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A Whole Systems View to Driving Decentralised Renewable Energy
Investments in Sub-Saharan Africa

Energy and Sustainability
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PhD
Academic Year: 2023- 2024

Supervisor: Prof. Nazmiye Ozkan
Associate Supervisor: Dr Gill Drew
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School of Water, Energy, and Environment
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This thesis is submitted in partial fulfilment of the requirements for
the degree of PhD

(NB. Remove if the degree award is based solely on examination of the thesis)

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Abstract

The scaling-up of decentralised renewable energy (DRE), such as solar mini-grids, is vital to achieving climate goals and universal electricity access in sub-Saharan African (SSA) countries. However, high investor risk perception continues to impede DRE investment in SSA, highlighting the importance of understanding investors' risk perception and developing appropriate risk mitigation actions. Yet, the risk management (RM) literature offers a fragmented and singular approach, where the multidimensional nature of risk factors and their interactions are overlooked. In addition, current studies do not consider DRE site-specificity alongside investor heterogeneity in quantifying the implications of mitigation actions on the evolution of investment decisions. In this context, and to address these research gaps, this thesis aims to develop, validate, and implement a unified RM framework incorporating an investment decision model to assess the impacts of actions on investment and electricity access spatially, thus offering a more holistic outcome for decision-makers. This thesis focuses on solar mini-grids in Nigeria, which has one of the highest electricity deficits in SSA. The framework is implemented in two phases. In phase one, investment risks and potential mitigations were evaluated as perceived by four investor groups and various stakeholders through questionnaires, semi-structured interviews, focus groups, and an analytic hierarchy process methodology. In phase two, a novel DRE decision-support model was deployed to enhance existing methods by using a system dynamics-agent-based modelling (SD-ABM) approach. This approach incorporates complex interactions and feedback between heterogeneous investor and location attributes to establish investment outcomes for various case study mitigation scenarios. This thesis the following contributions. Phase one provides new empirical data comprising: identifying 13 additional risk factors compared to the literature, establishing importance of risk factors as perceived by diverse investor groups in Nigeria, and proposing mitigation strategies, some of which were tested in phase two as scenarios. The results indicated variations in risk importance among investors, with the most critical risk factors being revenue risks, limited access to low-cost capital, currency risks, insecurity, and inadequate policy implementation. Phase two

contributes to the knowledge of how complex system modelling can be applied to evaluate the impact of mitigation actions on the spatial evolution of DRE investment in a liberalised market. The case study results revealed that the most impactful mitigation scenarios were increased funding availability and the implementation of renewable energy mandates for domestic finance institutions. Whilst our findings confirm the criticality of concessional investors as identified in the literature, we find that meeting electrification targets necessitates incentivising risk-averse non-concessional-type investors. The developed model can additionally enable policymakers to explore the potential implications of further policy actions and investors to identify potential projects that suit their investment profiles during the feasibility phase.

Keywords:

Investment risk management, agent-based modelling, system dynamics, Investment decision support, risk evaluation, risk mitigation

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List of Abbreviations

ABM	Agent-Based Modelling
AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
BAU	Business-As-Usual
CAS	Complex Adaptive Systems
CDM	Carbon Development Mechanism
CSP	Concentrated Solar Power
DE	Debt And Equity
DEG	Debt, Equity, And Gant
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DFI	Development Finance Institutions/Multilateral Agencies
DisCo	Distribution Company
DomDFI	Domestic Development Finance Institution
DomFI	Domestic Finance Institution
DRE	Decentralised Renewable Energy
E1	Revenue Risk
E2	Collection Losses
E3	Foreign Exchange Volatility
E4	Inability to Achieve Single Off Taker or Cluster Effect
E5	Non-Cost Reflective Tariff
EG	Equity and Grant
EPSRA	Electric Power Sector Reform Act
ETP	Energy Transition Plan
EU	Expected Utility
EUT	Expected Utility Theory
EV	Electric Vehicle
F1	High Cost
F2	Inadequate Access to Low-Cost Capital
F3	Short Loan Terms
F4	Limited Local Financial Sector Experience
F5	Limited Financial Capacity and Experience of Developers and Local Investors
F6	Difficulty Accessing/Repatriating Foreign Exchange
FiT	Feed-In-Tariff
FX	Foreign Exchange
GHI	Global Horizontal Irradiance
GW	Giga Watt
HC	Hard Currency
IEDN	Isolated Electricity Distribution Network
IMG	Interconnected Mini-Grid
IPP	Independent Power Plant

IRR	Internal Rate of Return
ISO	International Standards Organisation
IT2	Interval Type 2
LCOE	Levelised Cost of Electricity
M1	Sensitivity of RE to Fossil Fuel Prices
M2	Low Competitiveness of RE Due to Subsidies on Alternatives
M3	Lack Of Competitive Hardware and Labour Market
M4	Poor Data Availability
M5	Barriers Due to Regulations
M6	Uncertain Market Growth Potential
MAD	Market Disclaimer Approach
MCDA	Multicriteria Decision Analysis
MCS	Monte Carlo Simulation
MG	Mini-Grid
MSE	Mean Squared Error
MW	Mega Watt
NBET	Nigeria Bulk Electricity Trader
NERC	Nigerian Energy Regulation Commission
NS	Not Specified in the Literature
P4	Lack Of Policy Implementation
P5	Duplicative Policy Development
P6	Inconsistent Policy Application
P7	Uncertainties in IMG Regulations Implementation
P8	Grid Extension Uncertainty
P9	Political Changes/Instability.
PBG	Performance-Based Grant
PDF	Probability Distribution Function
PI	Public Institutions
PP	Policy and Political Risks
PSL	Priority Sector Lending
PV	Photovoltaic
RA	Risk Analysis
RE	Renewable Energy
REA	Rural Electrification Agency
REF	Rural Electrification Fund
REFiT	Renewable Energy Feed-In-Tariff
RESIP	Rural Electrification Strategy & Implementation Plan
RM	Risk Management
RMPSE	Root Mean Square Percentage Error
ROI	Return on Investment
RPO	Renewable Purchase Obligation
RPS	Renewable Portfolio Standard
S1	Scenario 1
S2	Scenario 2

S3	Scenario 3
S4	Scenario 4
S5	Scenario 5
S6	Scenario 6
SA	Sensitivity Analysis
SAS	Stand-Alone System
SD	Systems Dynamics
SD-ABM	Systems Dynamics-Agent-Based Model
SDG	Sustainable Development Goal
SE	Social and Environmental Risk
SE1	Lack of Social Acceptance
SE2	Poor Consumer Awareness
SE3	Lack of Integration of RE Systems
SE4	Difficulty in Acquiring Land
SE4ALL	Sustainable Energy for All
SE5	Insecurity
SHS	Solar Home System
SSA	Sub-Saharan Africa Countries
T1	Limited Training and Research and Development
T2	Technical Skills Limitation
T3	Limitation in Developer's Capability
T4	Limitation in Quality Control and Manufacturing Capacity
T5	Uncertain Load Profile
T6	Inadequate Infrastructure
T7	Uncertainties in Site Characteristics
TE	Techno-Economic
TOPSIS	Technique For Order Preference by Similarity To Ideal Solution
WACC	Weighted Average Cost of Capital
WTP	Willingness to Pay

1 Introduction

1.1 Background and motivation

Access to affordable and reliable electricity is essential for the socio-economic progress of a society (1). Studies have demonstrated that electricity access is linked to improvements in education, health, and poverty reduction in lower-income countries¹ (2,3). These benefits have been internationally recognised through the adoption of the United Nations' Sustainable Development Goals (SDGs) (4), with SDG7 specifically targeting 'universal access to affordable, reliable, sustainable and modern energy for all' by 2030 and 'increasing substantially the share of renewable energy (RE) in the global energy mix by 2030'. However, approximately 733 million people worldwide, mostly in Sub-Saharan Africa (SSA), still lack access to reliable electricity (5). The deployment of RE technologies can play a critical role in achieving electricity access and climate goals through emission avoidance for this population.

Electrification planning studies have identified an integrated planning approach to meeting electricity access goals through centralised (main grid extension) and decentralised systems from a mix of technologies (6,7). Decentralised systems are typically isolated from the main grid but can be interconnected with existing grid facilities as supplementary or backup systems. Examples of decentralised systems include mini-grid or off grid and standalone systems (SAS) powered by fossil fuels or RE sources such as solar, hydro, and wind. Decentralised renewable energy (DRE) refers to decentralised systems powered by RE sources and involve the small-scale generation and distribution of electricity from RE sources located close to the consumer.

DRE has been identified as a financially viable electrification solution for about 60% of the unelectrified population in SSA, mainly living in rural and peri-urban areas (8–10) is primarily due to the distance of the population from existing grid

¹ World Bank defines low-income and lower-middle-income economies as those with a GNI per capita, calculated using the World Bank Atlas method as of 2018, of \$1,025 or less and between \$1,026 and \$3,995 respectively (3).

infrastructure, abundance of RE sources, and low electricity demand or unreliability of existing grid infrastructure. Among the literature, Mentis et al. (8) combined techno-economic analysis and geospatial factors such as resource potential and infrastructural characteristics to identify least-cost technologies for achieving electricity access. They found SAS can play a key role in providing basic electricity access to remote settlements while mini-grid and grid extensions become more favourable for denser settlements with higher demand (8). Similarly, another study (11) indicated a mix of grid, SAS and mini-grid systems to achieve SSA electrification targets. Such studies mainly focused on least-cost technology selection using techno-economic analysis, supported by subjective multicriteria decision, and differentiation of geospatial factors (8,12,13) in identifying pathways to universal electricity access. However, the studies do not consider that techno-economically feasible and least-cost electrification options may not lead to actual investment mobilisation (14). Investment mobilisation is additionally dependent on other factors such as funding availability, attractiveness of the investment, investment barriers, risk perception and attitude, and the policy environment (14).

The investment in RE experienced a 55% increase globally between 2018 and 2022 (5). This growth is attributed to the enhancement of RE technology, increased production volumes, and reduced costs of production (5,13). Furthermore, this momentum of RE cost reduction, new DRE business models, and improvements in regulatory frameworks have contributed to the shift towards DRE (1,15). Despite the progress made, it is estimated that an additional investment of USD 600 billion worldwide is required by 2030 to meet electricity access and climate change targets (16). This investment deficit is higher in SSA countries, which received less than 1.5% of the global RE investment between 2000 and 2020 – equivalent to 25% of the investment needs (5). Similarly, only USD 0.5 billion out of a required USD 2.3 billion investment in DRE was made in 2021 (5).

The necessary level of investment mobilisation requires increased participation of various investors such as private equity investors, domestic and international

finance institutions, impact investors, developers, and development finance institutions (17). However, low investment in SSA has been attributed to factors such as high-risk perception, capital intensiveness, low competitiveness, and inadequate supportive policies (18–20). Investors tend to invest in projects that offer an attractive value proposition in terms of risks and returns (21). DRE project returns are influenced by costs and revenues, while risks are driven by location-specific factors and uncertainties to investment and the measures in place to mitigate these risks (22). Therefore, risks can affect the predictability of project revenues and returns, thus limiting the investors' choices on where and how much to invest.

1.2 Research gaps

Risk-return profiles can be improved through holistic risk management (RM) which entails identifying, analysing, and evaluating specific multidimensional risks and their interdependencies, followed by identifying effective risk mitigations which can enhance investor appetite for DRE projects (23). However, DRE risk literature is scant and presents a fragmented approach to RM (23). Additionally, the studies do not consider the multidimensional perspective of risks and their interdependencies (24). Instead, the studies mainly focus on identifying a limited set of risks and barriers from the technical and policy (25–27), economic (25) or political and social (26) perspectives. Furthermore, the difference in risk priorities across geographical locations (28,29) and among investor types and other relevant stakeholders (30–32), highlight the need for location-specific and investor-specific risk studies. Yet, there is little empirical data on the diverse investor perspectives of risks and their evaluation especially in SSA countries.

