	0.12	814.50	5.93*	6.13*	7.81*	3.37
Intercept	1001.83	388.63	2.58	0.01*	304.67	3.29	0.00*						
Household density	0.2229	0.05	4.42	0.00*	0.04	5.55	0.00*	0.31	803.38	19.58*	30.82*	0.40	5.96

Table 18: Simple OLS regression, model fit and diagnostics results

* indicates statistical significance at $p < 0.05$

When considering all the significant explanatory variables together (in a multiple linear regression analysis), only a combination of percent of minorities and percent of vegetation cover returned a statistically significant OLS model shown in ***Table 19***. These two variables together account for 27% of the variance in load shedding exposure.

LSe/Area (n = 46)	Coefficient	Standard Error (SE)	T-Statistic	Probability (Pr)	Robust SE	Robust T	Robust Pr	R^2	AICc	Joint F-Statistic	Joint Wald Statistic	Koenker (BP) Statistic	Jarque-Bera Statistic
Intercept	2615.03	512.44	5.10	0.00*	533.20	4.90	0.00*						
Percent of vegetation cover	-3407.20	1603.42	-2.12	0.04*	1359.83	-2.51	0.02*	0.27	808.04	8.08*	29.52*	5.02	3.51
Percent of minorities	46.77	19.07	2.45	0.02*	15.53	3.01	0.00*						

Table 19: Multiple OLS regression, model fit and diagnostics results

* indicates statistical significance at $p < 0.05$

The results obtained from geographically weighted regression (see ***Table 20***), when compared to OLS results, indicate an improvement in the predictive power of all predictor variables on the dependent variable. However, the difference between GWR and OLS results is not very big indicating that non-stationarity has a small impact on the relationship between load shedding exposure and the predictor variables. Even with GWR, household density remains the most important predictor of neighbourhood load shedding exposure with a global $R^2 = 0.35$ and housing quality indicator (global $R^2 = 0.16$) remains the least important predictor. Spatial autocorrelation results of the standard residuals of the GWR models are all statistically insignificant indicating spatial randomness of the model residuals.

LSe/Area (n = 46)	Household density	HQI	Percent of minorities	Percent of vegetation cover
GWR R^2	0.35	0.16	0.23	0.23
Std. residual autocorrelation	0.03	-0.05	0.04	-0.02

Table 20: Summary of Geographically Weighted Regression (GWR) results

5.1.2.3. Predictor variables of load shedding exposure: Mapping results of local R^2

Figure 35 is a representation of the performance of each explanatory variable in predicting load shedding exposure for each neighborhood. The descriptive statistics of the local R^2 results from GWR of load shedding exposure and select predictor variables are also given in ***Table 21***. From

Figure 35, the strength of the relationships between load shedding exposure and the predictor variables appears to be non-stationary and varies across space. For example, while the global GWR R^2 between load shedding exposure and household density is 0.35, the local (neighborhood-level) R^2 values range from 0.243 to 0.508. Other explanatory variables also exhibit similar variance in their relationships with load shedding exposure. Local GWR R^2 values range from 0.091 to 0.372 for percent of minorities, 0.122 to 0.213 for housing quality indicator, and 0.108 to 0.269 for percent of vegetation cover. Household density, percent of minorities and percent of vegetation cover tend to have low values of local R^2 (that is, less predictive power on load shedding exposure) in neighborhoods in the northern/north-western parts of the study area. Therefore, load shedding exposure in neighborhoods including Awoshie, Chantan, Kwashiema, Official Town and Santa Maria is less predicted by these three variables as compared to other neighborhoods. The highest predictive power (highest local R^2) of household density, percent of minorities and housing quality indicator on load shedding exposure is observed in the central parts of the study area, especially in the neighborhoods of Abbosey Okai, Kaneshie and Matehako. South-Eastern neighborhoods including Jamestown, Korle Dudor, Tudu and Victoriaborg have the highest local R^2 for percent of vegetation cover and lowest local R^2 for housing quality indicator. All in all, household density is still the most important predictor of variance in load shedding exposure, even at a local (neighborhood) level. However, different from the global OLS and GWR results, local R^2 results show that housing quality indicator is a stronger predictor of loading shedding exposure than percent of minorities and percent of vegetation cover in some neighborhoods in the northern/north-western parts of the study area.

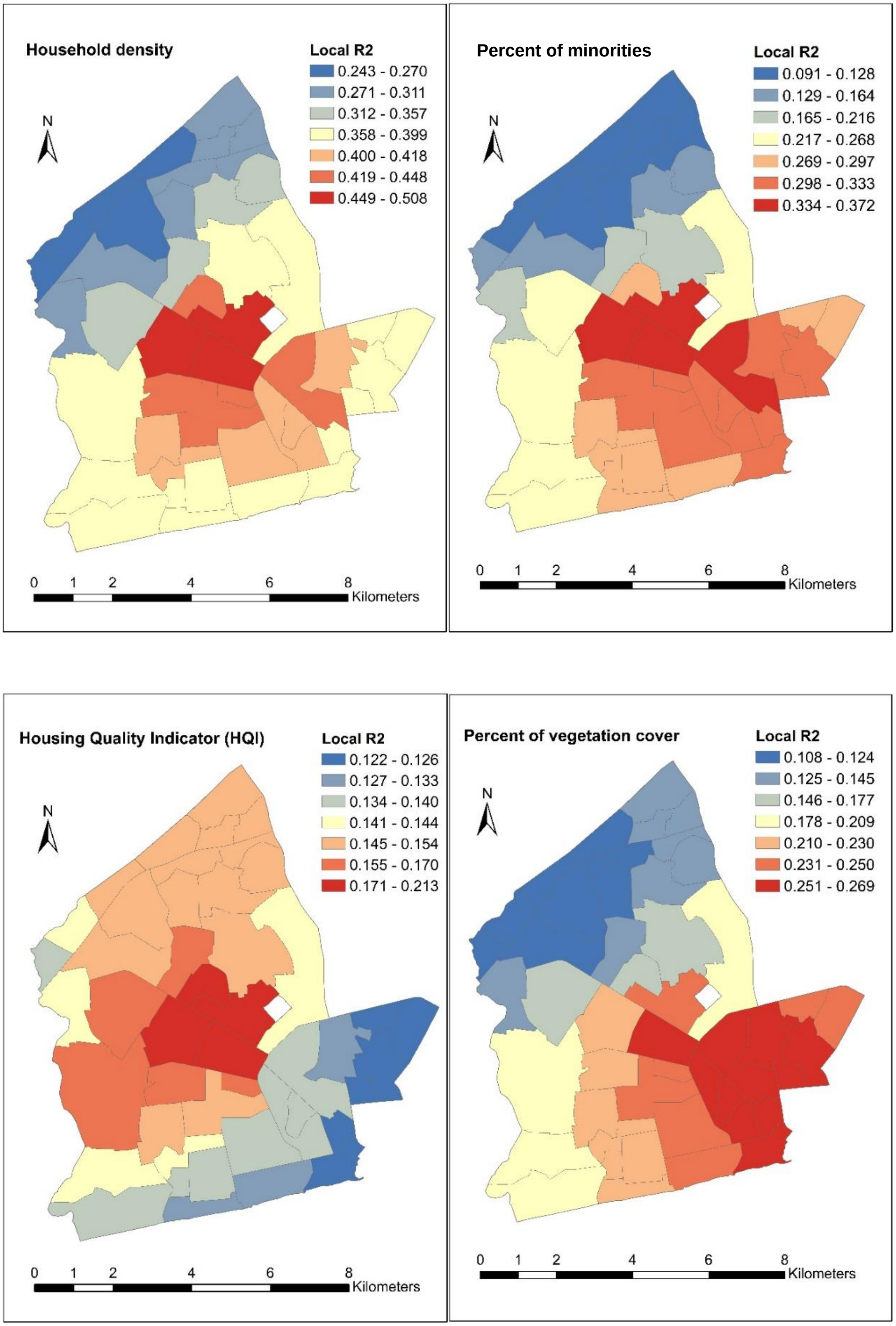


Figure 35: Distribution of local R-squared results from GWR of load shedding exposure and select predictor variables

LSe/Area (n = 46)	Household density	Housing quality indicator	Percent of vegetation cover	Percent of minorities
Maximum	0.508	0.213	0.269	0.372
Mean	0.370	0.148	0.194	0.243
Minimum	0.243	0.122	0.108	0.091
Standard deviation	0.067	0.018	0.055	0.086

Table 21: Descriptive statistics of local R-squared results from GWR of load shedding exposure and select predictor variables

5.1.3. Discussion

5.1.3.1. Spatial characteristics of load shedding at a neighborhood scale

First of all, there are considerable variations in load shedding experiences across neighborhoods in Accra. Some neighborhoods were exposed to twice as many load shedding hours as others. This result agrees with the results obtained by [4] which show that, in Accra, some neighborhoods received only 7.5 hours of electricity per day while others received up to 17.5 hours of electricity during the recent nationwide rolling blackouts. Additionally, neighborhoods having similarly high or low values of load shedding exposure were found to be more spatially clustered together than would be expected by random chance. This is an indicator that other spatial processes (socioeconomic, political, demographic and other factors) influenced the distribution of load shedding outages in Accra. This necessitated further analysis to determine which factors influence the observed spatial variations in load shedding exposure. Spatial clustering of load shedding exposure, LS_e values may be explained by several factors. Firstly, in the study area, several bordering neighborhoods were sometimes supplied by a single 11 kV electricity feeder. Because of this, some nearby neighborhoods could have the same or similar load shedding experiences. Secondly, nearby neighborhoods can experience similar load shedding exposure because they have similar socio-economic characteristics. A study by [4] has also shown that electricity (un)availability can be "targeted" basing on economic conditions of the neighborhoods. Therefore, because bordering neighborhoods often have closely related socioeconomic characteristics, according to Tobler's first law of geography, they may experience similar load shedding exposure.

Secondly, normalizing load-shedding exposure values with surface area, population and population density significantly altered the spatial distribution of load shedding exposure in Accra neighborhoods. Specifically, the strength of the spatial clustering of load shedding exposure values was greatly diminished when normalization was carried out. Normalization (also known as standardization) is a useful approach for transforming absolute measures to ensure some form of uniform comparison of experiences across neighborhoods. Moreover, it is also a useful way for introducing a societal perspective into the research. Normalization has been used in several studies, for example, to demonstrate the impact of different socioeconomic factors on the spatial distribution of electrical energy demand (EED) across several sectors and regions in Greece. Similar to what has been observed in the present study, the results revealed a more dispersed spatial pattern for the standardized EED than for the absolute (unstandardized) EED [87]. Additionally, normalization was important for understanding neighborhood load shedding experiences from different perspectives. For example, even if the overall load shedding exposure of a neighborhood may be high, load shedding exposure per capita may be low if the neighborhood population is similarly high. Ultimately, normalization of load shedding exposure with societal factors was useful for as an initial indicator of the potential societal considerations that influenced load shedding decisions made by the power utility managers.

Thirdly, several outage/load shedding hotspots have been identified among the Accra communities which further affirms the finding that load shedding outages are not equally distributed in Accra. Moreover, hot spot analysis and cluster and outlier analysis seemed to complement each other, particularly for identifying spatial clusters. While some differences have been observed in the cluster and spot results for the same variable, these may be attributed to the fact that clusters (and outliers) are only considered significant at $p < 0.05$, while hot/cold spots are classified from a 90% confidence level. This too highlights the uniqueness of the underlying calculations upon which the two local indicators of spatial association (LISA) approaches are based [91]. Therefore, depending on the purpose of the study, it may be beneficial to use both methods and compare their results. Additionally, both methods are useful for any study—including the present study—which is interested in identifying spatial clusters at varying confidence intervals (possible by hot spot analysis) as well as spatial outliers (possible by cluster and outlier analysis). In this case, the two methods play a supplementary role.

Last but not least, for load shedding exposure, LS_e, there was a general agreement between the spatial characteristics inferred from both visualization and spatial statistical tools. However, for normalized variables, this was not the case. For all normalized variables, visualization categorized most neighborhoods under the two lowest classification ranges on their respective maps. This seemed to suggest a higher possibility of finding many low-low clusters as well as a high likelihood of finding spatial outliers, especially high-low outliers. However, several neighborhoods that appeared to be cold spots, low-low clusters or high-low outliers from the visualized data were not identified as such when using spatial statistical tools. Therefore, while spatial visualization is a useful tool for data exploration, it should not be entirely relied upon for making concrete spatial interpretation [87]. It should be used in conjunction with other more robust spatial tools.

5.1.3.2. Significant drivers of load shedding exposure at a neighborhood scale

The distribution of load shedding in Accra neighborhoods has been found to be significantly predicted with a number of factors. The four identified drivers of load shedding exposure can be categorized as demographic factors (household density and percent of minorities) and wealth/socio-economic status indicators (housing quality indicator and percent of vegetation cover). In general, both OLS and GWR results indicate that demographic factors are more important predictors of neighbourhood-level load shedding exposure than wealth/socioeconomic factors. In particular, household density appears to have the highest influence on load shedding exposure. This implies that the distribution of load shedding outages in the study area was mostly influenced by the existing neighbourhood development model. Neighbourhoods that are more residential (with higher household density) were more likely to experience more load shedding hours than the less residential neighbourhoods (having commercial or industrial establishments) which have lower household density. It, therefore, follows that load shedding outages were likely more targeted at household-level electricity consumers as compared to commercial or industrial consumers. This observation is not unusual for two main reasons: First of all, residential electricity consumers in Ghana tend to default on their utility bill payments during times of outages [50]. Also, considering that industrial and commercial consumers are generally high electrical energy consumers, they guarantee a relatively high and stable inflow of income for the utility company during times of reduced revenue flows and may, therefore, be treated as priority consumers by the utility company. Secondly, because of their perceived importance to the economy, industrial and commercial establishments often have a higher lobbying influence (individually or through associations) on top decision makers than individual residential consumers. In some countries, large industrial institutions are said to have established ‘unwritten agreements’ with utility companies which guarantee them privileged and nearly uninterrupted power supply even during times of outages [43]. Therefore, for both economic and political reasons, the utility company may treat neighbourhoods with many commercial and industrial consumers favourably when implementing mandatory electricity rationing.

Furthermore, the relatively strong predictive power of percent of minorities on load shedding exposure is in line with several research studies which show that minority groups are more likely to be socially or economically disadvantaged than other groups. For example, minorities in the USA and other countries are known to disproportionately suffer from poverty, be exposed to more environmental hazards and as a result suffer more consequences [94] [95]. Within the energy research domain, some studies have shown that racial and ethnic minorities in USA may suffer more outage experiences [7] [10] [95]. This is in agreement with a wide body of research which shows that communities with high numbers of minority groups may suffer disproportionately more disadvantage in accessing public services than others.

Housing quality indicator and percent of vegetation have also been identified as important drivers of load shedding exposure among the neighbourhoods. In particular, neighbourhoods with a high housing quality indicator and high percent of vegetation cover – both proxies of neighbourhood wealth/socio-economic status – have lower exposure to electricity load shedding. This finding is in agreement with the results of a study by [4] who found that “*rolling blackouts in Africa disproportionately hurt the poor*.” Moreover, this result is also in general agreement with a wider body of research that links deprived energy access/use (for example, fuel poverty) to low-income groups/households [96].

5.2. Impacts of power outages on households and their predictors

5.2.1. Respondents' descriptive statistics

As already mentioned, the questionnaire survey captured responses from 564 households. However, not all questionnaires were fully completed as some had elements of missing data. Ultimately, only the fully completed questionnaires from 496 households were used for data analysis. This represents an 88% survey completion rate. The descriptive statistics of select respondent characteristics are given in ***Table 22*** below.

Variable categories	Code	Variable	Measurement	Mean	Standard Deviation
Demographic characteristics	X_1	Age	Less than 35 years = 0, 35 years or more = 1	0.48	0.50
	X_2	Sex	Female = 0, Male = 1	0.49	0.50
	X_3	Marital status	Single - Never married = 0, Married/cohabiting/divorced/widowed = 1	0.56	0.497
Housing characteristics	X_4	Occupying house as a family	No = 0, Yes =1	0.66	0.474
	X_5	Home ownership	Not self-owned = 0, Self-owned = 1	0.30	0.458
	X_6	Household size	Less than 5 occupants = 0, 5 or more occupants = 1	0.38	0.486
Socioeconomic characteristics	X_7	Annual income	< 6000 Ghana Cedis = 0, >= 6000 Ghana Cedis = 1	0.50	0.501
	X_8	Level of education completed	Tertiary level[2] = 0, Below tertiary level = 1	0.61	0.489
	X_9	Employment status	Formal employment = 0, Informal employment/unemployed = 1	0.58	0.494
Outage characteristics	X_{10}	Outage frequency per month	<=13 times = 0, >13 times = 1	0.34	0.474
	X_{11}	Average duration per outage	<=9 hours = 0, >9 hours = 1	0.25	0.431

Table 22: Descriptive statistics of select household/respondent characteristics

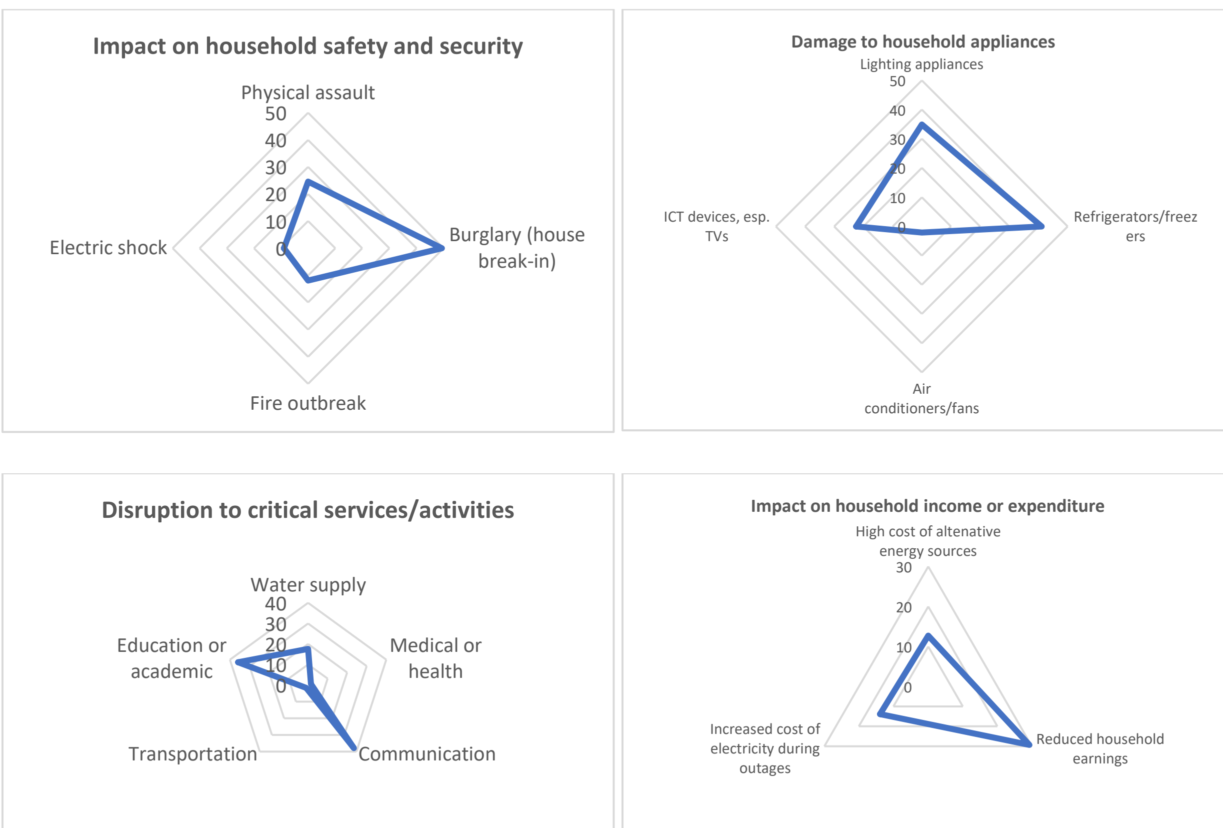
From ***Table 22***, slightly more than half of the respondents were female (50.5%), and less than 35 years of age (51.5%). With regard to marital status, 43.8% of respondents were single (never married), while 56.2% were officially married, cohabiting, divorced or widowed. 29.8% of the respondents lived in their own houses, 65.9% were living as a family (with family members) while 62.1% of the households had less than 5 occupants/members. 60.1% of the respondents had education below tertiary level, 42.2% were formally employed while 50.1% had an annual income greater than 6000 Ghana Cedis (GH¢). Additionally, with regard to electricity usage in homes,

[2] Tertiary level includes university level education or any other post-secondary school training such as, vocational and technical training

99.6% of respondents used electricity for lighting, 91.5% for information, communication and leisure (watching television, phone and computer charging, and playing video games), 85.2% for air conditioning (including ceiling fan), 82.4% for refrigeration, 75.6% for heating (including water heating and ironing) and only 9.7% used electricity for cooking. With regard to electricity outage experiences, 66% of respondents indicated experiencing at most thirteen outages per month during the mandatory load shedding while 75.5% of the respondents indicated that on average electricity outages lasted for nine hours or less.

5.2.2. Common impacts of outages in Accra households

The survey responses for outage impacts in households are reported in this section. The identified outage impacts are categorized into five main groups namely: impact on household safety and security; damage to household appliances; disruption to critical infrastructure services; impact on household income or expenditure; and impact on household access to food. **Figure 36** shows the percentages of the respondents identifying a particular outage impact as happening in their households.



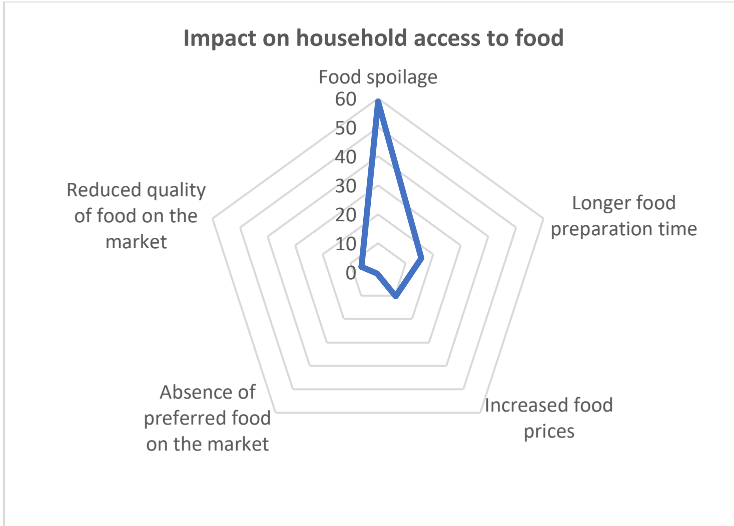


Figure 36: Reported impacts of electricity outages in Accra households

Across all the five outage impact groups, food spoilage (under impact on household access to food) emerged as the leading outage impact reported by 58.9% of the respondents, followed by burglary (under impact on household safety and security) and damage to refrigerators/freezers (under damage to household appliances) reported by 49.4% and 41.1% of the respondents respectively. The popularity of food spoilage as an outage impact indicates that electricity plays an important role towards easing access to food in urban households through supporting food storage/preservation in homes. This was emphasized by one respondent in Korle Bu: "*We usually buy raw food stuffs in bulk to avoid frequent trips to the market. We cook some and kept some (*of the raw food*) in the refrigerator. Even cooked food that is left-over, we don't throw it away. We preserve it in the refrigerator for several days without it going bad.*" Aside from supporting access to food, electricity also appears to be a vital aspect for ensuring security against burglars in Accra households. In Accra, electricity is commonly used to power electric fences around homes, operate anti-burglar alarms and provide outdoor lighting at night to deter would-be intruders. A high number of respondents indicating damage to refrigerators/freezers as an outage impact also suggests that power surge protection devices that shield electrical appliances from high voltage surges may not yet be in widespread use in Accra households.