Another gap identified in the existing RM literature is the limited quantification of the implications of risk mitigations for the investment decisions of different investor types and how these decisions impact spatial and temporal electricity access. Instead, existing studies mainly identify mitigation measures without quantifying their potential impact on DRE investment decisions (23). Investment decisions in DRE electricity markets are complex due to interactions between multiple interconnected components, agents such as investors, and their

emergent behaviours (33,34). The complexity of DRE investment decisions is increased by the diverse technology options and spatial variability in location factors (e.g., resource potential, demand, socio-economic characteristics) which can drive investment attractiveness and risk (14,35). These components and their complex interactions need to be accounted for in a unified framework when assessing the impact of risk mitigation measures and their implications for the spatial evolution of electricity access over time.

However, the existing models for DRE investment primarily incorporate least-cost considerations (8,12,36); they do not account for the additional complexities presented by diverse investors, location attributes, system interactions and feedback which can impact the evolution of investment decisions. Current approaches for analysing investment decisions in complex systems (35,37–39) such as system dynamics (SD) and agent-based modelling (ABM) predominantly represent grid-connected liberalised market structures and present some limitations for their application to DRE (refer to Chapter 4). The limitations can be overcome by integrating SD and ABM; whereby ABM represents the investment behaviour and decisions among heterogeneous investors while the macro-level perspective of the impact of investor decisions and feedback on supply-demand dynamics is modelled with SD. While few system dynamics-agent-based models (SD-ABM) (40,41), neither reflect the location specificity of DRE systems nor consider investor heterogeneity and risks in establishing spatial investment decisions and the consequences of mitigations on investment. Such an integrated SD-ABM model can be employed measure the spatial implications of different mitigation measures on investment decisions and electricity accessibility.

In addressing the above research gaps, this thesis seeks to enhance the literature on RM and DRE investment decision modelling by developing a holistic RM framework for DRE projects, establishing investor-specific DRE risk priorities, and examining the implications of risk mitigation measures on spatial investment and electricity access. The framework is applied to the SSA context with a case study of solar mini-grids in Nigeria.

1.3 Nigeria case study

Nigeria presents a relevant case study for SSA in this thesis due to her significant unelectrified population of over 90 million, and government commitment to achieving targets of 90% electrification by 2030, universal electricity access by 2040, and net zero emissions by 2060. Additionally, the high solar irradiation potential and dispersed population clusters make solar mini-grids the key DRE technology applied in Nigeria, and thus, the focus of this thesis. Moreover, scaling solar mini-grid investment in Nigeria can prove the commercial viability of mini-grids and encourage investment in other SSA countries (42). However, actual investment in solar mini-grids has been limited, with less than 10 MW installed in 2022 out of the 2.6 GW planned for mini-grids by 2030 (43). The electrification targets and low investment require deliberate actions to enable a de-risked environment to catalyse private sector investments.

1.4 Aims and objectives.

The aim of this research is to develop, validate, and implement a holistic RM framework that incorporates an investment decision model to evaluate the impact of risk mitigation actions on improvements in DRE investment and electricity access in a spatial context. The framework is applied to a case study of Nigeria while DRE in this context, refers to solar PV mini-grids due to its prominence in Nigeria.

To achieve this aim, the following objectives have been outlined below and Table 1-1 shows the relationships between the research objectives and the research gaps.

1. To develop a holistic RM framework for DRE projects that considers multidimensional risks and their interdependencies in identifying, evaluating, and mitigating investor risks.
2. To evaluate the risk perceptions of different investor types and establish the priority risks affecting investment in DRE in Nigeria and their mitigations.

3. To develop and validate an integrated System Dynamics-Agent-Based Model (SD-ABM) for simulating the spatial investment decisions by different investor types, reflecting risks, location factors, and their interactions.
4. To evaluate the effectiveness of different mitigation actions and draw their implications for spatial investment and electricity access.

Table 1-1 Relationships between research objectives and research gaps in the thesis

Research gaps	Objective			
	1	2	3	4
Scant DRE risk management literature, especially in SSA	x	x	x	x
Fragmented approach to RE and DRE risk management.	x	x	x	x
Limited of data on diverse investor perspectives of DRE risks.		x		
Limited quantitative risk evaluation methods deployed for SSA countries.		x		
Limitation in existing investment planning and decision models in the quantification of spatial and temporal DRE investment decisions.			x	x
Limited quantification of the effectiveness of risk mitigation actions on spatial and temporal investment decisions of different investor types and their impact on electricity access.				x

Dark and light shaded cells represent chapters with significant and moderate coverage of gaps respectively.

1.5 Research approach

1.5.1 Research philosophy

In addressing the research aim and objectives, selecting an appropriate paradigm to guide the research approach is crucial, as differing ontological and epistemological positions influence the research methodologies and methods employed. This thesis adopts a critical realist paradigm, which is guided by its key tenets, including the acknowledgment of knowledge fallibility, the concept of stratified reality, and the recognition of system complexity (44). Within the critical

realist paradigm, reality is understood to exist independently of our observations, and our understanding of reality is recognised as fallible, implying that knowledge developed in this thesis can evolve or be refined (44,45).

Critical realism posits an ontological perspective that delineates reality into three layers: the 'real' (comprising structures and entities with properties capable of activating causal mechanisms, whether observable or not), the 'actual' (where activated causal mechanisms result in observable events and effects), and the 'empirical' (observable events and effects) (44). Emphasising the importance of identifying causal mechanisms underlying observable phenomena, critical realism suggests that these mechanisms may not always be evident through empirical observations alone (46). In identifying the structures and entities, along with their properties and interactions, that generate causal mechanisms influencing investment decisions, this thesis adheres to critical realism's ontology emphasising the complexity in social systems such as in DRE investment decisions.

In acknowledging this complexity, critical realism underscores the interactions among multiple structures and entities, which can give rise to emergence, thereby altering the system (44–46). In line with this ontology, this thesis develops and implements a conceptual framework highlighting the complexity inherent in DRE investments. Unlike other paradigms such as positivism and interpretivism, the methodological approach of critical realism adopts a pragmatic stance, allowing for the utilisation of mixed methods in line with the study's context (45). To gain insights into actions to improve investments, this study examines various investors' risk perceptions and the effectiveness of actions to mitigate risks by considering the interactions among entities such as investors and locations and their characteristics that influence DRE investment decisions. Such risk perceptions and interactions can be explored through a combination of qualitative and quantitative approaches. Combining the two methods can be complementary, allowing for triangulation of findings (47).

1.5.2 Research methodological approach

This research implements a range of methods rooted in the critical realist paradigm to achieve the overall aim of the thesis. RE risk management literature is well established and could inform a framework for DRE risk management. Therefore, a holistic risk management framework development in objective 1 was achieved by a critical review and synthesis of RE risk management literature and extending the works of Ioannu et. al (48) and Painuly et. al (51). This informed a new conceptual framework for managing DRE investment risks covering the entire spectrum from risk identification to the evaluation of the effectiveness of risk mitigation measures, in accordance with the ISO31000 guidelines (49). The framework was applied to the SSA context, and this informed the methods applied in this thesis to fulfil the subsequent objectives. The overall methodological approach to meet research objectives and their relationships is presented in Figure 1-1. Figure 1-1 shows the critical literature review as the overarching phase that informed the developed framework using secondary data, while the framework was implemented in two subsequent phases.

Effective stakeholder engagement and communication are crucial for the success of RM, as per ISO 31000 guidelines (49). In the implementation of the conceptual framework, a participatory research method was thus employed during the two phases, creating an iterative framework involving various experts to collect and evaluate data, and discuss its implications – thereby increasing the relevance and acceptance of the analysis (50). Phase one involved primary data collection and analysis while phase two involved model development and evaluation. Phases one and two sequentially achieve objectives 2 and 3–4 respectively as follows. The evaluation of investment risk priorities of different DRE investors and other stakeholders in Nigeria in objective 2 (reported in Chapter 3), was achieved in phase one by conducting an expert online survey (N=70), drawn from the DRE sector in Nigeria in August–September 2021. These experts include investors (impact investors, developers, development finance institutions, domestic finance institutions) and other stakeholders (public-sector actors, development agencies, utilities, engineering service providers and consultants). This was followed by an evaluation of the survey using the analytical hierarchy process (AHP), and the

qualitative analysis of focus groups (N=3) and semi-structured interviews (N=17) of investors and other stakeholders in July–August 2022. Initially only focus groups were planned, however, some participants' unwillingness to participate in them necessitated using one-to-one interviews. The use of focus groups alongside other qualitative methods in such instances has been demonstrated in the literature (51). Phase one generated two outcomes which were utilised in subsequent analysis in Chapters 4 and 5. The first outcome is the variations in risk priority levels of different investor types, providing insights to risk drivers and interdependencies, as perceived by investors and other stakeholders. The participatory approach to interviews and focus groups provided an opportunity to corroborate and provide context to AHP results. Second is the identification of risk mitigation measures for the highest priority risks which could improve DRE investment.

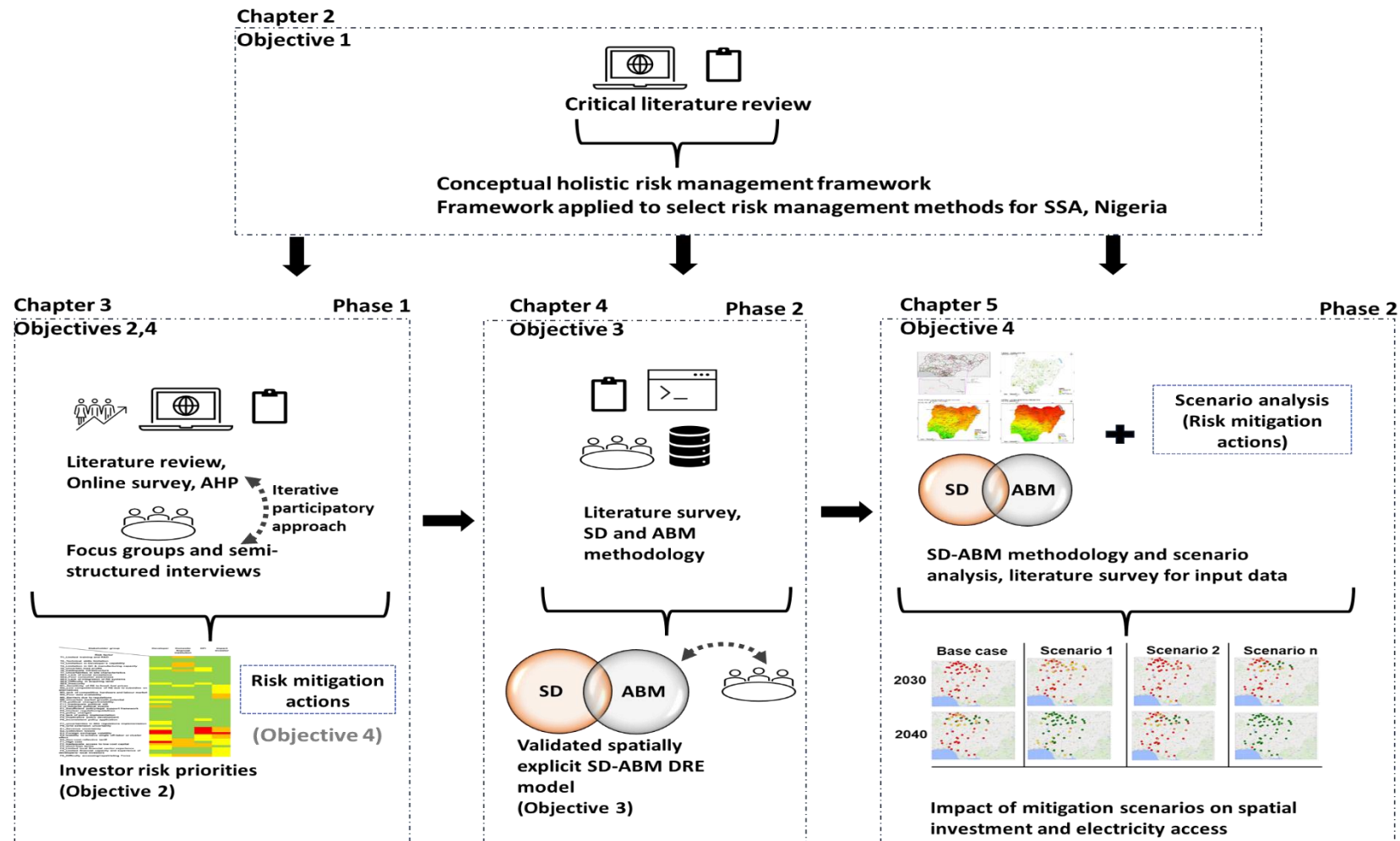


Figure 1-1 Overview of research approach.

Objectives three and four were achieved through the implementation of phase two of the framework. Objective three (Chapter 4) was achieved by developing and validating a novel DRE decision-support model which enhances existing methods by using an integrated SD-ABM approach for DRE investment decision and risk mitigation application, for the first time. The spatially explicit SD-ABM extends the DRE risk management literature and addresses the limitations of existing approaches (14,35,37,40,41,52) in quantifying the effects of risk mitigation actions on spatial investment and electricity access. The model incorporated inputs which include investor risk priorities informed by objective 3, and location and investor attributes. The model was validated using existing mini-grid data in Nigeria and following established validation methodologies (53–55). Within the iterative participatory approach, the model was shared in the interviews and focus groups to obtain feedback. The findings demonstrated the advantages of this integrated model in estimating the potential for investment, and access targets.

Following on findings from Chapter 3 and 4, the validated model was applied to potential mini-grid locations to explore spatial investment decisions of different investors. The locations are geographical population clusters identified in the literature (56) and government developed web-based geospatial applications (57) as potential viable mini-grid sites. These potential locations are defined by spatial attributes such as solar irradiation potential, poverty level, accessibility, conflict levels, and population sourced from databases. In objective 4, the impact of six mitigation measures, identified in Chapter 3, on the spatial investment decisions of the investor types and electricity access in the target years 2030 and 2040 were evaluated. Recommendations for policymakers and investors towards the improvement in investment were drawn from the model results.

1.6 Thesis outline

The thesis is presented as chapters in paper format. One paper (Chapter 2) is published, two are under review and one is in preparation. The structure of this thesis is illustrated in Figure 1-2 while the content, starting from Chapter 2 of the thesis is presented as follows:

Chapter 2: This chapter develops a 'holistic multi-dimensional investor risk management framework' for DRE based on the critical review and synthesis of RE risk management literature. The framework was reviewed from an SSA perspective to establish suitable methods to identify and evaluate risks and the effectiveness of specific mitigation actions towards improving investment and electricity access in a structured manner. The outcomes of this chapter laid the foundation for subsequent chapters.

Chapter 3: This chapter implements the RM framework for DRE in Nigeria. For the first time, this study collects and evaluates primary survey data and establishes the variation in the risk priority levels of four investor types and other stakeholders such as public agencies. Existing risk studies offer limited perspectives of risk priorities among different investors (1,25,26,58). Furthermore, from the qualitative analysis of interview and focus group data, the section brings together insightful perspectives to contexts and drivers of risks and draws on the insights to establish the potential risk mitigation measures for the highest priority risk factors for investors.

Chapter 4: This chapter introduces the novelty of a spatially explicit decision support model which uses an SD-ABM approach to establish spatial and temporal investment decisions of different investor types across modelled geographical locations and their consequent implications for electricity access. The model draws on existing DRE location planning models (8,14,36) and complex system decision models (14,35,37,40,41,52), integrating for the first time, location attributes, investor characteristics including risk priorities and attributes, system feedback and interactions, whilst considering consumer affordability, and willingness to pay to determine spatial investment patterns. These heterogeneous investor attributes and complex system perspective are often overlooked in existing DRE studies (8,12,14,36). The model validation output represented a close fit to historical data. Overall, the validated model and insights from the sensitivity analyses provide a platform and basis for testing the impact of mitigation measures on unelectrified population clusters earmarked for DRE.

Chapter 5: This chapter implements the model developed in Chapter 3 for 65 unelectrified locations in Nigeria to establish spatial investment by different investor types. Subsequently, it evaluates the impact of six mitigation actions on spatial investment decisions. The scenarios are selected from the outcomes of Chapter 3. By undertaking these analyses, this section can demonstrate how can risk management and investment decision making can be integrated into a spatially explicit SD-ABM model to better inform mitigating actions that drive investment and electricity access (41). The Chapter additionally draws implications of the mitigations for electricity accessibility targets and offers policy recommendations.

Chapter 6: This chapter presents a general discussion of the overall thesis findings, linking the outcomes from all the chapters. It additionally highlights wider implications of the thesis for policymakers and investors.

Chapter 7: This concluding chapter provides the thesis' empirical and methodological contributions to knowledge. Furthermore, the key limitations of this research are identified with the recommendations for future research.

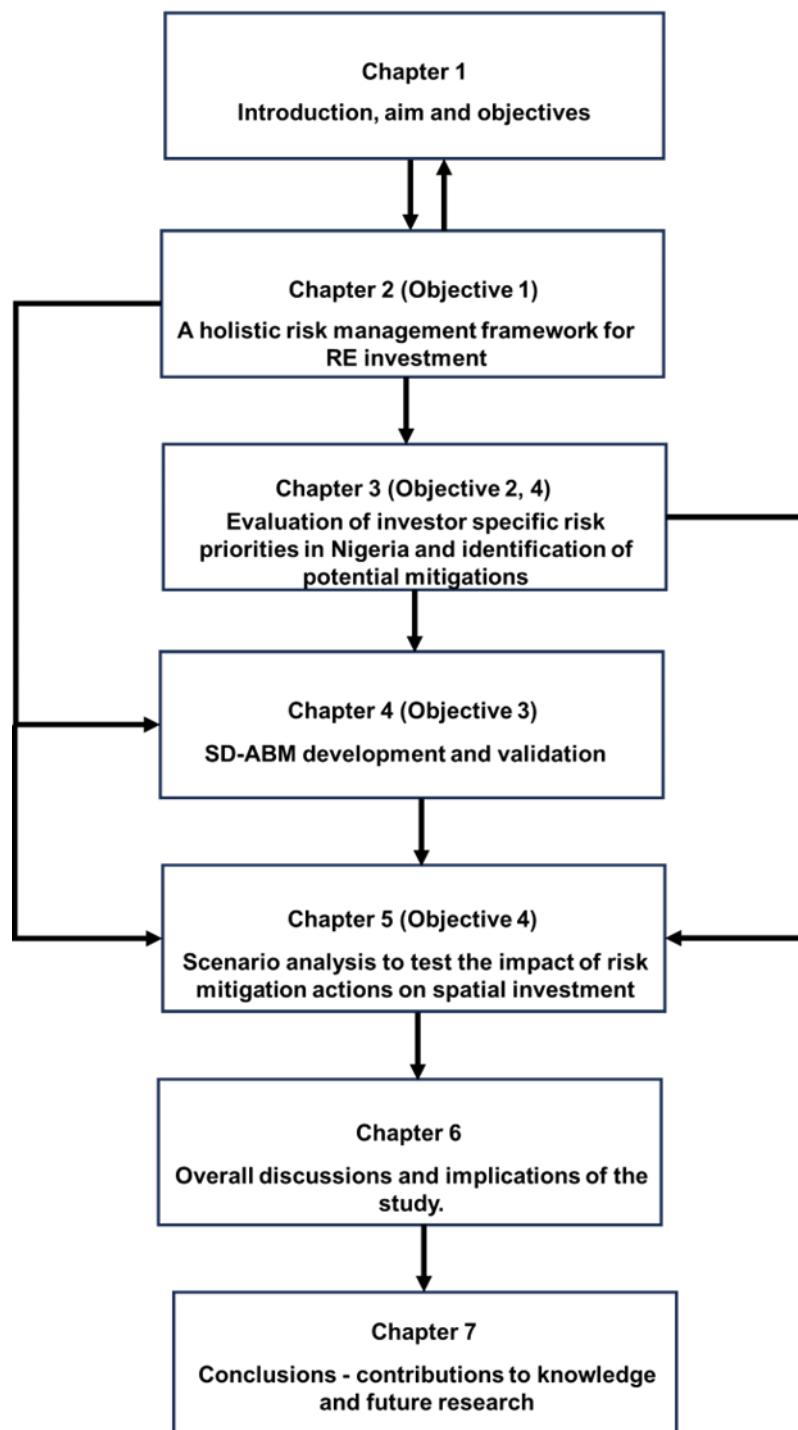


Figure 1-2 Thesis structure and interconnections of the chapters.

2 A holistic risk management framework for renewable energy investments

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Abstract

Private investments are critical enablers in achieving energy access for over 770 million people worldwide. Despite decreasing capital costs, investments in renewable energy (RE) projects in developing countries are low due to unattractive risk-return profiles. Through understanding key risk drivers and their interactions, actionable insights can be drawn to mitigate investment risks, making energy more accessible. This paper reviews RE risks and methods used for risk assessment and mitigation for developed and developing countries with a focus on Sub-Saharan African countries (SSA). The review finds that while risk analysis and evaluation mainly employed semi-quantitative multicriteria decision analysis (MCDA) and system dynamics (SD) methods for developing countries, qualitative methods were used to identify mitigations. The methods assessed technical and economic risks at a minimum, while MCDA and SD methods can assess social, political, and policy risks. The efficacies of mitigations were tested using SD and quantitative methods such as agent-based modelling and Monte Carlo simulation. The paper further introduces a 'holistic multi-dimensional investor risk management framework' which can be used to identify actions to improve investment risks in a structured manner. The framework addresses four fundamental limitations observed in the existing literature, recognising that RE risks are complex and involve multidisciplinary perspectives having interactions and system feedback. This review provides a valuable reference to investors, policymakers, and researchers, providing a catalogue of risks, and methods deployed in literature, including a framework to identify impactful actions to improve risk levels.

2.1 Introduction

Affordable energy is vital to the socioeconomic growth of any society. This is recognised by the United Nations Sustainable Development Goal (SDG) 7, which aims to ensure 'universal access to affordable, reliable, sustainable and modern energy for all' by 2030. In achieving this goal, SDG7 seeks to increase the share of renewable energy (RE) in the global energy mix substantially by 2030. About 75% of people without reliable energy access worldwide live within lower-income Sub-Saharan Africa (SSA). More than half of the unelectrified African population live in rural areas, typically low-density remote areas far from electricity grids, making decentralised energy systems a viable solution to bridge the energy access gap (6,7). Consequently, some scholars argue that a mix of grid extension, off-grid and standalone systems are needed to bridge the gap (7,8,10).