Other commonly reported outage impacts in Accra households include disruption to communication services (37.9%) and disruption of academic activities (35.8%), which are the top two impacts identified under disruption of critical services. Additionally, damage to lighting appliances (34.9%) was a common impact under damage to household electrical appliances while reduced household earnings (29.3%) was reported as the leading outage impact under the category of impact on household income/expenditure. Other outage impacts including physical assault (24.6%), damage to ICT devices especially TVs (22.5%), disruption to water supply (17.6%), longer time for preparing food (15.7%), increased unit cost of electricity during outages (13.9%), high expenditure of alternative energy sources (12.7%), fire outbreak (11.9%) and increased food prices of the market (10.3%) were identified by more than 10% of the respondents. Less common impacts – with less than 10% of the valid responses – include electric shock (8.9%), reduced quality of food on the market (6%), damage to air conditioners/fans (2.1%), disruption to transportation (1.6%) and medical (1.4%) services, and absence of preferred food on the market (0.6%).

5.2.3. Bivariate correlation results: dependent vs explanatory variables

In ***Table 23***, bivariate correlation analysis results indicating the relationships between dependent variables (outage impacts) and several potential explanatory variables (respondent/household characteristics) are presented. Outage impacts identified by at least ten percent of the respondents are the dependent variables. The relationships are based on the Pearson Chi-square test which returns a Pearson correlation coefficient, X^2. Significant relationships ($p<0.05$ and $p<0.01$) are highlighted in bold in the table. *** and ** indicate statistically significant result with $p < 0.01$ and $p < 0.05$ respectively.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
Y_1	**4.006****	1.373	0.175	0.016	0.945	1.799	**6.046****	0.002	**43.540*****	**4.146****	2.628
Y_2	1.573	**8.039*****	0.384	0.008	**5.742****	**4.823****	0.114	**4.187****	**7.177*****	**21.525*****	**19.788*****
Y_3	0.190	2.713	1.883	**4.698****	0.028	0.001	**20.824*****	1.324	**3.877****	**5.437****	2.255
Y_4	0.498	0.000	0.003	1.704	0.357	**4.083****	**14.321*****	1.389	0.180	**7.556*****	0.496
Y_5	0.001	0.974	1.756	0.255	0.083	**6.690*****	**6.778*****	**4.598****	1.216	**16.548*****	3.297
Y_6	**9.335*****	**3.973****	3.498	0.772	**7.508*****	0.355	**24.786*****	3.655	**10.500*****	**4.071****	**8.891*****
Y_7	**13.593*****	3.321	0.834	0.031	1.277	0.662	0.521	**10.266*****	**11.503*****	1.663	**7.578*****

Table 23: Bivariate correlation results between outage impacts and respondent characteristics

From the analysis, each outage impact was found to be significantly associated with at least three potential predictor variables. Physical assault (Y_1) is significantly correlated with the respondent's age (X^2 = 4.006, p<0.05), annual income (X^2 = 6.046, p<0.05), employment status (X^2 = 43.540, p<0.01) and number of outages per month (X^2 = 4.146; p<0.05). Burglary/house break-in (Y_2) was found to be significantly correlated with the sex of the respondent (X^2 = 8.04, p < 0.01), building ownership (X^2 = 5.74, p < 0.01), number of people in the household (X^2 = 4.82, p < 0.05), respondent's level of education completed (X^2 = 4.19, p < 0.05) and employment status (X^2 = 7.18, p < 0.01), number of outages in a month (X^2 = 21.53, p < 0.01), and average duration of each outage (X^2 = 19.79, p < 0.01). Disruption in water supply (Y_3) is significantly associated with occupying house as a family (X^2 = 4.70, p < 0.05), the respondent's annual income (X^2 = 20.82, p < 0.01) and employment status (X^2 = 3.88, p < 0.05), and the number of outages in a month (X^2 = 5.44, p < 0.05). Disruption of communication services (Y_4) was found to be significantly correlated with only three explanatory variables, that is, number of people in the household (X^2 = 4.08, p < 0.05), respondent's annual income (X^2 = 14.32, p < 0.01) and number of outages in a month (X^2 = 7.56, p < 0.01). Disruption of academic activities (Y_5) is significantly correlated with number of people in the household (X^2 = 6.69, p < 0.01), respondent's annual income (X^2 = 6.78, p < 0.01), level of education completed (X^2 = 4.60, p < 0.05) and number of outages in a month (X^2 = 16.59, p < 0.01). Reduction in household earnings (Y_6) was found to be significantly correlated with the respondent's age (X^2 = 9.34, p < 0.01), sex (X^2 = 3.97, p < 0.05), annual income (X^2 = 24.79, p < 0.01) and employment status (X^2 = 10.50, p < 0.01), as well as with building ownership (X^2 = 7.51, p < 0.01), number of outages in a month (X^2 = 4.07, p < 0.05) and average duration of each outage (X^2 = 8.89, p < 0.01). High expenditure on alternative energy sources (Y_7) is significantly associated with the age (X^2 = 13.59, p < 0.01), level of education (X^2 = 10.27, p < 0.01) and employment status (X^2 = 11.50, p < 0.01) of the respondent and the average duration of each outage (X^2 = 7.58, p < 0.01).

The frequency of outages in a month is correlated with reporting all but one outage impact, that is, high expenditure on alternative energy sources (Y_7) while outage duration is correlated with three outage impacts. Among the socioeconomic variables, both the respondent's annual income (X_7) and employment status (X_9) are significantly associated with five of the seven outage impacts while level of education completed (X_8) is associated with four outage impacts. Housing characteristics, that is, occupying house as a family, home ownership, and household size are significantly correlated with one, two and three outage impacts respectively. With regard to demographic characteristics, age and gender are significantly associated with three and two outage impacts respectively, while marital status is not significantly associated with any outage impact.

5.2.4. Bivariate correlation results: Multicollinearity test for explanatory variables

Pearson correlation coefficients between variables under household socioeconomic, demographic, housing and outage characteristics were calculated to test for multicollinearity. As shown in ***Table 24***, some pairs of variables exhibited strong and statistically significant associations and are therefore, multicollinear. These include age and marital status (X^2 = 155.178, p < 0.01); marital status and occupying house as a family (X^2 = 60.106, p < 0.01); home ownership and outage duration (X^2 = 7.448, p < 0.01); family occupancy and household size (X^2 = 46.864, p < 0.01), household size and outage frequency (X^2 = 11.067, p < 0.01), annual income and level of education completed (X^2 = 44.600, p < 0.01), annual income and employment status (X^2 = 21.294, p < 0.01) and, outage frequency and outage duration (X^2 = 91.478, p < 0.01) among others. All the significant correlations are highlighted in bold in the table. *** and ** indicate statistically significant result with p < 0.01 and p < 0.05 respectively.

In regression modelling, using explanatory variables that are multicollinear compromises the accuracy of the model equation since one of the correlated predictor variables will be redundant (explaining the same variance in the model equation). Dimension reduction approaches such as principal component analysis (PCA) are used to address multicollinearity. In this study, categorical principal component analysis (CATPCA) was used to transform the correlated variables into a smaller number of uncorrelated principal components which account for most of the variance in the data.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X_1	-	**9.386*** **	**155.178*** **	**27.426*** **	0.171	**11.020*** **	**13.185*** **	1.259	0.258	0.694	1.674
X_2			**17.260** **	**8.473*** **	1.077	0.408	2.840	**10.997*** **	2.137	**5.354** **	0.953
X_3				**60.106*** **	0.006	3.428	1.252	0.758	**6.720** **	0.924	0.101
X_4					**6.079** **	**46.864*** **	0582	0.201	0.658	0.932	**4.680** **
X_5						**3.937** **	1.446	0.189	0.077	0.723	**7.448*** **
X_6							0.114	0.379	1.830	**11.067*** **	0.754
X_7								**44.600*** **	**21.294*** **	2.821	**7.062*** **
X_8									**32.339*** **	3.005	1.442
X_9										0.296	**5.148** **
X_{10}											**91.478*** **
X_{11}											-

Table 24: Bivariate correlation results between respondent/household characteristics

5.2.5. Categorical Principal Component Analysis (CATPCA) results

The summary of the CATPCA model results generated in this study are presented in **Table 25** below.

Dimension	Cronbach's Alpha	Variance Accounted For	
		Total (Eigenvalue)	Percentage of variance
1	.481	1.708	15.527
2	.403	1.625	14.773
3	.388	1.564	14.218
4	.364	1.434	13.036
5	.140	1.110	10.091
Total	**.952[a]**	**7.441**	**67.645**

Table 25: Model summary for CATPCA

Rotation Method: Varimax with Kaiser Normalization.

a. Total Cronbach's Alpha is based on the total Eigenvalue.

As shown in **Table 25**, five dimensions/components were obtained using categorical principal component analysis. The components were identified basing on the Kaiser criterion (with varimax rotation), where components with eigenvalues greater than one (1) were deemed to have a significant contribution to the total variance of the transformed variables. The first component had an eigenvalue of 1.708 and contributed 15.527% to the total variance in the transformed variables. The second component (eigenvalue = 1.625) and third component (eigenvalue = 1.564) explained 14.773% and 14.218% of the total variance respectively. The fourth and fifth components contributed 13.036% and 10.091% to the total variance accounted for respectively. The selected components cumulatively account for a total variance of 67.645% in the original variables.

The loadings (correlation coefficients) between variables and components/dimensions are given in **Table 26**.

Variables	Dimension				
	1	2	3	4	5

X_1	**.901**	-.082	.042	.079	.005
X_2	-.119	-.125	-.149	-.135	**.818**
X_3	**.827**	.096	-.055	.188	-.166
X_4	.292	.140	-.055	**.737**	-.163
X_5	-.026	.276	.099	.383	**.552**
X_6	.037	-.240	.057	**.775**	.126
X_7	.305	-.185	**-.603**	-.203	.174
X_8	.092	.102	**.760**	-.005	-.115
X_9	.030	-.190	**.760**	-.080	.135
X_{10}	.067	**.816**	.050	-.165	-.051
X_{11}	-.060	**.833**	-.017	.088	.045

Table 26: Matrix of rotated component loadings

Variable Principal Normalization.

Rotation Method: Varimax with Kaiser Normalization.

For each principal component, variables with correlation coefficient greater than 0.5 (rotated values) are deemed to have significant loading on the principal component. The variables that effectively load on each of the five components are highlighted in bold in **Table 26**. Component 1 (COMP 1) had positive loadings on respondents above 35 years of age (0.901) and those who are married or have been married before (0.825). These variables mostly represent respondents who have reached the adult stage of human growth. This component is, therefore, classified as adult/mature respondents. Component 2 (COMP 2) had positive loadings on monthly outage frequency exceeding thirteen times (0.816) and average outage duration exceeding nine hours (0.833). This component depicts respondents who experience more power outages than others. Component 2 is, therefore, classified as high outage exposure respondents. The third component (COMP 3) had positive loadings on education attainment below tertiary level (0.760) and on employment status other than formal employment (0.760). This component also had a negative loading on annual income level exceeding 6000 Cedis (-0.603). The component represents those respondents who have a ‘low standing’ in society as regards education, employment and income. Component 3 is, therefore, classified as socio-economically disadvantaged respondents. Component 4 (COMP 4) loads positively on respondents who are living with family members

(0.737) and those living five or more members in the household (0.775). This component, therefore, characterizes respondents living in a large family setting, and it is categorized as such in this study. The fifth and final component (COMP 5) loads positively on male respondents (0.818) as well as on respondents who owned their homes (0.552). For want of a better description, this component is categorized as male home-owners.

5.2.6. Modelling results

In this section, model equations showing the relationships between outage impacts and various respondent characteristics are presented. Specifically, the principal components are used as the predictor variables in the place of individual respondent characteristics. Binary logistic regression was used since both the dependent and the independent variables have binary responses. Variables that are significantly associated with selected outage impacts are modelled according to the results presented in the corresponding tables below. Only the final model results, showing components that are significantly associated with the dependent variable, are presented. Several goodness of fit statistics including Hosmer and Lemeshow test, -2 Log likelihood, and overall predictive accuracy are also given. Nagelkerke R Square shows the strength of association between the components and the dependent variable.

Physical assault

From the model results shown in ***Table 27***, only two components, that is, high outage exposure and socio-economic disadvantage were identified to be significantly associated with reporting physical assault as an outage impact. High outage exposure was found to be positively associated with physical assault. Respondents who are exposed to more power outages are one and a half times more likely to report experiencing physical assault during outages than those with less exposure to outages (odds ratio = 1.591; $p < 0.05$). On the other hand, socio-economic disadvantage exhibited a negative association with reporting of physical assault. The odds of reporting physical assault as an outage impact were more than four times lower for socio-economically disadvantaged respondents than for others (odds ratio = 0.246; $p < 0.001$). The *Nagelkerke pseudo* R^2 statistic indicates that this model explains 13.4% of the variance in the dependent variable and it accurately predicts 75.3% of the respondents' answers.