RE investments increased globally from US\$ 200 billion to US\$ 315 billion between 2005–2018 (59). This increase is driven mainly by lower capital costs due to technological advances and volume-induced savings in wind and solar PV technologies(60). However, there is a need to increase RE investments to an estimated US\$ 600 billion worldwide by 2030 to widen energy access while meeting climate change targets (59). The investment deficit is higher for SSA, where studies have estimated US\$ 11–9 billion/annum compared to annual investment needs of US\$ 40–43 billion (11,61). In SSA, power sector investments are primarily funded by the public sector with reliance on international development finance and grants (20,28,62–64). Studies identified a scale-up in private investments as a critical enabler to bridging this gap(11,65,66).

Low investment in RE projects in developing countries is attributed to capital intensiveness and unattractive risk-return profiles (28,63,65,67,68). Additionally, Zeng et al. (65) identified limited financing channels and poor adaptability of policies to changing markets and, consequently, risks and opportunities as contributors. De-risking policies and incentives are a means of unlocking RE potential (62,69,70). Different investors weigh opportunities and risks differently between countries (71). Understanding risks, risk levels, and their dynamic interactions from the investor perspective can enable a more deliberate approach

towards identifying appropriate actions that can lower investment risk exposure. This holistic understanding can provide more clarity on drivers of changes in key risks. Insights on the impact of mitigations, such as policy actions on improving financing conditions, cost competitiveness, and accelerating diffusion, can make RE investments more accessible and affordable (70,72,73).

There are three main strands of research employing RE investment risk management methods focusing on risk identification (68,74–78), risk assessment (28,29,32,68,72,79,80) and risk mitigation (62,64,67,81,82). Ioannou et al.(83) offer a review of risk analysis methods, while Painuly et al.(84) provide a framework for identifying RE penetration barriers and possible measures to overcome them. Within the existing body of literature, the review and application of risk methods are fragmented. This paper offers three contributions; firstly, it expands the scope of previous reviews (83,84) and presents a systemic review of RE investment risks and methods used for risk assessment and mitigation for developed and developing countries. Secondly, insights are drawn to introduce a 'holistic multi-dimensional investor risk management framework'. The framework unifies four key considerations treated in a fragmented manner in existing literature: consideration for (i) multi-dimensional perspective of risks (ii) interdependencies of risks and interactions within a complex system, (iii) dynamic nature of risks and (iv) holistic approach to risk identification, assessment, and mitigation of priority risks. Lastly, the new framework is reviewed from an SSA perspective and identifies suitable methods that could be employed to determine specific actions to reduce investor risks and consequently improve energy access in a structured manner.

The objectives of this paper are to (i) critically assess methods used in literature for the assessment and mitigation of RE investment risks for developed and developing countries, (ii) identify specific risk factors and appropriate risk management methods, and (iii) propose a conceptual framework that uses a holistic approach to identify actions for managing investment risks.

The paper is structured as follows: Section 2.2 provides an overview of risk management. Section 2.3 sets out the methodology. Findings on risk

identification are presented in section 2.4, while findings on risk analysis, evaluation, and mitigation methods are presented in section 2.5. Section 2.6 presents a conceptual framework for holistic risk management, discussions, and considerations from an SSA perspective. Section 2.7 offers conclusion.

2.2 Overview of risk management

ISO 31000 (49) defines risk as the effect of uncertainty on an organisation's ability to meet its objectives. Additionally, barriers may also introduce challenges to achieving an organisation's objective. IRENA (76) defines barriers as obstacles or challenges in developing, financing, investing in, or operating projects. Project development risks and barriers can increase investors' perception of the overall difficulty of the investment environment. Hu et al. (85) note that actual and perceived risk factors influence the risk of RE investment. Risk perception is a function of risk judgement (defining risk levels) and risk attitude (reflecting the emotional attitude of an investor towards a judged risk) (85), which can impact an investment decision. Attributes that can increase risk perception could be in the form of psychological, behavioural, or institutional characteristics such as lack of knowledge and experience or path dependence where historical investments in a particular technology, e.g. thermal generation, may impact RE risk perception and investment decisions (85). These attributes need to be considered contextually due to the impact on the perceived investment value proposition and corresponding investment decisions.

ISO 31000 (49,86) provides the guideline for effective risk management which includes (i) establishing the context, (ii) risk identification, (iii) risk analysis, (iv) risk evaluation, and (v) risk treatment(49,86). In establishing the context, the following needs to be considered: the scope of the project, its boundaries, location, stakeholders, objectives, and what level of risks are considered acceptable. The next step is to analyse the risks to determine risk levels based on likelihood and consequence. These risks are prioritised at the evaluation stage to determine acceptability. Outputs from this stage determine which risks require treatment. Risk treatment involves the implementation of controls to mitigate risks. This study uses 'risk mitigation' instead of 'risk treatment,' which is more

prevalent in the reviewed literature. The risks are reviewed and updated at each risk assessment and mitigation stage via stakeholder communication and consultations.

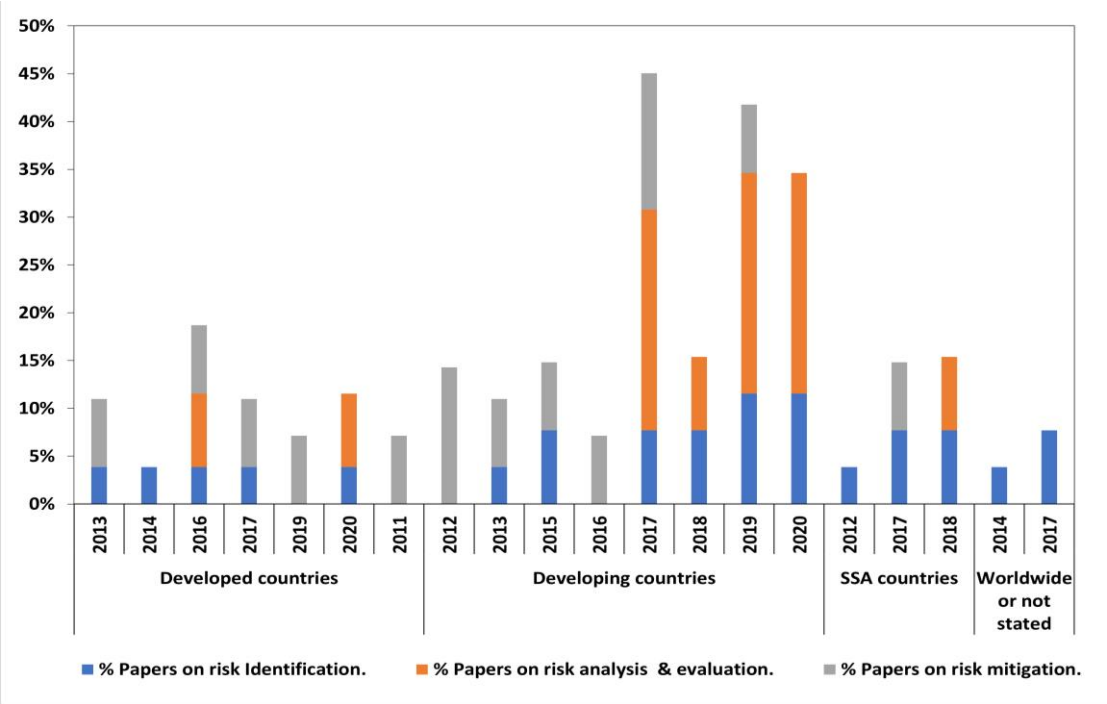
2.3 Methodology — Identification and selection of relevant studies

This section outlines the methodology for the critical literature review employed in identifying, selecting, and synthesising the relevant literature considered in this study. The process for identifying the relevant literature consisted of Scopus searches limited to the years 2010 to 2020. To ensure comprehensive coverage of RE investment risk literature regardless of geographical location, the searches were conducted with the keywords ‘Investor risk renewable energy investment’, and ‘Investor risk economic renewable’, resulting in 242 and 111 papers respectively. Additional studies were identified by reviewing cited references in the relevant papers meeting the search criteria. This snowballing approach allows for the identification of topical papers more reliably than a database search; however, results are dependent on the starting papers (87,88).

The papers were analysed by initially reviewing the abstracts, followed by full paper examination to determine relevance based on the following criteria: their coverage of risk management methods encompassing risk identification, analysis, evaluation, and mitigation. Papers related to assessing the effectiveness of mitigations such as policy actions were classified under risk mitigation. Papers falling outside of these classifications were excluded from the review. Consequently, 42 papers were selected. The papers were subsequently analysed based on spatial and temporal distributions, methods, and technology application.

Figure 2-1 and Figure 2-2 show the distribution of papers. Geographically, 52% of studies covered other developing nations like China, while 24% and 19% of studies covered SSA and developed countries, respectively. More focus has been on semi-quantitative risk analysis and evaluation in other developing countries than SSA. While studies covering developed countries focused on

quantitatively exploring the effectiveness of mitigations, papers related to SSA mainly focused on the qualitative identification of risks and mitigations.



* Distribution is only shown for periods where relevant studies were identified.

*' Worldwide or not stated' countries do not have specified locations and may include SSA. 'Other developing countries' exclude SSA.

Figure 2-1 Geographical and temporal distribution of reviewed papers

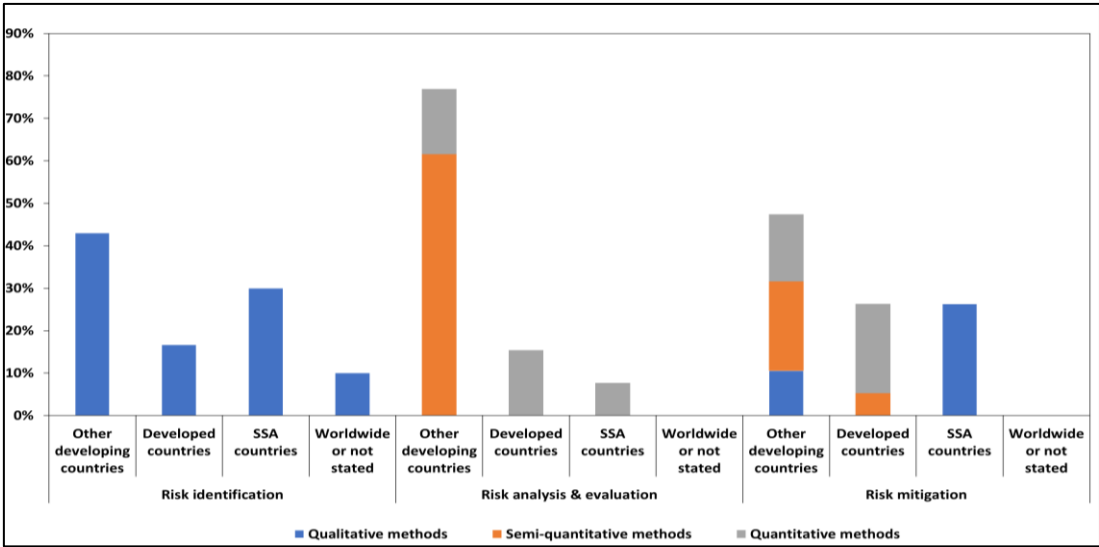


Figure 2-2 The distribution of studies by methods and relevance to risk management framework

Figure 2-3 presents an overview of methods reviewed in the literature. Qualitative methods ranging from literature reviews to interviews and surveys have been used for risk identification, while risk analysis (RA) and evaluation have used semi-quantitative and quantitative methods. Risk mitigations were identified via qualitative methods, while quantitative methods tested their effectiveness.

Findings from the literature review are arranged in the following order according to the risk management framework and grouped based on methods, spatial distribution, application, and coverage of risk factors. RA, evaluation, and mitigation are grouped in the same section for continuity as similar methods have been used in the literature.

- i. Risk identification.
- ii. RA, evaluation, and mitigation.