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B) Lower	Upper
Model (Y_1)	COMP 2 (1)	.464	.231	4.034	1	.045	1.591	1.011	2.503
	COMP 3 (1)	-1.402	.228	37.794	1	.000	.246	.157	.385
	Constant	-.591	.168	12.372	1	.000	.554		
Goodness of fit statistics	-2 Log likelihood			484.988					
	Nagelkerke R Square			.134					
	Hosmer and Lemeshow Test			2.987		.225			
	Overall predictive accuracy			75.3%					

Table 27: Multivariate binary logistic regression results between physical assault and explanatory variables

Burglary (house break-in)

The model results presented in ***Table 28*** show that four components (high outage exposure, socio-economic disadvantage, male home-owners, and living in a large family setting) are significantly associated with reporting burglary/house break-in as an outage impact. High outage exposure is positively associated while socio-economic disadvantage, male home-owners, and living in a large family setting are negatively associated with reporting burglary as an outage impact. Respondents with high exposure to power outages are about three times more likely to report burglary during power outages than those with low outage exposure (odds ratio = 2.941; p = 0.000). Respondents who are male home-owners and those living in large family settings are 44.1% (odds ratio = 0.559; p = 0.004) and 41.6% (odds ratio = 0.584; p = 0.009), respectively, less likely to report burglary during power outages than others. The odds of socio-economically disadvantaged respondents reporting burglary during outages are about two times lower (odds ratio = 0.507; p = 0.001) than the others. The *Nagelkerke pseudo* R^2 statistic indicates that the model explains about 12.7% of the dependent variable while the model accurately predicts 60.6% of the respondents' answers.

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B) Lower	Upper
Model estimates (Y_2)	COMP 5 (1)	-.581	.202	8.240	1	.004	.559	.376	.832

		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
	COMP 4 (1)	-.538	.205	6.868	1	.009	.584	.390	.873
	COMP 3 (1)	-.679	.208	10.631	1	.001	.507	.337	.763
	COMP 2 (1)	1.079	.238	20.472	1	.000	2.941	1.843	4.692
	Constant	.654	.218	8.976	1	.003	1.923		
Goodness of fit statistics	-2 Log likelihood			581.372					
	Nagelkerke R Square			.127					
	Hosmer and Lemeshow Test			10.775		.149			
	Overall predictive accuracy			60.6%					

Table 28: Multivariate binary logistic regression results between burglary and explanatory variables

Disruption of water supply

In ***Table 29***, two components are identified to be significantly associated with reporting disruption of water supply as an outage impact. Living in a large family setting is positively associated while socio-economic disadvantage is negatively associated. Respondents who live in a large family setting are about two times more likely (odds ratio = 1.965; p = 0.018) to report outage-related disruption of water supply than those not living in large family settings. Respondents categorized as being socio-economically disadvantaged are about 70% less likely (odds ratio = 0.304; p = 0.000) to report disruption of water supply due to power outages as compared to others. The *Nagelkerke pseudo* R^2 statistic indicates that the model explains 10.0% of the dependent variable while the model accurately predicts 81.2% of the respondents' answers.

								95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model estimates (Y_3)	COMP 4 (1)	.676	.286	5.589	1	.018	1.965	1.122	3.441
	COMP 3 (1)	-1.192	.274	18.966	1	.000	.304	.178	.519
	Constant	-1.436	.258	31.025	1	.000	.238		
Goodness of fit statistics	-2 Log likelihood			388.674					
	Nagelkerke R Square			.100					
	Hosmer and Lemeshow Test			4.418		.110			
	Overall predictive accuracy			81.2%					

Table 29: Multivariate binary logistic regression results between disruption in water supply and explanatory variables

Disruption of academic activities

The model results presented in ***Table 30*** show that two components are significantly associated with reporting disruption of academic/education activities as an outage impact. Both socio-economic disadvantage and high outage exposure are negatively associated with disruption in academic/education activities. Socio-economically disadvantaged respondents are 32.5% less likely to report disruption of academic activities due to power outages than the others (odds ratio = 0.675; p = 0.048). Respondents with high exposure to power outages are 57% less likely to report disruption of academic activities as an outage impact in their households (odds ratio = 0.428; p = 0.000) as compared to those with low outage exposure. The *Nagelkerke pseudo* R^2 statistic indicates that the model explains only 6% of the dependent variable while the model accurately predicts 64.3% of the respondents' answers.

								95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model estimates (Y_5)	COMP 3 (1)	-.393	.198	3.915	1	.048	.675	.458	.996
	COMP 2 (1)	-.850	.219	15.083	1	.000	.428	.279	.657
	Constant	-.090	.161	.314	1	.575	.914		
Goodness of fit statistics	-2 Log likelihood			599.328					
	Nagelkerke R Square			.060					
	Hosmer and Lemeshow Test			.060		.970			
	Overall predictive accuracy			64.3%					

Table 30: Multivariate binary logistic regression results between disruption in academic activities and explanatory variables

Reduction in household income

Variables that significantly predict reporting of reduction in household income as an outage impact were modelled according to the results in ***Table 31***. In the table, four components are shown to be significantly associated with reduction in household income. Male home-owners and high exposure to outages are both positively associated with reporting reduction in household income because of outages, while adult respondents and the socio-economically disadvantaged are negatively associated. Adult respondents are more than two times less likely to report reduction in household income due to outages than others (odds ratio = 0.465; p = 0.004). Male home-owners are two times more likely to report outage-induced reduction in household income than others (odds ratio = 2.055; p = 0.006). Respondents categorized as being socio-economically disadvantaged are over two and a half times less likely to report reduction in household income due to power outages than others (odds ratio = 0.374; p = 0.000), while those experiencing high exposure to power outages are about two and a half times more likely to indicate reduced household income as an outage impact than others (odds ratio = 2.517; p = 0.000). The *Nagelkerke pseudo* R^2 statistic indicates that the model explains about 17.1% of the dependent variable while the model accurately predicts 76.5% of the respondents' answers.

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Model estimates (Y_6)	COMP 1 (1)	-.766	.268	8.193	1	.004	.465	.275	.785
	COMP 5 (1)	.720	.265	7.408	1	.006	2.055	1.223	3.453
	COMP 3 (1)	-.983	.266	13.632	1	.000	.374	.222	.630
	COMP 2 (1)	.923	.259	12.723	1	.000	2.517	1.516	4.179
	Constant	-1.166	.269	18.731	1	.000	.312		
Goodness of fit statistics	-2 Log likelihood			384.699					
	Nagelkerke R Square			.171					
	Hosmer and Lemeshow Test			3.722		.881			
	Overall predictive accuracy			76.5%					

Table 31: Multivariate binary logistic regression results between reduction in household income and explanatory variables

High expenditure on alternative energy sources

From the model results presented in ***Table 32***, three components: high outage exposure, adult respondents and socio-economic disadvantage are significantly associated with reporting high expenditure on alternative energy sources as an outage impact in Accra households. High outage exposure is positively associated while both adult and socio-economically disadvantaged respondents are negatively associated. Adult respondents were about 65% less likely to report outage-induced high expenditure on alternative energy sources than others (odds ratio = 0.348; p = 0.002). Similarly, socio-economically disadvantaged respondents were 55% less likely to report high expenditure on alternative energy sources because of outages than others (odds ratio = 0.451; p = 0.009). Respondents who have high exposure to power outages are over two and a half times more likely to report high expenditure on alternative energy sources than those with lower exposure to outages (odds ratio = 2.700; p = 0.002). The *Nagelkerke pseudo* R^2 statistic indicates that this model explains 11.8% of the dependent variable while the model accurately predicts 86.9% of the respondents' answers.

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Model estimates (Y_7)	COMP 1 (1)	-1.056	.334	10.013	1	.002	.348	.181	.669
	COMP 2 (1)	.993	.317	9.802	1	.002	2.700	1.450	5.027
	COMP 3 (1)	-.796	.306	6.784	1	.009	.451	.248	.821
	Constant	-1.358	.253	28.858	1	.000	.257		
Goodness of fit statistics	-2 Log likelihood			293.089					
	Nagelkerke R Square			.118					
	Hosmer and Lemeshow Test			.335		.997			
	Overall predictive accuracy			86.9%					

Table 32: Multivariate binary logistic regression results between high expenditure on alternative energy sources and explanatory variables

5.2.7. Discussion

The study has shown that the impacts of power outages in Accra households are diverse, ranging from safety/security concerns, to disrupted access to social services, and diminished household income among others. Through correlation and regression analysis, the study has also shown that household-level impacts of electricity outages in Accra are significantly associated with several factors, particularly, socioeconomic, demographic and outage-related characteristics of the households. For example, being socioeconomically disadvantaged was found to be negatively associated with reporting outage impacts in all the regression model results. This is likely because socioeconomically disadvantaged respondents are often less dependent on electricity for their wellbeing or day-to-day activities as compared to those of a higher socioeconomic status. Therefore, they possibly derive less value from having access to uninterrupted electricity. Because of this, they are likely more insulated from impacts of power outages as compared to those of a high socioeconomic status. Moreover, those with a high socioeconomic status (who are not socioeconomically disadvantaged) tend to attach a high value on the quality and reliability of services, including electricity.

The result which shows that socioeconomically disadvantaged respondents are less likely to report safety concerns (assault or burglary) as outage impacts may be attributed to two reasons. First of all, socioeconomically disadvantaged people potentially live in socioeconomically disadvantaged neighbourhoods, which – according to the Social Disorganization theory – have high concentration of crime [97] [98]. Because of this, they may not associate having uninterrupted electricity with improved personal or household safety. Secondly, because they live in areas with high crime rates, socio-economically disadvantaged people may have already developed other mechanisms to overcome existential threats to their safety. [99] has noted that socioeconomically disadvantaged people living in 'poor urban neighbourhoods' may rely on community social networks to protect their property during outages.

Living in a large family setting and being a male homeowner are other factors that were associated with less reporting of safety issues, particularly burglary, as an outage impact. There is a wide body of research that links family size to various socioeconomic outcomes. Large family size has been shown to have a negative effect on schooling, food security, and mental health [100] [101] [102] [103]. However, large family living can also confer some benefits including social skills gained from interacting with siblings [104] and reduced likelihood of divorce for married couples who had more siblings in their childhood [105]. This study identifies safety as an additional benefit of living in a large family, implying that large households (and their members) indirectly create and benefit from a "safety-in-numbers" effect against threats during outages. The contribution of male homeowners to improved household safety is, potentially explained by two factors. Owning a home gives the owner a leeway to make structural modifications necessary for improving the safety of the household [106]. Also, in many traditional African contexts, having a male household head is generally associated with a feeling of security in a home.

Large family living has also, as expected, been associated to a higher likelihood to report disruption in water supply due to outages. Large families are indeed expected to use more water than smaller households simply because of the big number of household members. However, when water supply is disrupted by outages, it is expected that everyone connected to the water supply system will be affected. In Accra, many households have water storage systems to buffer any short-term shortfalls in water supply. When a household size is big, the draw down from the water storage system will be faster and the potential for experiencing a water shortage will be higher than for a small household.

Furthermore, the finding that the socioeconomically disadvantaged are less likely to report high expenditure on alternative energy sources as an outage impact is in agreement with results from other studies. [99] has observed that due to their precarious socioeconomic condition, the urban poor in Ghana are often not able to afford better outage coping options/technologies (e.g., solar photovoltaics, generator) and therefore mainly utilise improvised low-cost options to cope with power supply interruptions in their households and communities. Additionally, according to a report published by the Australian Energy Market Commission [107], low-income households are significantly more likely to "do nothing" in response to long-duration electricity outages[3] as compared to other households. This is potentially because they have limited or no capacity to respond.

The negative relation between socioeconomic disadvantage and disruption in water supply and disruption of academic activities also underscores the fact that access to water and engagement in academic activities in socially and economically marginalized households may not be linked to electricity access. With regard to water supply, some studies in Ghana and elsewhere have shown that the rich often have higher access to portable water (distributed by the water utility company) than the poor [107] [108]. Water supply systems operated by utility companies utilise electricity to treat, pump and distribute water over a wide geographic area. This makes water supply through these systems susceptible to disruptions during extended outages. Since socioeconomically disadvantaged people have low access to piped water, they are largely insulated from the water supply disruptions that may be triggered by power outages. Moreover, the theory that associates

[3] Long-duration electricity outages are defined in the report as electricity interruptions that last for between four and 24 hours

access to electricity with increased participation in education activities is based on the assumption that access to electricity in households frees up children from some household chores or need to participate in employment activities, allowing them to participate in school/academic activities [61] [109]. However, this assumption may not be relevant in households at the lowest levels of the socioeconomic ladder, where the social and economic contribution of every member of the household (including children) can be vital for the survival and wellbeing of the household. Children from such households are, therefore, less likely to be aided by electricity to attend school or undertake home-based academic activities, and as a result, are less likely to experience outage-related disruption to their academic activities.

High outage exposure, representing high outage frequency and duration, was also positively associated with most of the reported impacts of outages in households. This is generally in line with prior expectations and agrees with most existing outage research that associates increased outage frequency and/or duration to high outage-related losses [53]. A study of power outage costs in Cyprus found that the residential sector, which experienced most outages in summer 2011, also suffered the highest costs (economic losses) [57]. High outage exposure was, however, found to be negatively associated with the likelihood to report disruption of academic activities due to outages. This is because households which are exposed to more outages are also more likely to have/utilise outage coping mechanisms, such as backup generation, candles, etc. These can still support academic activities during outages especially by providing light for studying in the night. However, some outage coping measures such as using candles, kerosene lamps, or rechargeable lamps may not be able to support academic activities especially for household members who use electronic gadgets (computers, tablets) for learning.

5.3. Outage coping choices, their drivers and associated socioeconomic and demographic factors

5.3.1. Outage response (coping) choices considering different household electricity uses

To analyse coping choices used by households during power outages, responses were first grouped under each of the common household electricity needs/uses, namely: lighting; cooking; heating; refrigeration; air conditioning; and information, communication and leisure. Four general categories of outage coping measures were identified from the household survey. These include: use of back-up electricity generation systems; use of electricity storage devices; use of non-electric energy resources; and waiting out the outage/using other coping measures. Further explanation for each outage coping category is given in ***Table 33***.

From **Figure 37**, it can be seen that when electricity supply is interrupted, most respondents choose to wait out the outage/use other coping measures. This is particularly common in households which use electricity for refrigeration and air conditioning (about 90%), information, communication and leisure (over 70%) and heating (over 50%). However, this option was less popular for coping with the loss of light during an outage with only 8.2% of the respondents indicating that they would not use any other light source during an outage. As far as providing light during an outage is concerned, the use of electricity storage devices is the most popular power outage coping choice within households, with 46.2% of respondents indicating that they use this option. Similarly, the use of non-electric energy resources for lighting during an outage is common with 41.5% of the respondents selecting this option. These findings are comparable to the results of another study in Accra, Ghana which showed that 42.5% of University of Ghana respondents use rechargeable lamps or cell phones (examples of electricity storage devices) to cope with outages as compared to 25.5% who use torchlight or candles (examples of non-electric energy resources) [110]. The use of non-electric energy resources is also a popular outage coping option among respondents who use electricity for cooking or heating, with 51.1% and 41.5% of the respondents respectively choosing this coping option to meet the two mentioned energy needs during a power outage. However, use of non-electric energy resources is the least common outage coping option for meeting refrigeration and air conditioning needs during a power outage (less than 10% of the respondents for both). Using electricity storage devices for coping with outages is rare for other household electricity needs other than lighting. Less than 10% of the respondents use electricity storage devices as a response option to meet information, communication and leisure, and air conditioning needs during outages while no respondent uses this coping option to meet cooking, heating or refrigeration needs during outages. Similarly, the use back-up generation systems (diesel generator or rooftop solar home system) as an outage coping measure remains very uncommon, with less than 5% of the respondents using this coping option across each of the household electricity needs, including cooking with 0% response. Backup generators and solar systems are, indeed, an expensive outage coping option for many households in Accra, especially those in the lower income range [99]. However, backup generation systems are a common outage coping choice used by business enterprises [111].

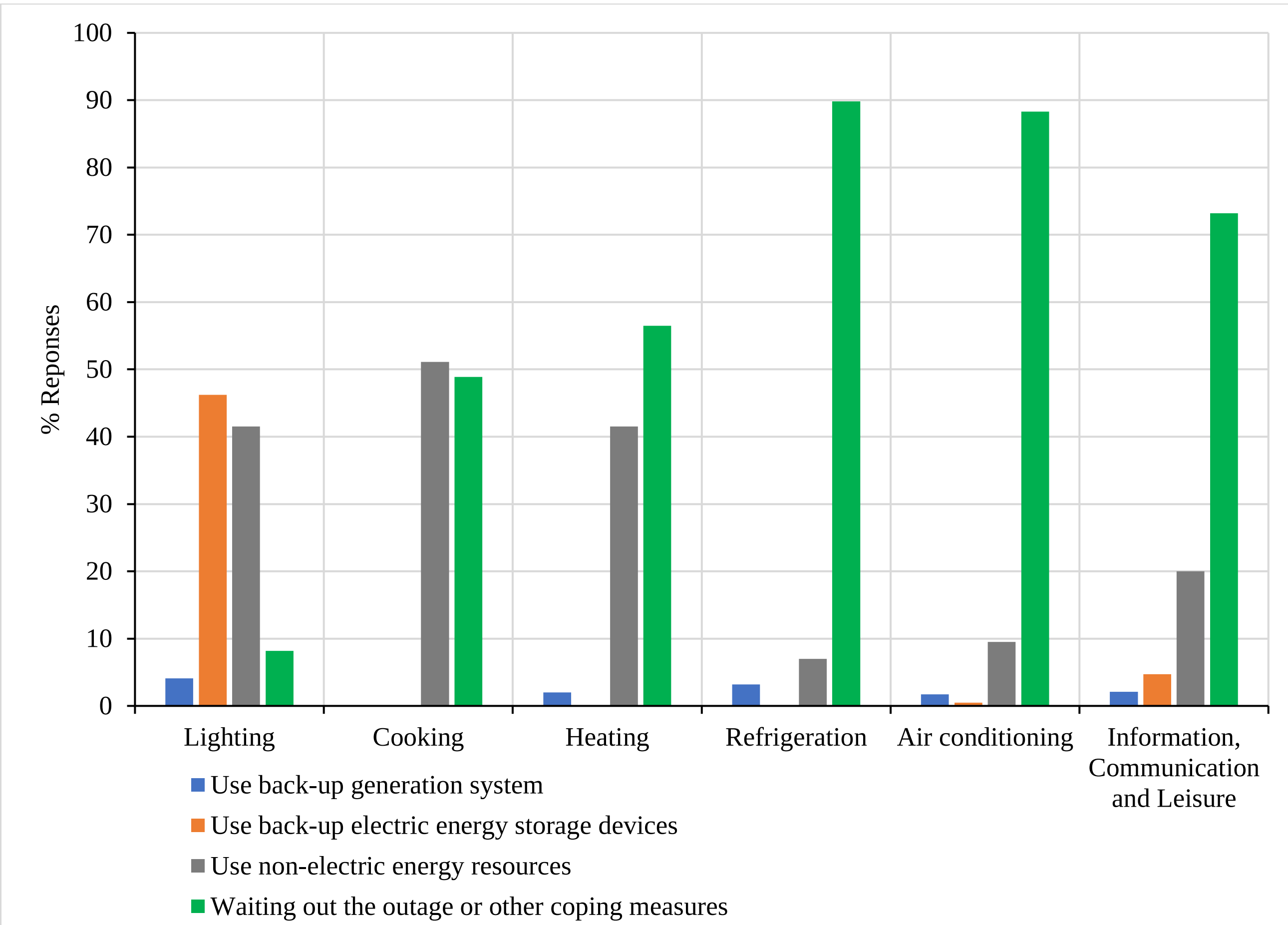


Figure 37: Electricity outage coping responses for different household electricity uses/needs

Outage coping measure	Explanation/Examples

Back-up electricity generation system	This includes diesel generator, rooftop solar home systems, or access to electricity from a mini-grid system
Rechargeable electricity storage devices	This includes home inverter systems, rechargeable solar lanterns and batteries, rechargeable lighting devices e.g., lamps, torches, mobile phones
Non-electric energy resources	These may differ depending on the energy need. Examples include natural gas for cooking/water heating, charcoal for ironing clothes, cell battery-operated torch/radio, kerosene lanterns, candles
Waiting out the outage or using other coping measures	This includes suspending activities or energy use until power supply is restored. These are households that "do nothing" in response to an outage. It also includes, for example, relying on newspapers instead of television for information and communication, eating out instead of cooking, not heating water or ironing clothes, going without refrigeration, accessing electricity at a friend's place, work place, or public areas

Table 33: Explanation of outage coping measures

5.3.2. Outage response choices across different socioeconomic groups

Several respondent/household socioeconomic and demographic factors were found to be significantly associated with outage response (coping) choices in Accra households. As shown in ***Table 34***, these include the respondent's gender (X^2 = 11.384, p = 0.010), age (X^2 = 11.054, p = 0.011), marital status (X^2 = 11.357, p = 0.010), level of education completed (X^2 = 26.593, p = 0.000), employment status (X^2 = 9.688, p = 0.021), and annual income (X^2 = 27.129, p = 0.000).

Characteristic	Measure	N	Back-up electricity system (95% CI)	Electricity storage devices (95% CI)	Non-electric energy resources (95% CI)	Wait out the outage (95% CI)	X^2
Sex/gender	Female	254	4.4 (1.9, 6.9)	42.8 (36.7, 48.9)	47.6 (41.5, 53.7)	5.2 (2.5, 7.9)	**11.384**
	Male	242	3.8 (1.4, 6.2)	49.6 (43.3, 55.9)	**35.3** (29.3, 41.3)	**11.3** (7.3, 15.3)	
Age	Less than 35 years	254	5.2 (2.5, 7.9)	42.2 (36.1, 48.3)	40.9 (34.9, 46.9)	11.7 (7.7, 15.7)	**11.054**

	35 years old or more	242	2.7 (0.7, 4.7)	**52.1** (45.8, 58.4)	40.6 (34.4, 46.8)	**4.6** (2.0, 7.2)	
Marital status	Single	216	3.8 (1.3, 6.3)	43.6 (40.0, 50.2)	39.8 (33.3, 46.3)	12.8 (8.3, 17.3)	**11.357**
	Married, cohabiting, divorced, widowed	280	4.4 (2.0, 6.8)	48.0 (42.1, 53.9)	43.2 (37.4, 49.0)	**4.4** (2.0, 6.8)	
Level of education completed	Tertiary	194	5.9 (2.6, 9.2)	52.7 (45.7, 59.7)	28.5 (22.1, 34.9)	12.9 (8.2, 17.6)	**26.593**
	Less than tertiary	302	**2.4** (0.7, 4.1)	**42.8** (37.2, 48.4)	**49.7** (44.1, 55.3)	**5.2** (2.7, 7.7)	
Employment status	Formal employment	210	5.0 (2.1, 7.9)	53.0 (46.2, 59.8)	34.5 (28.1, 40.9)	7.5 (3.9, 11.1)	**9.688**
	Informal employment, unemployed, retired, student	286	3.7 (1.5, 5.9)	**39.9** (34.2, 45.6)	**47.3** (41.5, 53.1)	9.2 (5.9, 12.5)	
Family occupancy	No	170	4.2 (1.2, 7.2)	41.1 (33.7, 48.5)	44.6 (37.1, 52.1)	10.1 (5.6, 14.6)	3.250
	Yes	326	4.0 (1.9, 6.1)	48.9 (43.5, 54.3)	39.9 (34.6, 45.2)	7.2 (4.4, 10.0)	
Household size	Less than 5 members	308	3.6 (1.5, 5.7)	45.4 (39.8, 51.0)	42.8 (37.3, 48.3)	8.2 (5.1, 11.3)	0.859
	5 or more members	188	4.9 (1.8, 8.0)	47.6 (40.5, 54.7)	39.5 (32.5, 46.5)	8.1 (4.2, 12.0)	
Home ownership status	Owning	147	**7.8** (3.5, 12.1)	42.6 (34.6, 50.6)	40.4 (32.5, 48.3)	9.2 (4.5, 13.9)	7.000
	Not owning	349	2.7 (1.0, 4.4)	48.1 (42.9, 53.3)	41.2 (36.0, 46.4)	8.1 (5.2, 11.0)	
Annual income	< 6000 Ghana Cedis	246	4.3 (1.8, 6.8)	34.1 (28.2, 40.0)	53.1 (46.9, 59.3)	8.5 (5.0, 12.0)	**27.129**
	>= 6000 Ghana Cedis	250	4.2 (1.7, 6.7)	**57.2** (51.1, 63.3)	**29.3** (23.7, 34.9)	9.3 (5.7, 12.9)	