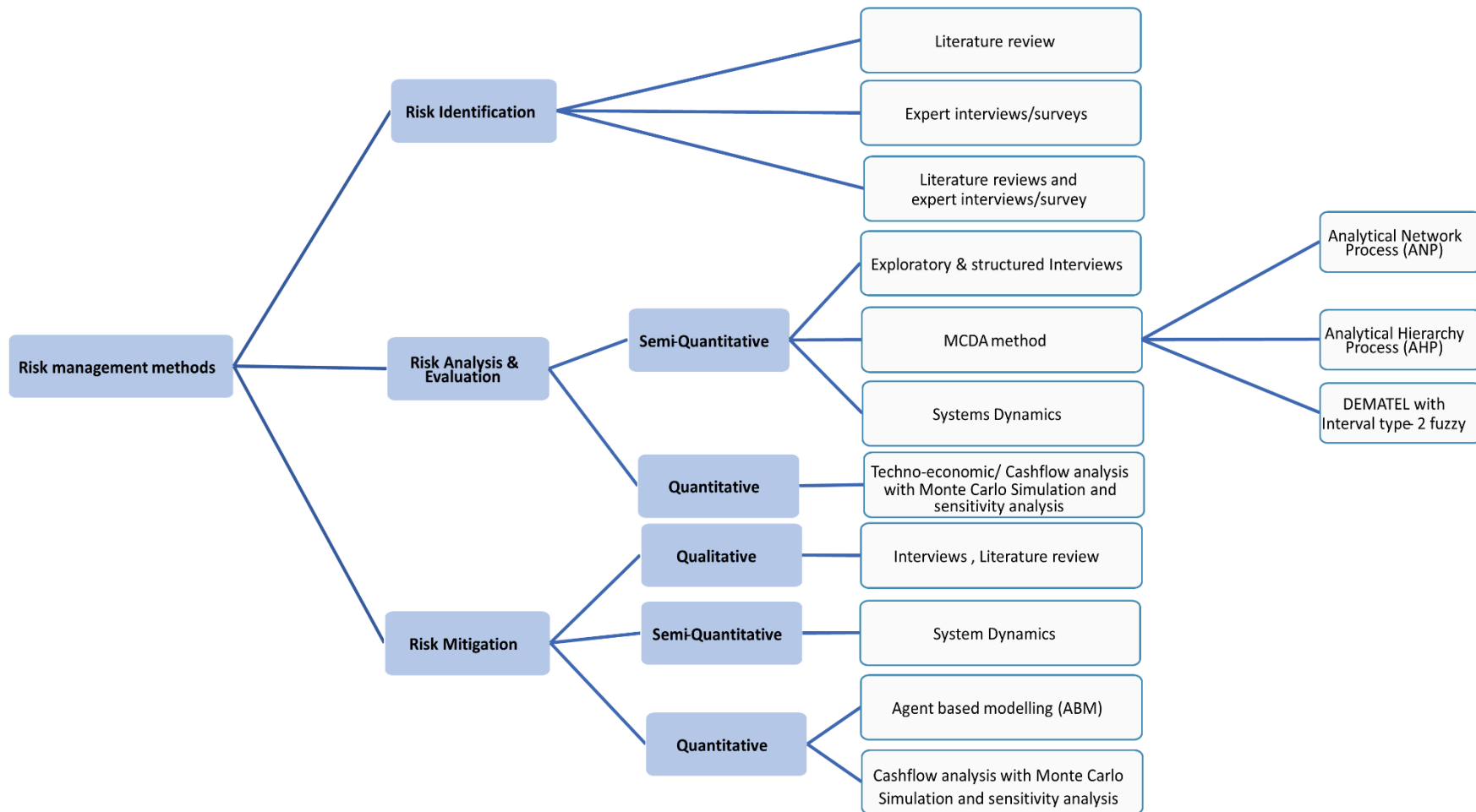


Figure 2-3 Overview of RE risk management methods in the reviewed literature

2.4 Review of RE risk identification

2.4.1 Risk classification and coverage

Classification of RE risks was done broadly according to barriers or uncertainties by focusing on (i) location, (ii) stakeholders (iii) project phases. Within these broad rationales, barriers have been categorised differently according to the focus of the study. For example, Soshinskaya et al. (77) categorised barriers into technical, regulatory, financial and stakeholder barriers, whilst Williams et al.(22) identified technical, financial, and policy/regulatory barriers as crucial barriers to RE uptake in developing countries. Bhattacharyya et al.(74) found technical, policy, financial, revenue, and political risks as factors impacting mini-grid implementation to scale in developing countries. Schmidt et al. (62) additionally considered risks according to barriers that stem from stakeholders at local, national, and international levels along revenue sources. This approach enabled a line of sight between barriers to revenue and measures required at the different stakeholder levels. Malhotra et al. (28) classified risks according to barriers from stakeholders who influence the cost of financing for a portfolio of projects. Risks were categorised such that they are mutually independent to enable independent analysis. Interactions were thus not considered. In contrast, Liu et al. (80) considered that risk factors dynamically change through feedback loops. This approach provided a system perspective involving risks and their interactions.

Different barriers can translate into investment risks at different project phases thereby, discouraging investments (62). Hu et al.(85) grouped risk factors according to the stage of the project (preliminary risk scanning, appraisal, capital access, and project development stages) with a view that as projects mature, more information becomes available, and the level of uncertainty becomes clearer. Additionally, as a project matures, the type or level of risks can also change. Barroco et al.(89) classified risks according to project phases (feasibility, pre-construction, financing, construction, and operations phases) and in the context of developing countries. The study provides a view of how risks change with project phasing. Knowledge of risks per project phase provides an opportunity to address risks timely.

Risk identification studies in the literature have used different risk categorisation themes according to their intended study focus. Some studies identified barriers without formal categorisation, e.g., inadequate technical skills, poor policy frameworks, and access to finance (25,26,75,90) as barriers to RE in SSA. This review uses the following definitions adopted from the literature to standardise the categorisation of risks (presented in Table 2-1).

- **Technical risks** arise from factors related to the type of technology, e.g. technology maturity, resource capacity and factors that can affect the technical design and implementation (22,80).
- **Resource risks** are the risk of lower revenues due to inaccurate resource potential estimation, such as variability or intermittency of radiation in solar development (72,80).
- **Policy and regulatory risks** refer to uncertainties in meeting project objectives due to legal frameworks, policies, or regulations changes.
- **Political risks** arise from political events that can impact investments, e.g., government change, political will, institutional structures, security events, embargoes, and currency inconvertibility (25,29,80,85).
- **Economic and finance risks** may arise from economic or financial factors that impact the project value or deployment. These can include changes in the economic environment on the macro level, e.g., currency fluctuation, uncertainties in accessing appropriate financing, and revenue uncertainty (22,26,74,89).
- **Market risks** refer to uncertainties brought by variations in markets, e.g., market access barriers, and changes in market conditions (74,80,85).
- **Curtailment risks** account for lower revenues due to unexpected curtailment (72).
- **Social risks** emerge due to changes in social conditions, e.g. public resistance impacting adoption patterns, and demography (29).
- **Environmental risks** may result from changes in environmental regulations or impacts caused by characteristics of energy systems, e.g., toxic waste, and emissions (91).

Table 2-1 Risks to RE deployment in various regions from the reviewed literature

Risk Category	Risk Factors	Developed country	Developing country - other	Developing country - SSA	Reference
Technical	Technology maturity	•	•	•	(29,32,65,76,90,92–94)
	Technology progressiveness impacting on efficiency and quality	•	•		(29,77,80)
	Limited technical skills and capacity in operations and maintenance		•	•	(22,25,26,28,62,75,76,95,96)
	Limitations in the developer's capability to effectively design, construct and operate a project		•		(28,62)
	Limited training, research, and development capacity		•	•	(26,29,80,95)
	Availability of alternative technology		•	•	(29,75,80)
	Limitations in the quality control and availability of hardware		•	•	(25,28,95)
	Variability in demand leading to uncertain load profile		•	•	(22,29,62,68)
	Uncertainty in population distribution patterns		•	•	(22)
	Higher maintenance cost due to technology novelty and unpredictability	•			(72)

	Limitations with dual-mode operations, i.e., grid-to-off-grid transitioning for grid-connected systems	•			(77)
Resource	Uncertainties in estimating power potential and its variability	•	•	•	(25,29,32,68,72,76,94,96)
Policy and Regulatory	A retroactive change in policy, e.g., feed-in-tariff, tax, regulation	•	•	•	(29,72,78,80,90)
	Inability to efficiently and transparently administer mini-grid-related licensing and permits.		•		(28,89)
	Uncertainty in grid extension plans and technical regulations for integration of mini-grids into the main grid		•	•	(22,27,28,74,96)
	Lack of long-term policies			•	(26,95)
	Insufficient supporting policy frameworks and incentives, e.g., low support for foreign direct investments, high taxes, disparity between energy policies and development blueprint and uncertain fiscal policies		•	•	(25–27,75,80,85,94,95)
	Policy and regulatory uncertainty, e.g., policy consistency, implementation	•	•	•	(22,26,74,77,90,92,96)
	Difficulty in acquiring land, competition with land uses		•	•	(25,29,89,95)
	Unattractive regulated tariff		•	•	(22,25,62,85)
	Limitations in regulations on interconnection of mini-grids to main grids and enabling bi-	•			(77)

	directional flow of power mini-grids to main grids				
Political	Effect of political changes, e.g., reshuffling of institutions.		•	•	(26,27,29,74)
	Complex Institutional structures with overlapping responsibilities		•	•	(22,26,27,62)
	Insecurity of infrastructure			•	(25,95)
	Political events that adversely impact the value of investments (e.g., war, currency inconvertibility, breach of contract, non-honouring of obligations)		•	•	(76,95,97)
	Bribery and Corruption		•	•	(26,29,96)
	Lack of political will to diversify into clean energy			•	(26,90,95)
	Legislative changes		•	•	(29,90)
	Political decision-making and target setting impacted by political will, political cycle, the influence of vested interest and perception of a social mandate to act	•		•	(93,95,96)
	Inadequate decisions and non-involvement of relevant experts in energy decision-making			•	(95)
Economic Finance	High initial cost		•	•	(25,27,74,94–98)
	Limited access to affordable finance		•	•	(22,26,32,62,74,76,80,96)
	High-interest rate		•	•	(22,32,75,89,90,96)

	Refinancing risk – Inability to secure loan refinancing due to mismatch between short loan terms and project lifetime.		•	•	(76)
	Currency risk - Foreign exchange challenges leading to cost-revenue mismatch		•	•	(28,29,68,76,89,97,98)
	Limited domestic investor capital		•		(28,62)
	Risk of price volatility within a stable policy regime	•	•		(32,72,98)
	Poor economic conditions		•		(29,89,95,96)
	Limited experience in the financial sector and domestic investors' lack of familiarity with RE		•	•	(74,76,94,95)
	Off-taker risk - Revenue uncertainty due to default by off-taker, potential customers with insufficient financial track records, unwillingness to pay, low affordability, seasonal income		•	•	(22,28,29,32,74,89)
Market	Sensitivity of competitiveness of RE to prices of conventional energy sources		•	•	(25,68,75,89,90,96,98)
	Market fluctuations due to speculative markets, e.g., land, and foreign exchange markets		•		(29)
	Market distortion issues: Market access barrier, non-market-oriented research for solar energy technology and application, unavailability of investment-ready projects			•	(26,74,76,80)
	Limited market and consumer data availability		•	•	(27,62,74)

	Vulnerability to external market volatility due to dependence on imports		•		(80)
Curtailment	Lower revenues due to unplanned curtailment, e.g., grid bottlenecks	•	•		(28,72)
Social	Inability to gain the buy-in and trust of constituents for the development of mini-grid	•		•	(22,77)
	Construction of a social relationship network in an unfamiliar investment environment		•	•	(22,29)
	Poor understanding of customer needs or usage patterns		•	•	(62,96)
	Public resistance to change to RE technology		•	•	(26,28,29,94,95)
	Poor awareness of solar benefits			•	(26,94–96)
	Instability caused by social events, e.g., riots		•		(29,97)
	Uncertainties in Consumer Technology Adoption pattern and societal Attitudes	•			(93)
Environmental	Public resistance to projects due to environmental influence		•		(29)
	Force majeure e.g., due to natural disasters		•		(29,97)

*Countries are grouped based on the United Nations classification (99).