Table 34: Frequency and relationship of outage response choices with socioeconomic characteristics of respondents

Female respondents were significantly more likely to choose non-electric energy resources as outage coping measures (47.6% vs 35.3%, p = 0.005) and significantly less likely to choose to wait out the outage (5.2% vs 11.3%, p = 0.013) than male respondents. Respondents who were 35 years old or more were more likely to use electricity storage devices as a coping measure during outages (52.1% vs 42.2%, p = 0.027) and less likely to choose to wait out the outage (4.6% vs 11.7%, p = 0.004) than those who are less than 35 years of age. Respondents who choose to wait out the outage were more likely to be single than married (12.8% vs 4.4%, p = 0.001). Respondents who had attained tertiary education were more likely to use backup electricity generation system (5.9% vs 2.4%, p = 0.046) and electricity storage devices (52.7% vs 42.8%, p = 0.031), and less likely to use non-electric energy resources (28.5% vs 49.7%, p = 0.000) as outage coping measures when compared to those who had no tertiary education. Those who were formally employed were more inclined to utilise electricity storage devices (53.0% vs 39.9%, p = 0.004) and less likely to utilise non-electric energy resources (34.5% vs 47.3%, p = 0.004) as an outage coping option than those who are in informal employment, unemployed, retired or students. Respondents who owned their homes were more likely to use a backup electricity generation system as an outage coping measure than those who did not own their homes (7.8% vs 2.7%, p = 0.010). Those who had an annual income greater than 6000 Ghana Cedis were also more inclined to use electricity storage devices (57.2% vs 34.1%, p = 0.000) and less likely to use non-electric energy resources (29.3% vs 53.1%, p = 0.000) as outage coping mechanisms than those with an annual income less than 6000 Ghana Cedis. Having a small or large household size did not significantly influence the choice of outage coping measures.

Several research on coping with disturbances have associated high income with increased ability/capacity to cope. With regard to power outages, this implies a high tendency to adopt the best available coping options especially a backup generation system [38] or using electricity storage devices. The finding in this study that income has no effect on the likelihood to use backup generation is rather striking. But this is likely because of the binary nature of the income variable used, which could have over-generalized the income groups. Indeed, as noted in another study, the cost of a simple back-up generation system in Ghana is prohibitively high [99]. This means that it can only be acquired by elites in the highest income category [38] and not necessarily by those in the middle-income category, who may also have an annual income greater than 6000 Ghana Cedis. This notwithstanding, for this study, the finding that high income (>= 6000 Ghana Cedis) is associated with the use of electricity storage devices further supports the notion that income is an important enabler of coping with stressors. Use of electricity storage devices such as inverters and rechargeable lamps is considered a better outage coping mechanism than non-electric energy sources such as candles, kerosene lamps or cell batteries which are commonly used by the urban poor [99].

With respect to education level, more educated people are more likely to be aware and appreciative of the various options available for coping with outages. Moreover, their coping choices are likely influenced by the knowledge that they have acquired, for example, on potential negative social and environmental impacts of some response options. This may have influenced their preference for electricity storage devices rather than non-electric energy resources. Moreover, since the more educated people are also likely to have higher incomes, this could have enabled them to acquire backup electricity systems.

5.3.3. Self-reported respondent’s drivers of coping choices to electricity outages

Several factors influence how households choose to respond to (cope with) power outages. **Figure 38** summarises the extent to which certain factors influenced people to choose different outage coping measures. In general, availability/accessibility of an outage coping option was the most popular determinant. 53% of the respondents considered outage coping options that were easily available or accessible to them. Besides this, close to 40% of the respondents were influenced by economics (price/cost) of the coping options. Other determining factors including ease of use, quality of service provided, and durability of the different coping options were also considered important by over 20% of the respondents. The factor considered by the least number of respondents in selecting an outage coping option was environmental impact (about 10%) followed by safety of use (11%) of the available options.

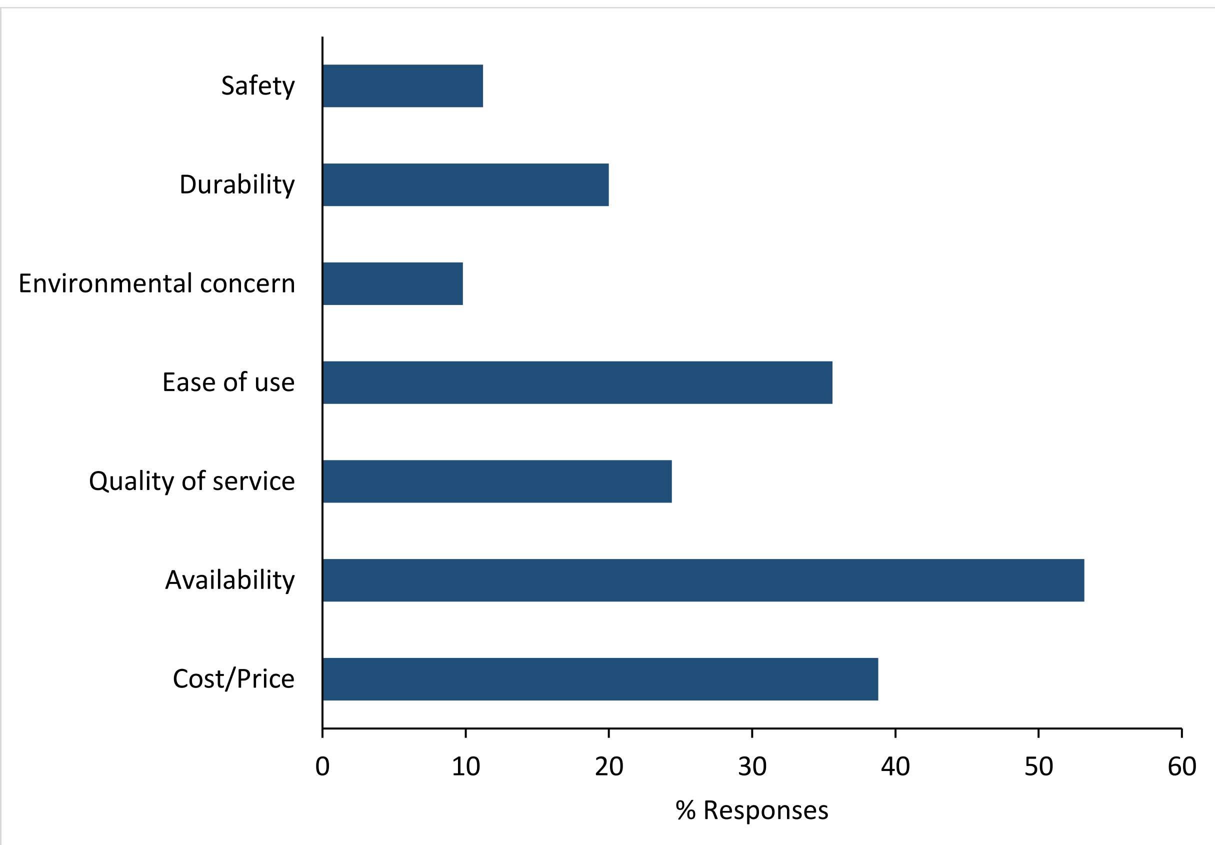


Figure 38: Self-reported determinants of outage coping choices in households

5.3.4. External enablers of coping with electricity outages

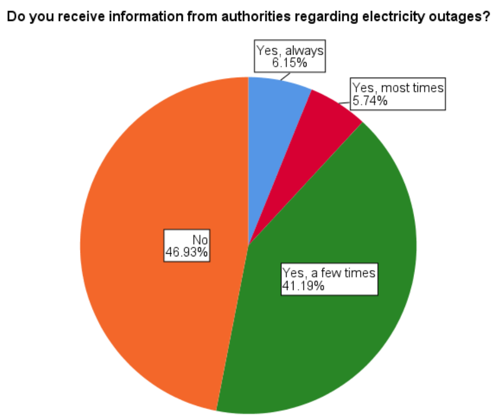
This study also analyzed the extent to which respondents had access to external enablers of outage coping. Specifically, the study analyzed respondents' access to outage-related information, channels of information delivery and content of the communication. Additionally, the study also analyzed respondents' access to natural resources that may be useful for coping with outages. The specific natural resources analyzed include: access to sufficient sunlight as a possible outage coping measure for lighting the home during the day, sufficient airflow in a home, and access to outdoor spaces that may aid in coping with hot environments which are typical in Accra.

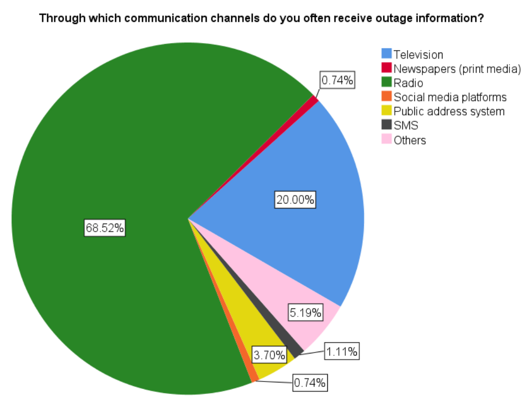
5.3.4.1. Information and communication

Effective information and communication about power outages is an important way through which formal agencies can support electricity users to effectively cope with power outages. One of the ways through which outage information supports better coping with outages is by enabling planning/preparedness [6]. For example, prior notice about outages can help households to schedule their activities and minimize the disruption/impact caused by outages [74]. In this study, respondents were asked whether they received information/communication about power outages from utility companies or other sources, and if yes, the kind of information received. As shown in **Figure 39**, about 47% of the respondents reported not receiving any kind of information about power outages, whether prior, during or after an outage. 41% of the respondents received outage information only a few times while about 12% reported receiving outage information most of the times or always.

For those who reported receiving outage information, when asked about the kind of information received about power outages, 76% of the respondents remember the main message to have been a notice about a planned or on-going outage, 20% report that the main message also included expected outage duration (or restoration time), while 1.5% of the respondents say the message included advice about outage coping measures. Close to 3% reported getting other types of outage-relevant information such as, protection of people and property during outages and electricity efficiency and conservation measures. Regarding source of outage information, 69% reported hearing the information through radio broadcasts while 20% got it through television channels. The other respondents got the information through public address systems (sound trucks), SMS alerts, print media, social media platforms and other sources. Those who received information through other sources got it from neighbors, colleagues, and through direct phone calls to the utility company.

Discussion: With 88% of the respondents receiving little or no outage information, it suggests that the utility companies' engagement to support coping with or resilience to power outages in Accra remains very low. While it is generally believed that power utility companies will take steps to communicate upcoming or ongoing outages to customers, it appears that, in the case of Accra, outage information is not reaching most of customers. One likely reason for this is because of the overreliance on radio and television for information dissemination. Information transmission between sources and receivers may also be disrupted during a power outage especially for those who rely on electricity-dependent channels, including, television and radio [112]. The impact of lack of access to outage information is that electricity users are left to speculate on whether/when electricity outages may occur, which hinders effective planning for coping/adaptation.





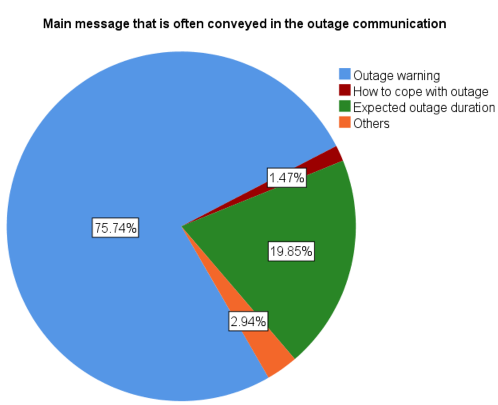


Figure 39: Access to electricity outage information in Accra households

5.3.4.2. Access to natural resources

Natural or ecological resources can be useful options for coping with electricity outages. For example, when power goes off, people may rely on natural sunlight to light homes during the day. And in the absence of electricity for powering air conditioning systems, people may rely on natural air circulation to cool their homes or spend more time outdoors. However, in crowded urban centres such as Accra, many people may not have access to these natural resources. Indeed, the extent to which people, especially in urban areas, have access to/can rely on these natural resources as a coping option for power outages remains largely unknown. In this study, respondents were asked to indicate the extent to which they had access to some 'natural' outage coping options, that is, sufficient natural light, natural airflow, sufficient outdoor area and community green spaces.

As shown in **Figure 40**, about 79% of the respondents indicated receiving sufficient natural light in all or most of the rooms in their homes. Therefore, if power outages occur during the day, these households may not require any form of artificial lighting. 12.5% of the respondents indicated receiving sufficient sunlight only in half the rooms while 8% do not receive sufficient sunlight in all or most of the rooms in their homes. These would need to use artificial lighting options as an outage coping measure to cope with power outages, even during day time. With regard to natural airflow, close to 73% of the respondents indicated having sufficient natural airflow in all or most of the rooms in their homes. These may choose to cope with outage-induced loss of electric-powered air conditioning by mostly keeping the doors and windows open. 15% of the respondents indicated receiving sufficient natural airflow in half of the rooms while 12% do not receive sufficient airflow in all or most of the rooms. These would need to rely on other coping mechanisms other than natural airflow. 84% of the respondents indicated having sufficient personal outdoor area for leisure and relaxation while 16% had none or not sufficient outdoor area. 63.5% of the respondents had somehow or completely sufficient access to community open spaces for relaxation/recreation purposes while 29.2% had none or mostly not sufficient access to community open spaces. 7.3% of the respondents did not know whether they had access to community open spaces or not. Access to natural resources (sufficient airflow and outdoor spaces) may explain why most respondents choose to wait out the outage, that is, not to use other energy-based coping options particularly following the loss of air conditioning during outages.

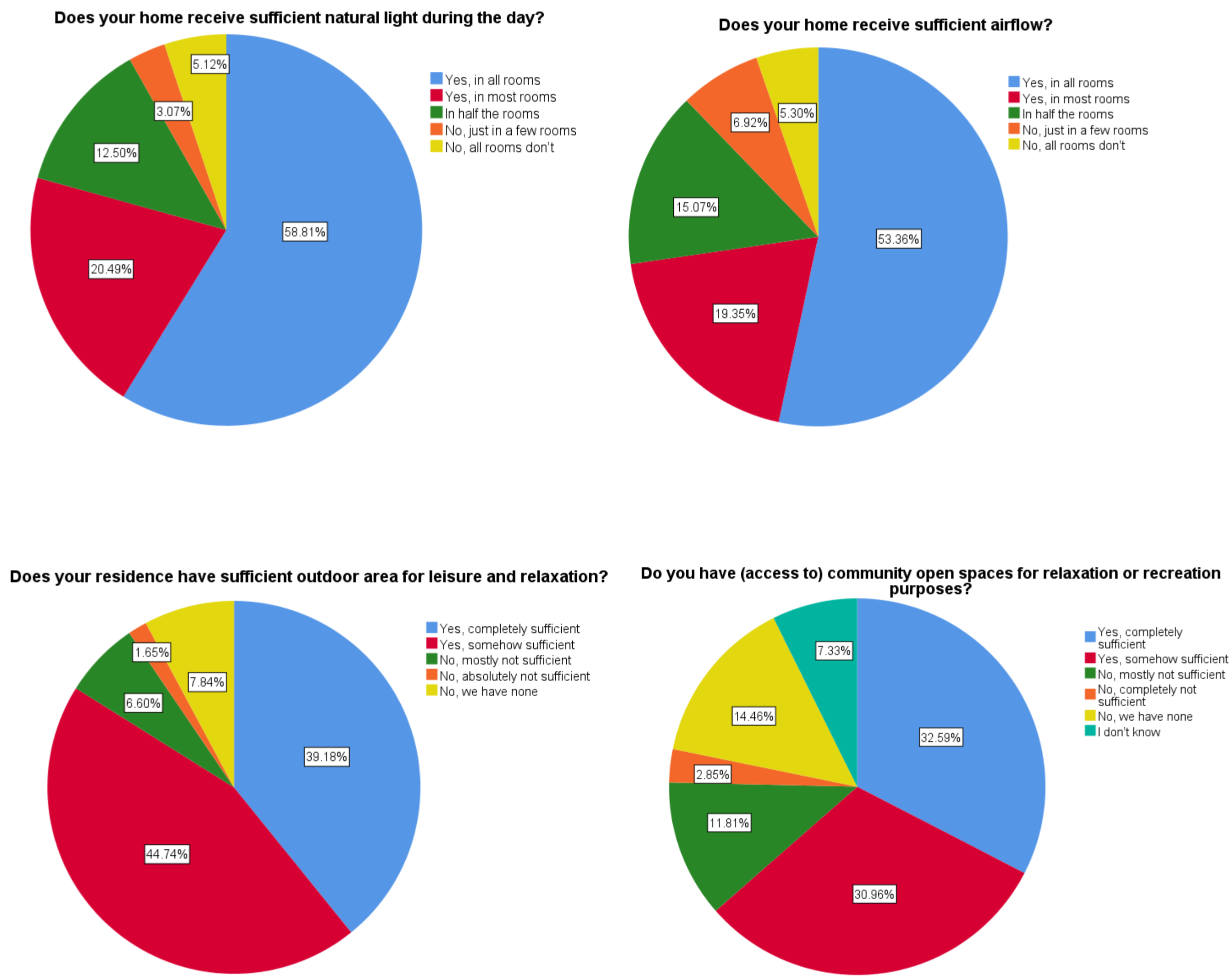


Figure 40: Access to natural resources for coping with electricity outages in Accra households

6. CONCLUSION

Under this chapter, the overall conclusions for each research question are presented as well as potential areas for future research.

Research question 1: How do levels of electricity outages experienced across communities in Accra Metropolis vary?

In this study, electricity outage (load shedding) segments in Accra, Ghana were linked to respective communities using spatial techniques. A standardized outage variable – outage exposure – was defined and used to measure the extent of electricity outages experienced in each community. Furthermore, the outage exposure value for each community was transformed using relevant community factors, followed by assessment of spatial patterns and production of relevant maps. To the best of our knowledge, no previous study has used such a spatial approach to comprehensively quantify, analyse and present electricity outage experiences in Ghana at such a small geographical scale. Additionally, the use of an extensive, year-long outage dataset from the electricity utility company has enabled the study to present a more complete picture of community outage experiences beyond what was previously reported in other studies. The mapped results are also very easy to understand by a wide range of stakeholders including utility-level decision makers, local leaders and residents. Moreover, the spatial quantification approach used in the study was useful for disaggregating available macro-level outage data to determine micro-level outage experiences in small communities. The approach can be used in other places/countries, especially in Africa, where electricity outages are rampant yet micro-level outage data for determining outage experiences at small geographical scales is generally unavailable.

The distribution of outages across communities in Accra, Ghana was found to vary across geographic space with tendency towards spatial clustering. The implication of this is that underlying community-level factors are influencing how outages are distributed in Accra. Communities which are hotspots (high outage-exposure clusters) as well as those with relatively low levels of outages (cold spots/low outage-exposure clusters) have been identified. By pinpointing the location of outage hot/cold spots and clusters, this research provides useful spatial information to utility-level decision makers in Accra. In case of future electricity supply shortages, the electricity utility company can utilize these results to guide outage planning in the study area towards improving fairness in electricity (outage) distribution. Hot spots, high-high clusters and high-low outliers also indicate potential priority communities for implementing targeted interventions to support resilience against electricity outage impacts, for example, targeted information campaigns about effective coping measures. Moreover, a further investigation of any unique characteristics of the low-high outlier communities may provide useful information about potential drivers of outage decisions made by utility managers, such as, prioritization of critical infrastructure.

An analysis of the relationship between outage exposure and community-level socioeconomic and demographic characteristics shows that outage exposure is moderately associated with some wealth and demographic factors. The nature of the relationships generally supports the hypotheses which state that: 1) electricity outages are targeted at the residential sector while commercial or industrial establishments are treated favourably, 2) the wealthy experience fewer outages than the poor, and 3) communities with a high percent of minority groups suffer more electricity outages. These conclusions are generally aligned with findings from other studies on electricity outages in several countries, which identify similar factors as drivers of outage distribution.

Research question 3: What impacts do electricity outages have on the social and economic wellbeing of the people in Accra, Ghana? What makes people more or less susceptible to outage impacts?

A survey of households in several communities in Accra, Ghana has found that power outages have diverse impacts on households ranging from safety/security issues, to access to food, income and access to social services. These findings present a bigger picture of impacts of outages in Accra, by going beyond identification of common direct impacts (for example, loss of light) to identifying societal implications of electricity outages. Furthermore, the tendency to report certain outage impacts was found to be significantly associated with socioeconomic, demographic and outage characteristics of the respondents/households. Respondents/households of lower socioeconomic status were generally less likely to report impacts of power outages. This could be attributed to several factors including their limited use/reliance on electricity. The finding that households exposed to more electricity outages are more likely to report outage impacts agrees with most outage research which shows a positive relationship between outage intensity and outage impacts. Other household characteristics, such as living in a large household see to provide insulation from one outage impact while increasing the likelihood of another outage impact being reported.

It is worth mentioning that modelling of reporting of some outage impacts (for example, food spoilage, disruption of communication services,) with potential explanatory factors did not yield statistically significant results. Additionally, the Nagelkerke pseudo–R Square values for all the significant models are small. This indicates that the predictive capacity of the identified predictor variables on the outage impacts was small, and therefore, some important predictor variables could be missing in the regression models. Future research should seek to integrate other possible predictor variables in order to enhance the accuracy of the model. This notwithstanding, the benefits of binary regression modelling go beyond having all significant predictor variables in the model equation. Identification of the relative odds of reporting (or not reporting) a particular outage impact by different socioeconomic groups used in this analysis has provided vital information on who is more (or less) likely impacted by outages and therefore, can enable implementation of targeted measures to support coping with frequent power outages.

Research question 4: How do households cope with or adapt to frequent electricity outages and what explains their response choices?

Identification and analysis of household coping strategies to outages was carried out using a survey and statistical analysis. Four categories of outage-coping choices were identified, each of which is preferred – to varying degrees – by households depending on the household electricity needs. For most electricity needs, households indicated that they choose to “wait out the outage”, which implies that, either, households lack sufficient capacities or options to cope with electricity outages, or, household needs that require electricity are not critical for the wellbeing of the household members and can be foregone in the absence of electricity. Nonetheless, as evidenced by the small proportion of people choosing the “wait out the outage” option with respect to lighting as an electricity need, lighting appears to be the most critical household need that requires electricity. Additionally, most households possibly have the capacity to access alternative lighting during outages since available coping options with regard to lighting may be inexpensive. On the other hand, most people chose to forego refrigeration and air conditioning potentially making them the least critical household needs that utilize electricity. Still, the reason for foregoing refrigeration and air conditioning during outages may be because of lack of suitable coping options.

In examining the link between outage coping choices and respondent/household characteristics, it is found that outage coping is influenced by socioeconomic factors including high income and high education attainment among others. This is further evidenced by the finding that cost/price is one of the leading internal determinants of outage coping choices reported by many respondents/households. Lastly, as evidenced by the limited access to outage information among the respondents, it appears from this research that institutional support towards enabling resilience to prolonged outages is insufficient or inefficient. On the other hand, most households seem to have high access to some natural resources that could aid in coping with outages. This, in some instances, may explain why many households choose the "wait out the outage" option.