2.4.2 Risk identification methods

Painuly et al.(84) broadly identified the following three complementing approaches to identifying barriers in RE: analysis of existing literature via literature survey, insights from site visits to existing projects and interactions with stakeholders through interviews and questionnaires. In the literature, scholars mainly use three qualitative risk identification approaches (Table 2-2): analysis of previous studies via literature reviews, surveys/questionnaires, interviews, or a combination. 70% of papers studied reviewed existing literature for barriers and risks related to similar locations or technologies. 27% of studies used a combination of literature review and surveys or interviews to identify risks. Malhotra et al and Egli et al.(28,72) conducted a combination of literature review and exploratory interviews to identify the most relevant risk given the location, technology, and timeframe of the study. While Mohamed et al. (31) used a combination of literature reviews to establish risks and questionnaires or surveys to identify important risks. Schmidt et al.(62) iteratively used a combination of field research (including interviews) and literature review to identify barriers and mitigation measures for RE investments in Indonesia. Wells et al.(92) used interviews for risk identification.

A literature review provides a good starting point and can allow an expanded review of barriers that could be applicable, whilst interviews can help narrow down specifics and provide further insights on interdependencies. Most studies that used interviews for risk identification went on to further analyse or evaluate risks.

Table 2-2 Risk identification methods and categories in the reviewed literature

Risk identification method	Region (Technology)	Reference	Risk category										Risk and barrier categorisation rationale according to:			% of reviewed papers
			Technical	Resource	Policy/Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	No categorisation	Location	Stakeholders and location	Project development stages	
Literature reviews	China, India, Brazil, Mexico, Russia, Indonesia, Turkey (Wind)	(97)				•	•	•	•				•			70%
	USA, Netherlands, Japan, Norway (RE)	(77)	•		•		•		•				•			
	Africa (RE)	(75)	•		•		•						•			
	Developing countries (RE Minigrid)	(74)			•	•	•	•	•				•			
	Philippines (NS)	(89)	•		•	•	•		•	•					•	

	Nigeria (RE, fossil)	(27)			•	•	•						•			
	RE generation projects	(85)	•		•		•	•								•
	Nigeria (solar)	(25)			•	•	•					•				
	Nigeria (Grid solar)	(26)	•		•	•	•	•	•				•			
	Worldwide (RE)	(76)	•		•		•	•					•			
	Worldwide (RE)	(98)										•				
	Asia (Solar PV)	(32)	•		•		•			•		•		•		
	Brazil (Distributed system)	(79)					•						•			
	Developing countries (RE Mini-grid)	(22)	•		•	•	•	•	•				•			
	Rwanda (decentralised RE and hybrid)	(68)	•	•			•	•				•	•			
	China (Wind)	(80)	•		•		•	•					•			
	54 developing countries	(29)	•	•		•	•		•				•			

	(Grid and decentralised Solar)															
	Germany, France (wind)	(78)			•								•			
	Cote d'Ivoire (RE)	(94)	•	•	•	•	•		•			•	•			
	Africa (RE)	(96)	•		•	•	•		•				•			
	South Africa (RE)	(90)	•	•	•	•	•	•	•			•	•			
Exploratory and semi-structured Interviews	UK (RE)	(92)			•	•	•						•			3%
Literature reviews and survey	China (EV charging infrastructure)	(100)	•			•	•						•			7%
	India (Grid & decentralised Solar)	(31)	•		•		•						•			
Literature review, Exploratory and semi-structured Interviews	India (Mini-grids)	(28)	•				•				•			•		20%
	Middle East (Power plant)	(91)								•			•			

Literature review, Exploratory Interviews/f ocus group	UK, Germany, Italy (wind, solar)	(72)	•		•		•				•		•				
	Indonesia (RE)	(62)	•		•		•	•						•			
	UK (Energy transition)	(93)	•		•		•						•				
	Nigeria (RE)	(95)	•		•	•	•	•	•				•				

NS - not specified in the literature.

2.5 Methods for RA, evaluation, and mitigation

RA involves understanding the causes, probabilities of occurrence and impact of risks (86). Risk evaluation uses the output of RA to compare risks, their priorities and whether they are tolerable. The most relevant risks can then be focused on for risk mitigation. Options for risk mitigation as set out by ISO 31000 include risk avoidance by not progressing the activity, taking the risk, removing the risk source, changing the likelihood or consequence, and risk sharing (86). The process involves iteration between risk mitigation and evaluation as control is evaluated to test for acceptable risk reduction. A risk could be deemed acceptable if the cost of mitigation outweighs the benefits or the level is considered low against what is tolerable.

Risk assessment can be qualitative, quantitative, semi-quantitative or a combination (86). Ioannou et al.(83) conducted a systematic literature review of risk assessment methods and grouped findings into quantitative and semi-quantitative methods. Findings on methods are grouped using categorisation by Purdy (86). Table 2-3 summarises the findings categorised based on location, technology type, method, and validation methods where specified.

2.5.1 Qualitative methods

Qualitative risk methods are subjective assessments typically used when numerical data are inadequate, unavailable, or limited resources (101). It may involve assessing the probability and impact of risks and identifying mitigations using subjective techniques. Methods applied in the reviewed literature include interviews and literature surveys. Qualitative analysis is simple and can explain mechanisms that drive investment risks.

2.5.1.1 Literature reviews and analysis

Studies have identified barriers and recommended mitigations by reviewing and analysing data from existing literature. Studies (25,90,95,96) identified barriers to RE applications in Africa. They recommended mitigations such as adequate and enforceable policies with strong political will in financial and subsidy incentives, compensation for land use and encouragement of community participation or ownership to mitigate security issues. In these studies, the feasibility and impact of the mitigations were not further analysed.

2.5.1.2 Exploratory and structured interviews with literature review

Schmidt and Diemuodeke et al. (62,95) identified barriers to RE utilisation and possible mitigations. Schmidt et al.(62) conducted a barrier analysis to identify barriers, understand risks and consider measures to assist investors for RE-based village grids in Indonesia. They identified that barriers could be along local, national, or international levels at project phases. Through interviews with investors, mitigations such as improving access to finance, policy reforms and fossil fuel subsidy redistribution were identified.

2.5.2 Semi-quantitative methods

Semi-quantitative methods have the flexibility to consider statistical and non-statistical risks (83). These methods are characterised by interviews and placing numerical values on risk levels and priorities. The following section discusses three broad semi-quantitative methods identified in the literature: exploratory and structured interviews, multicriteria decision analysis (MCDA) and system dynamics (SD).

2.5.2.1 Exploratory and structured interviews

Malhotra et al.(28) conducted structured interviews to refine risks identified in the literature and obtain quantitative ratings of likelihood and impacts using the Likert scale. The authors determined the contribution of each risk category to the cost of capital using an approach proposed by Waissbein et al. (102). The limitation of this method is risks were considered independently. The authors determined the effect of spatial diversification strategies on the levelised cost of energy as a means of addressing risks and found that risk profiles of mini-grid projects can be made more attractive by aggregating projects in a spatially diverse portfolio.

Egli et al. (72) drew on a mixed-method approach using existing literature data and exploratory and structured interviews combined with the Borda count method to identify and refine findings on the most important risks (given the context of technology, timeframe, and location). Borda count was selected for its straightforward interpretation and wide use(72). This approach enabled corroboration and improvement of the validity of findings. Network text analysis of interview data was used to identify risk drivers and links between risk types. Technology, price, policy, curtailment, and resource risks were most important to RE investments, with levels

changing over eight years. The authors subsequently put forth a techno-economic model that considers the revenue impact of relevant risks. There was no analysis done on actions that can reduce risk levels.

Gatzert et al. (78) developed a framework for studying policy risks for RE investments. The authors used interview and fuzzy Delphi probability prediction method to obtain the likelihood and impact of the considered policy risk scenario. Mozuni et al. (103) defined Delphi as a survey technique used to gain consensus knowledge from a group of experts over multiple rounds. The model was calibrated using expert interview data for two countries and the Delphi technique.

2.5.2.2 Multicriteria decision analysis

MCDA is a family of decision-support analysis methods which have been applied in the energy sector to evaluate alternative energy sources, policy analysis, decision-making, and consideration of risk perceptions due to their ability to incorporate multiple actors' opinions (83,104). MCDA methods rely on relationships such as priority and outranking. It takes judgements from stakeholders to evaluate weighted priorities of decision alternatives. With regards to its application to risk assessment, outputs are usually in the form of risk ranking. The methods have therefore been applied to RA and evaluation. MCDA methods encountered in the literature include the Analytical Network Process (ANP) (29,100), Analytical hierarchy process (AHP) (31,32) and decision-making trial and evaluation laboratory (DEMATEL) (97).

In the ANP method, a pairwise comparison of risks is made (105). ANP allows for feedback and interaction – such that elements in a network can communicate with each other (29,106). ANP combined with interviews presents flexibility that enables the simultaneous use of quantitative and qualitative criteria, including review consistency (106). For instance, Wu et al. (29) used Delphi combined with expert interviews to express the probability and consequences of risks in linguistic terms for 54 countries. The authors used a combination of the ANP method to determine relationships between risks and the weighting of risks and a cloud model to express linguistic terms in numerical form and assess risk levels. They grouped countries according to risk levels and provided recommendations for investors according to risk levels.

Wu et al.(29) used a combination of interviews, ANP for weighting calculations and grey fuzzy assessment to prioritise risks for electric vehicle (EV) charging infrastructure, thereby identifying critical risk factors to be managed. The result shows that operation incomes, costs, industrial standards, and technical risk factors were the most important. Robustness checks carried out include sensitivity analysis testing the impact of (i) subjectivity in human judgement and (ii) expert sample size on risk values. Risk mitigations were suggested but were not further evaluated for their effectiveness.

AHP can also translate qualitative inputs into numerical relations. Mohamed et al.(31) used AHP to identify major risks and weightings, while Kim et al.(32) used a combination of interviews and fuzzy AHP to determine financial risk factors as the most important. The study showed differences in the relative importance of risk factors for the different stakeholders, which is essential in determining specific risk strategies. Fuzzy AHP considers that there is uncertainty in the human decision-making process. Although AHP conducts a pairwise comparison, it assumes factors in the hierarchical structure are independent, making it unsuitable for representing complex systems (107).

Qui et al. (97) applied combined two MCDA methodologies – Interval type 2 (IT2) fuzzy DEMATEL to determine risk levels and IT2 fuzzy VIKOR for risk ranking. The authors further deployed IT2 fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution; a fuzzy MCDA method) as a robustness check for ranking. Wang et al.(108) used fuzzy DEMATEL for determining which criteria were critical from the RE investment and policy perspective. None of the reviewed studies further quantified risk mitigations.

2.5.2.3 System dynamics

SD combines qualitative and quantitative analysis, including synthesis reasoning (80), to identify problems, primary variables, and interactions. SD is characterised by feedback loops and time delays to model complex system behaviours. The method can be used for sensitivity analysis and scenario simulations (109).

Liu et al. and Al Mashaqbeh et al.(80,91) evaluated RE investment risks using SD and noted that static models could not adequately model RE investment risk complexity resulting from interdependencies and interactions. Al Mashaqbeh(91) developed an SD conceptual model to assess non-technical risks for power plants considering

interdependencies and the dynamic nature of risks. Li et al.(80) studied RE investment risks in China and developed an assessment model consisting of technical, policy and market risk sub-models to simulate system behaviours as a feedback system over ten years. The study determined how risk importance changes over time, which is vital for investment timing. Although the study analyses technical, policy and market risks, including interactions, it could be further improved by expanding to analyse other applicable risk factors to understand their importance. Risk mitigations were not explored in the study.

Another set of literature has deployed SD for policy assessments in support of RE investments. Hsu et al.(64) used SD with cost-benefit analysis to assess policies for promoting solar PV applications such as feed-in tariffs (FiT) and capital subsidies to achieve solar PV installation and CO₂ emission reduction targets under various conditions. Results showed that goals might be attained by applying reasonable FiT or subsidies, including some compulsory regulations and punitive measures. Historical data on solar PV installations between 2001 and 2010 in Taiwan were used to validate the model.

Trappey et al.(110) used a cost-benefit evaluation methodology based on SD to assess the effectiveness of policies and the corresponding benefits for carbon reduction. Guo et al. (111) used SD with sensitivity analysis to evaluate China's policy environment and interaction with variables considering technical and economic factors. The model was used to explore the impact of policies on PV power generation, investment and installed capacity over 20 years. A limitation of the model is that it did not consider interactions such as energy sources, and social, and political factors with PV system investments. Movilla et al (112) used SD to analyse the dynamic behaviour of the Spanish PV market under different support policy scenarios to assist policymakers in designing energy policies. Results indicate that the sector would be profitable with continued policy support and a gradual subsidy reduction with PV developments. The model was validated by the reproduction of historical data.

2.5.3 Quantitative methods

Quantitative risk-based evaluation methods deal with statistical data and probabilities to determine risk levels, consequence analysis and risk reduction via numerical or computer-based models. Quantitative methods identified in the literature include

Monte Carlo simulation (MCS), Sensitivity analysis (SA) combined with techno-economic (TE)/cashflow analysis, and agent-based modelling (ABM).

2.5.3.1 Technoeconomic /cashflow analysis (with MCS or SA)

SA and MCS were combined with TE in the reviewed literature. TE combines technical parameters and financial metrics to assess the economic potential of a project. SA is a simplified method that enables the identification of the most impactful variables. For example, Okoye et al.(113) conducted SA to test the effects of fluctuations in inflation rate, loan interest rate, electricity price, loan repayment time, and income tax rate on NPV.

MCS is a method that allows for uncertain input parameters and can be employed to produce probabilistic valuation models which incorporate risk (83). MCS has been applied widely in literature and integrated into financial models to determine cashflows and investment criteria ranges. MCS has been used in combination with other techniques such as SD (68,79), real options and cashflow analysis using the market disclaimer approach (MAD) (114) and ABM to improve the robustness of the model.

For instance, Williams et al.(68) conducted a quantitative study considering a range of scenarios, including various technologies and tariffs, to quantify the effect of technical design and business models on investor risks. Deterministic SA was used to identify important uncertainties. Probabilistic SA determined variables that contributed most to project risks as fuel price, foreign exchange rate, demand for electricity, and price elasticity which vary depending on technology and tariff structure.

Zaroni et al.(79) assessed the economic risk associated with decentralised energy systems in Brazil using MCS. Although not an RE system, the method is considered applicable and, therefore included in this review. Similar to Williams et al.(68), a deterministic SA was performed to rank input variables by associating the variables with probability distribution functions (PDF). Using MCS, mean peak energy price, generator parameter, and fuel price were determined as the most impacting variables on NPV PDF.

Kim et al.(114) proposed a framework for investment decisions in RE projects for developing countries in the planning, design, and construction phases. Steps employed in the study included cash flow analysis, real options valuation of the RE

project using a 3-point estimate and MAD approach. SA and MCS were conducted to identify influential variables (tariff, energy production) and quantify their impact to arrive at decisions at the different project phases. Real options allow for the incorporation of investor choices in decision-making in the model. The authors emphasise risks associated with revenues and did not consider uncertainties in capital costs, such as access to affordable capital or policy changes during project phases.

Gatzert et al. (78) determined the impact of mitigations, e.g., changes in FiT and cross-country diversification, on risk-return profile using cashflow analysis with MCS and SA. Cross-country portfolio diversification and increased FiT over a short period were found to decrease the impact of policy risk on the risk-return profile. In determining this impact, the study assumed the independence of policy risk factors.

Bhattacharyya et al.(67) used discounted cash flow analysis to assess the viability of new policies to attract private investments in rural India when applied to small-scale mini-grid and large-scale grid-connect solar PV systems. The authors found mini-grid support such as subsidies or low-interest debt would be required to attract private investments under the studied policy regime, while large-scale solar projects were an attractive proposition for investors. The impact of risks on cash flow was not included in the analysis. All the reviewed studies did not consider the interactions or interdependencies between risk factors.

2.5.3.2 Agent-based modelling

ABM is a dynamic model consisting of agents with the ability for learning. It allows the representation of behaviours and feedback of agents such as investors, consumers, and policymakers by representing discrete decision-makers and focusing on agent decisions and interactions over time (115).

ABM was not used to assess risks in the reviewed literature but was used to evaluate policy effectiveness. These policies could be viewed as mitigations or responses to barriers. ABM has been widely used in market diffusion, technology adoption, and policy evaluation for climate targets and investments. Schiera et al.(81) used ABM to assess the impact of regulatory schemes on the adoption of rooftop PV. Zhang et al.(82) integrated ABM, real options and social networks to assess RE adoption. The model incorporates the customer risk preferences into real option decisions to determine the customer's willingness to invest. Chappin et al.(116) developed a

modular ABM approach to explore electricity and emissions policies that can interact with each other and tested its robustness under uncertainties of input parameters such as fuel price and demand. Al Irsayd et al.(117) used ABM to evaluate policy effect on solar PV investments, emissions, and economic output

Table 2-3 Review of methods for RA, evaluation, and mitigation

RA, evaluation, and mitigation methods		Region (System)	Reference	Application		Risk category									Validation
				RA & Evaluation	Risk Mitigation	Technical	Resource	Policy/Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	
Qualitative methods	Literature review	Nigeria (solar development)	(25)		•			•	•	•					
	Literature review	South Africa (RE)	(90)		•	•		•		•	•		•		
	Literature review	Africa (RE)	(96)		•	•		•	•	•	•				
	Literature review and questionnaire	USA, Netherlands, Japan, Norway (RE–grid and decentralised)	(77)		•			•		•		•			

	Literature review and expert Interview	Indonesia (RE)	(62)		•			•		•	•				Interviews
		Nigeria (RE)	(95)		•	•		•	•	•	•	•			
Semi-Quantitative methods	Literature review, Structured Interview	UK, Germany, Italy (wind & solar)	(72)	•				•		•				•	Literature data and interviews
	Structured and exploratory interviews with Linkert scale	India (mini-grids)	(28)	•				•	•	•	•			•	
	Expert Interview with Delphi and Fuzzy set theory establishing likelihood and impact	Germany, France (wind)	(78)	•				•							Expert interview data
	AHP, Interviews/surveys and Literature reviews	India (Grid & decentralised Solar)	(31)	•				•		•					
	Fuzzy AHP and Interview	Asia (Solar PV)	(32)	•				•		•					Literature review, expert interviews
	ANP-Cloud and Interviews with Delphi	Middle East, Russia, India (Grid &	(29)	•		•	•		•	•		•			

		decentralise d Solar)													
	ANP-Cloud and Interviews with Delphi for RA and fuzzy comprehensive assessment method for evaluation	China (EV charging infrastructure)	(100)	•					•	•					Expert interview with SA
	Literature review combined with Interval type 2 (IT2) fuzzy DEMATEL	China, India, Brazil, Mexico, Russia, Indonesia, Turkey (Wind)	(97)	•		•	•		•	•	•	•			Robustness check with IT2 fuzzy TOPSIS
	SD, cost-benefit analysis and SA (Assess policies for promoting solar PV)	Taiwan (Solar PV), Taiwan (Solar PV and heating)	(64,110)		•			•							Reproduction of historical data
	SD and SA (Assess policies for promoting solar PV)	China (Solar PV)	(111)		•			•							
	SD with scenario analysis (To evaluate policy	Spain (PV grid)	(112)		•			•							

	effect on PV competitiveness														
	SD	China (RE)	(80)	•				•			•		•		Expert Interview
		Middle East (Power plant)	(91)	•									•		Interviews, focus groups
	SD	Malaysia (Solar PV)	(109)		•			•							Boundary accuracy and structural verification per[74]
Quantitative methods	TE analysis with SA	Rwanda (decentralised RE and hybrid)	(68)	•		•	•			•	•			•	
	SA and MCS combined with cashflow analysis (MAD) and real options approach	Indonesia (wind)	(114)	•		•	•	•		•			•	•	
	TE analysis and MCS combined with SA	Brazil (Distributed sys - diesel, gas)	(79)	•						•					
	Interviews and literature review	Egypt, Morocco,	(63)		•					•					

	with cashflow analysis	Tunisia, Algeria (CSP)													
		India (mini-grids)	(28)		•		•			•					
	Cashflow analysis & SA with MCS	Germany, France (wind)	(78)		•			•							Expert estimates
	Cashflow analysis (marketed asset disclaimer approach) combined with real options, SA and MCS	Indonesia (wind)	(114)	•	•	•	•	•		•			•	•	
	ABM (To test policy effectiveness) ABM (With SD)	EU (RE) US (Solar PV)	[72,75]	•				•							Reproduction of historical data
	ABM (To evaluate policy effect on investments, emissions, and economics)	Indonesia (Solar PV)	(117)	•				•							

2.6 Discussion

This section introduces a conceptual holistic framework for investment risk management to identify factors that can improve investor risk profiles. It further highlights key findings from the literature review, comparing methods used for risk assessment and mitigation. Findings are further discussed from an SSA perspective, drawing on existing literature to identify suitable methods.

2.6.1 A holistic multi-dimensional investor risk management framework

‘RE investment risk evaluation is a complex system’ (80). Complex systems can be defined as many interacting parts known as actors, agents, or components (119). Interactions between agents and their actions can result in effects that cannot be easily predicted by studying the individual agents. The impact of actions such as policy changes within these interactions can be better understood by identifying actions taken by the combination of actors (120). This perspective can enable the identification of impactful policies to mitigate risks. The framework presented in Figure 2-4 addresses four limitations observed in the literature, which may have been addressed in a fragmented manner within the existing body of literature.

Firstly, in assessing investment risks, many studies have focused only on techno-economic factors (22,79,114) or one key risk factor, e.g. (78). Policy analysis has traditionally focused on techno-economic uncertainties. However, an inclusive, multidisciplinary approach that considers other perspectives enables more suitable solutions to address risks (93). Risks need to be considered contextually. Policymakers and investors need to consider the impact of location-specific risks, e.g., TE models may not incorporate location-specific social risk factors in the analysis of investment parameters. Overlooking the impact of socio-economic risk factors such as affordability can lead to revenue risks. During decision-making, investors need to consider the impact of human behaviours, such as a person’s willingness to pay for and adopt a technology, on investments (121).