Limitations and potential future research

Whereas every effort was made to undertake a comprehensive study covering the whole city of Accra, due to data limitations, the study was limited to communities in the western part of Accra Metropolis which are under the jurisdiction of a single electricity utility branch. Therefore, results can only be interpreted within the context of this study area and may not fully represent the experiences across the entire city of Accra. Analysing electricity outage experiences across all the communities in Accra may offer a complete picture of city-wide experiences. However, extra caution needs to be taken when analysing city-wide outage distribution for Accra using this approach. Since Accra metropolis is served by two branches of the utility company, there is a potential risk of introducing data-related errors into the analysis. There is no guarantee that both utility branches consistently collect all the outage statistics over a long period of time.

Finally, future studies should also seek to understand how communities experience other types of electricity outages, such as unplanned outages and the underlying causes of these recurrent outages. This may further shed light on the persistent challenges in electricity supply in developing countries, for example, aging infrastructure, electricity pricing, maintenance scheduling, and governance challenges.

7. RECOMMENDATIONS AND POLICY IMPLICATIONS

The results of this study provide important insights for electricity governance, urban planning, and social policy in Ghana. The findings demonstrate that load shedding is neither randomly distributed nor socially neutral. Rather, it is spatially clustered, systematically patterned, and associated with measurable household-level impacts. These results call for a shift from purely technical approaches to electricity rationing toward a more spatially informed, socially responsive, and equity-oriented framework.

First, the statistically significant spatial clustering of load shedding exposure suggests that outage allocation during supply deficits follows identifiable patterns. Neighbourhoods with high household density and higher concentrations of minority populations experience disproportionately greater exposure. This finding underscores the need for greater transparency in outage scheduling and allocation decisions. Electricity rationing frameworks should be guided by clearly articulated and publicly available criteria. Institutionalizing GIS-based monitoring systems within utility planning departments would allow for routine spatial audits of outage distribution. Such audits could help ensure that particular neighbourhoods are not systematically overburdened and that electricity rationing adheres to principles of distributive fairness.

The strong influence of household density on load shedding exposure also raises important policy questions regarding the balance between residential and commercial prioritization. The results indicate that predominantly residential neighbourhoods bear a greater share of outage hours compared to areas with commercial or industrial establishments. While protecting industrial productivity and economic output is a legitimate objective during supply shortages, excessive protection of commercial consumers at the expense of residential communities may deepen social inequities. Policy reforms should, therefore, seek to establish minimum reliability guarantees for residential areas and adopt rotational models that distribute outage burdens more proportionately across consumer categories.

The study further reveals that socioeconomic and demographic characteristics shape both exposure to outages and the impacts experienced at the household level. Percent of minorities and indicators of neighbourhood wealth (housing quality and vegetation cover) significantly predict load shedding exposure. These findings highlight the importance of integrating social vulnerability indicators into electricity planning processes. Energy governance should be aligned with broader social inclusion objectives to ensure that historically disadvantaged communities are not disproportionately exposed to service unreliability. Embedding demographic vulnerability metrics into planning models would enable more equitable rationing strategies.

At the household level, the impacts of outages are wide-ranging and include food spoilage, burglary, appliance damage, income reduction, and disruption to water and communication services. High outage exposure is positively associated with reporting most of these adverse impacts. This underscores the need to strengthen household resilience alongside improving supply reliability. For instance, the high prevalence of refrigerator damage suggests the need for policies that promote affordable surge protection devices and voltage stabilization measures. Public awareness campaigns on appliance protection and safe usage during outages could further mitigate losses.

The findings also show that burglary and physical assault are significant concerns during outage periods. These safety-related impacts indicate that electricity reliability is closely linked to public security. Policy responses should, therefore, extend beyond the energy sector to include coordinated action with urban security agencies. Increased police patrols during prolonged outages, community-based security initiatives, and the promotion of solar-powered security lighting systems could reduce vulnerability during blackout periods.

The disruption of water supply due to outages further reveals the interdependence between electricity and other critical infrastructure systems. Many water treatment and distribution facilities depend on electricity for pumping and purification. Strengthening backup generation capacity at water utility facilities and encouraging household-level water storage systems in high-density neighbourhoods would reduce cascading service failures. Integrated planning between electricity and water utilities is, therefore, essential to enhance urban resilience.

Interestingly, socioeconomically disadvantaged households were found to be less likely to report several outage impacts. While this may appear counterintuitive, it likely reflects lower dependence on electricity-intensive services and limited capacity to invest in alternative coping technologies. However, this does not imply reduced vulnerability; rather, it suggests structural exclusion from electricity-enabled benefits. Policymakers must, therefore, avoid interpreting lower reported impacts as reduced need. Instead, targeted interventions such as subsidized access to basic backup lighting, micro-financing for small-scale solar systems, and community-level shared energy solutions should be prioritized in low-income neighbourhoods to prevent the widening of resilience gaps.

The study also demonstrates the value of spatial statistical tools, including Moran's I, hot spot analysis, and geographically weighted regression, in uncovering hidden patterns of service inequality. These methods should be institutionalized within utility planning and regulatory oversight processes. Regular publication of disaggregated outage data would improve transparency and enable evidence-based policy adjustments. Regulatory agencies should establish clear service reliability benchmarks and enforce reporting standards that allow for spatial comparison across neighbourhoods.

Beyond short-term mitigation measures, long-term strategies must focus on diversifying supply sources and enhancing decentralized energy solutions. Encouraging rooftop solar adoption, battery storage systems, and hybrid mini-grid development in high-density urban residential areas would reduce dependence on centralized supply during periods of generation shortfall. Incentive structures, including tax relief and targeted subsidies, could accelerate the uptake of distributed renewable energy technologies. Such investments would not only reduce outage exposure but also contribute to broader sustainability and climate resilience goals.

In conclusion, the findings of this study reinforce the concept that electricity reliability is not merely a technical engineering concern but a matter of social justice and urban equity. Load shedding decisions shape patterns of opportunity, safety, and economic wellbeing. Energy planning in Accra must, therefore, evolve toward a model that integrates spatial analytics, social vulnerability assessment, resilience, and transparent governance mechanisms in order to achieve a more just, sustainable, and socially inclusive urban energy system.

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ANNEX 1: HOUSEHOLD OUTAGE SURVEY QUESTIONNAIRE

Preamble

Access to reliable electricity is essential for household welfare, economic productivity, and overall quality of life. However, many households experience electricity supply interruptions that can lead to losses, disruptions, and changes in daily routines. This survey seeks to better understand how households in Accra, Ghana use electricity, how power outages affect them, and the strategies they adopt to cope with these disruptions. The information collected will contribute to research and policy interventions aimed at improving electricity reliability, household resilience, and energy planning.

Your participation in this survey is voluntary, and all information provided will be treated with strict confidentiality. The responses will be used solely for academic and policy research purposes and will be reported in aggregate form, without identifying any individual or household. There are no right or wrong answers. We are interested in your honest experiences and perspectives. We greatly appreciate your time and contribution to this important study.

SECTION A: Respondent Profile

1. Name (optional): ________________________ Phone: __________________________

2. Sex: ☐ Female ☐ Male Age: ________

3. Relationship to household head: ☐ Head ☐ Spouse ☐ Child ☐ Parent ☐ Sibling ☐ Other ________

4. Marital status: ☐ Single ☐ Married ☐ Widowed ☐ Divorced ☐ Separated ☐ Consensual union

5. Religion: ☐ Christian ☐ Muslim ☐ Traditional ☐ None ☐ Other ________

6. Highest education completed: ☐ None ☐ Primary ☐ JHS ☐ SHS ☐ Vocational ☐ Tertiary ☐ Other ________

7. Employment status: ☐ Government ☐ Private formal ☐ Self-employed ☐ Casual ☐ Student ☐ Unemployed ☐ Other ________

SECTION B: Household Characteristics

8. Locality: _________________________________

9. Household size: Adults ____ Children ____

10. Rooms occupied (excluding toilet/bathroom): ________

11. Building type: ☐ Bungalow ☐ Semi-detached ☐ Apartment ☐ Improvised

12. Occupancy status: ☐ Own ☐ Rent ☐ Rent-free ☐ Perching

13. Years lived in this house: ________

14. Monthly household income (in Ghana Cedis): ☐ <100 ☐ 101–500 ☐ 501–1500 ☐ 1501–3000 ☐ 3001–6000 ☐ >6000

SECTION C: Household Energy Use

15. Main energy sources used for the following (specify appliance where relevant):

- Lighting: ____________________
- Cooking: ____________________
- Heating (water/ironing): ____________________
- Refrigeration: ____________________
- Cooling (AC/fan): ____________________
- ICT & entertainment: ____________________

16. Average monthly electricity expenditure: __________

17. Other monthly energy expenditures (gas, charcoal, wood, etc.): __________

18. Energy efficiency measures used (tick all that apply): ☐ Efficient bulbs ☐ Efficient appliances ☐ Behavioural change ☐ Sensors ☐ None ☐ Other ________

19. Motivation for energy saving: ☐ Reduce cost ☐ Environment ☐ Government policy ☐ Avoid outages ☐ Other ________

SECTION D: Electricity Outage Experience and Impacts

20. Outage frequency (past month): ☐ None ☐ 1–3 ☐ 4–6 ☐ 7–10 ☐ >10 times

21. Average outage duration: ☐ <1hr ☐ 1–3hrs ☐ 4–7hrs ☐ 8–12hrs ☐ 13–24hrs ☐ >24hrs

22. Priority electricity use during outages (rank 1 = highest): Lighting, Cooking, Heating, Refrigeration, Cooling, ICT

23. Items damaged due to outages: ☐ Bulbs ☐ Fridge ☐ AC ☐ TV ☐ Phone ☐ Computer ☐ None ☐ Other ________

24. Main disruptions during outages: ☐ Water ☐ Health ☐ Communication ☐ Education ☐ Transport ☐ Other ________

25. Economic impact of outages: ☐ Reduced income ☐ Higher alternative energy cost ☐ No effect ☐ Other ________

26. Food impact of outages: ☐ Spoilage ☐ Higher prices ☐ Delayed preparation ☐ None ☐ Other ________

27. Safety impact of outages: ☐ Assault risk ☐ Burglary risk ☐ Fire risk ☐ None ☐ Other ________

28. Compensation expectation per outage (minimum acceptable amount): ____________________

29. Willingness to pay to avoid outage (maximum amount): ____________________

SECTION E: Coping Strategies and Resilience

30. Alternative energy sources used during outage (generator, solar, storage, fuel, etc.): ____________________

31. Ownership: ☐ Individual ☐ Shared (with whom?) ____________________

32. Percentage of electricity needs met during outage: ☐ 100% ☐ 80% ☐ 60% ☐ 40% ☐ 20% ☐ Other

33. Duration you can sustain coping strategy: ____________________

34. Best long-term solution: ☐ Generator ☐ Solar ☐ Storage ☐ Fuel substitution ☐ Other ________

35. Loads willing to postpone during peak time: ____________________

36. Does your home receive sufficient natural light during the day?

☐ Yes, in all rooms ☐ Yes, in most rooms ☐ In half the rooms ☐ No, just in a few rooms ☐ No, all rooms don't.

37. Does your home receive sufficient airflow?

☐ Yes, in all rooms ☐ Yes, in most rooms ☐ In half the rooms ☐ No, just in a few rooms ☐ No, all rooms don't.

38. Does your residence have sufficient outdoor area for leisure and relaxation?

☐ Yes, completely sufficient ☐ Yes, somehow sufficient ☐ No, mostly not sufficient ☐ No, absolutely not sufficient ☐ No, we have none ☐ I don't know

39. Do you have sufficient (in terms of quality and quantity) open spaces (e.g., green parks) in your community for relaxation or recreation purposes?

☐ Yes, completely sufficient ☐ Yes, somehow sufficient ☐ No, mostly not sufficient ☐ No, absolutely not sufficient ☐ No, we have none ☐ I don’t know

SECTION F: Social Networks and Institutional Support

40. Are you a member of any of the following social groups? ☐ Community ☐ Work ☐ Religious ☐ Family ☐ None ☐ Other ________

41. Type of support received from social group: ☐ Financial ☐ Material ☐ Training ☐ Legal ☐ Other ________

42. Do you receive official outage information? ☐ Always ☐ Sometimes ☐ Rarely ☐ No

43. What is the source of information: ☐ Utility ☐ Regulator ☐ Media ☐ Social media ☐ Other ________

44. Are you aware of any support towards outage resilience? ☐ Yes ☐ No (If yes, specify): ____________________

45. Please provide any other suggestions for improving outage resilience: ____________________

End of Questionnaire

Thank You for Your Participation.