Secondly, many studies have addressed risks independently without considering interdependencies and interactions within the complex system. RE deployment involves actions and complex interactions between actors such as investors, developers, financing institutions, policymakers, regulators, and customers of various

demographics. These interactions can be driven by factors such as environment, decisions, and actions taken by actors (120), which can be driven by risks resulting from multi-dimensional factors, e.g. social, market, economic, technical, and political factors. For example, without considering interdependencies and feedback, it may not be apparent that a fossil fuel subsidy policy can introduce additional market risks for RE investments and may subsequently impact investments over time.

Thirdly, many studies do not consider the dynamic nature of risks. Risks can change over time, e.g., technological advances, the impact of policy change (72,112) and across project phases (85,89). Understanding the dominant risk factors at a given project phase and period can provide focus on relevant risks and timely mitigations. Lastly, whereas different aspects of risk management have been studied separately, the framework calls for a holistic approach to identifying, assessing, and mitigating priority risks using the ISO 31000 risk management guideline. By systematically following risk management guidelines and applying the multi-dimensions of risks and their interactions, an assessment of associated risk factors and their relative importance in terms of impact on investment decisions can be made. This can provide a more impactful approach to mitigating risks. The framework can be applied from different stakeholder and location perspectives.

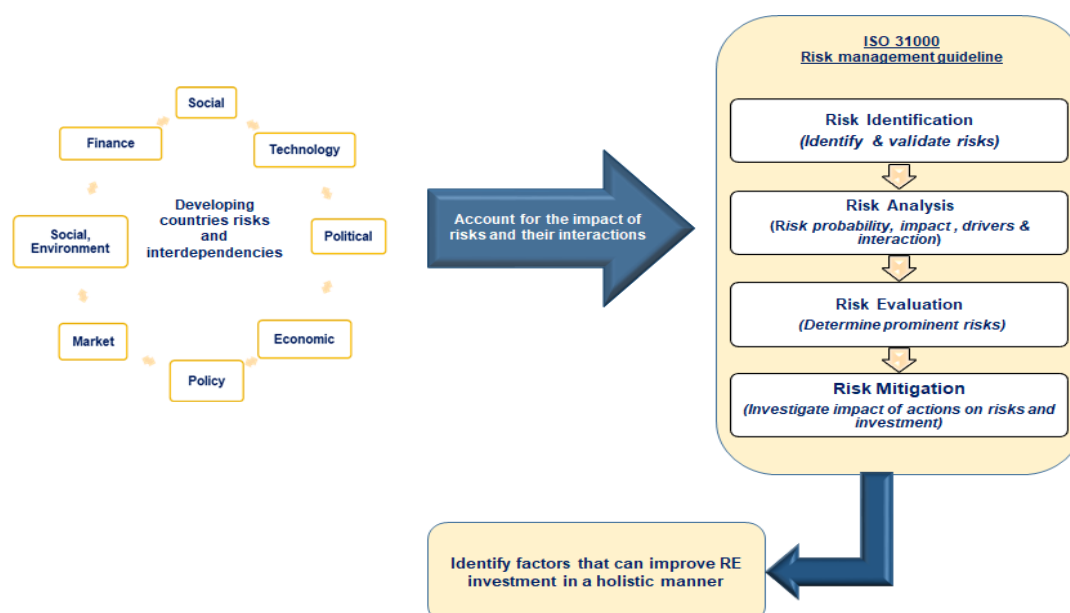


Figure 2-4 Proposed conceptual ‘holistic multi-dimensional investor risk management framework’.

Adapted from (20,49,63,93).

2.6.2 Key findings on risk identification and methods

Out of the reviewed literature, 30% of papers identified risks and barriers applicable to SSA countries while 43% and 8% applied to other developing and developed countries, respectively. It is noted that although some investment risk categories can be generalised between developing (including SSA) and developed countries, risk causal factors and their level of impact may not be the same. For instance, developed country technical risks can be attributed to technological issues related to efficiencies, commercial availability of technologies and limited research and development (77,93). In contrast, technical risks in developing countries include hardware quality and availability issues due to importation, limited availability of skilled personnel from project development through execution, competing alternative technology and technology novelty (22,25,28,62). Policy risk levels also differ. Whilst developed country investments are open to risks due to retroactive changes in policy and tariffs, developing countries include policy inconsistencies and implementation uncertainties, insufficient policy frameworks for supporting investment and uncertainties in grid extension plans(27,29,72,93). The dimensions of social and economic risk factors also vary significantly [20,26,40,47,50,79]. Developed country's social risk factors comprise uncertainties in technology adoption and changes in societal attitudes and demography. Social risks for developing countries can result from resistance to change due to a lack of awareness of RE benefits, and revenue and demand uncertainty due to socio-economic conditions such as willingness to pay and low affordability. Although high implementation costs affect all countries, developing countries face further economic barriers, including lack of access to affordable capital, high cost of capital, the competitiveness of RE compared to alternatives, payment default, and limited domestic investors' experience with RE (22,26,29,72,74).

In the review of risk identification methods (Table 2-2), literature review was the most prominent method, followed by interviews with literature review. Although easy to implement, a literature review may not adequately identify relevant location-specific risks. Additionally, it neither captures the dynamic nature of risks that may vary across project phases and stakeholders nor provides an understanding of risk interdependencies with other risks and actors. It can be refined by supplementing with surveys or expert interviews. Results depend on the diversity and experience of the experts as well as the depth of interviews. Methods such as Delphi have been used in

literature to achieve a consensus between experts (106). Risk levels determined via expert interviews could be influenced by the number of experts and their subjective judgement. Therefore, it may be necessary to perform a SA to test the robustness of the responses (100).

2.6.3 Key findings on RA, evaluation, and mitigation

Of the reviewed literature, MCDA methods and TE or cashflow analysis with MCS and SA were most widely used for RE RA and evaluation. SD and ABM were mainly used to explore the likely effectiveness of risk mitigation approaches. The impact of uncertainties on investment matrices has been tested by applying SA to TE (113). Although easy to communicate, sensitivity changes are typically random without regard for the relative importance of the variables; this does not provide a reasonable basis for decision-making (123).

TE has also been combined with interviews, SA, MCS and real options analysis in the case of Kim et al.(114) for RA and evaluation. In these studies, SA was used to quantify the impact of variables and MCS to identify the most important variable. Incorporating MCS into uncertainties in input parameters also produced probabilistic outcomes for cashflows. The results' accuracy depends on the statistical modelling of input variables and probability distribution function (83). Input variables need to be statistically independent to prevent misinterpretation of results. Therefore, these methods did not account for feedback relationships between variables.

Furthermore, the sensitivities were only related to economic and technical risk factors. Williams et al.(68) noted the gap in quantifying risks for rural microgrids in SSA. They developed a TE model to quantitatively assess the impact of risk drivers on the business model and technology decisions using SA and MCS. However, the authors did not evaluate the effectiveness of the proposed risk mitigations. Further, although a detailed assessment of risk drivers was carried out, interactions between various risk drivers were not assessed. For example, it was considered that the exchange rate impacts fuel price fluctuation; however, it was not considered that this could impact consumer disposable income, thereby changing demand patterns and thus affecting investor revenue.

A range of methods in the MCDA family was used in literature for RA and determination of risk priority levels based on interview or survey data. Methods used include AHP, fuzzy AHP, ANP-Cloud and IT2 Fuzzy DEMATEL methods. The impact of the proposed risk mitigations was not explored in the reviewed literature. Although MCDA allows for the use of quantitative and qualitative data, a general weakness is the inability to accommodate feedback between risks or criteria. Within the MCDA family, ANP allows for limited feedback and interaction. However, ANP cannot capture uncertainties in relationships due to exact or crisp values allocated to pairwise comparison (105). In literature for decision-making studies, fuzzy ANP was considered an improvement to ANP whereby instead of a crisp value, a range of values was applied to account for uncertainties in human judgements. However, fuzzy ANP poses the limitation of some alternatives incorrectly being ranked the same and consequently being treated equally. Noting this limitation, Hefny et al. (107) applied Gaussian fuzzy ANP to improve decision-making among the alternative power generation scenarios. This method provided a more precise distinction between ranking alternatives than fuzzy ANP. Gatzert et al. (78) conducted RA and evaluation using Fuzzy set theory combined with MCS, SA and cashflow analysis to estimate the impact of mitigation measures on policy risk reduction. Interactions of mitigations on other risks were not evaluated.

Complex interactions were modelled using SD and ABM. SD has been applied in RA (80,91) and to explore the potential policy mitigation effectiveness (64,112). These SD studies covered environmental, policy, and market risks. Al Mashaqbeh et al. (91) indicated that SD could also be applied to other risk areas. SD allows for the modelling of complex systems from a cause-effect perspective which enriches the analysis capabilities of the model (109). SD requires comparably less quantitative data for building a model than ABM (116). SD has its limitation in representing social interactions within social networks that can generate a diversity of behaviours in individuals, such as willingness to adopt new patterns (115). In comparison, ABM can be applied when choices and behaviours need to be incorporated into investment preferences. Although SD requires long-term data for model development and validation, the validation process is more structured than ABM and gives emphasis to qualitative information (115).

Movilla et al.(112) developed an SD model to simulate different futures against various policy scenarios. The model's validity was tested by reproducing historical data before running scenarios. Scenario review shows how policy changes may affect investments. The authors appear to assume that the investment decision parameters are solely payback period and profitability. Other investment decision drivers that could be considered include portfolio comparison rather than individual projects, checks against investment criteria, NPV, debt service coverage ratios, and political, and environmental drivers. Modelling investors as part of the SD model could improve the authenticity of the analysis.

Liu et al.(80) quantified the most important risks over time based on interactions with the system and other risks. The model was able to show that dominant risks change over time based on feedback loops. The authors note that the risks considered were not exhaustive, which could impact system feedback loops. For example, one of the scenarios simulated reviewed the effect of increasing tariff subsidies; the resulting system behaviour was that policy risks decreased over time. As the government or regulatory body was not modelled as a separate actor, the developed system would not capture responses from the regulator. Such a response could be to continue the increase in tariff subsidies as modelled (this is unlikely due to limitations in the budget), or where the risk of policy change declines, the regulator could decrease or maintain a maximum tariff increase. This interaction or learning behaviour could be modelled using ABM due to its capability to model non-optimal decision-making and simulate the learning behaviour of agents (124,125).

2.6.4 Review of risks from the SSA perspective

RE investment risk is multi-dimensional, dynamic, location and stakeholder dependent. In addition to the risk factors discussed in section 2.4.1, further specific factors are highlighted for SSA. These include lower levels of in-country technical skills in manufacturing and implementation, insufficient supporting policy frameworks such as low support for foreign direct investments, high interest rates and taxes, and policy uncertainties (75,90,94,96). Studies highlighted socio-cultural and behavioural barriers such as poor awareness and negative perception of RE, security issues, non-involvement of relevant experts in decision-making, political, market, access to finance, and economic barriers (90,95,96). Some studies investigated barriers to solar

development, given its abundance in Africa (25,26) and cited political will, policy, incentives, availability of market data and security challenges as some of the barriers to implementation (25,26).

Within the same country, risk dimensions also vary across geographical areas and jurisdictions at national, state, and local levels, as observed by Schmidt and Malhotra (28,62). For instance, the importance of variability in demand due to population distribution patterns will vary between urban and rural areas characterised by low density, dispersed populations, and low-income levels. Sparse populations require increased distribution infrastructure leading to elevated cost of development [83]. These differences will affect risk perception and risk levels and thus affect investment decisions. Therefore, to better understand the effects and design appropriate measures to reduce risks and improve investments, it is necessary to focus on specific locations at local levels as implemented by Malhotra(28). For example, aggregation of a spatially diverse portfolio can be a means to improve the risk profile whilst improving energy access. 90% of studies related to risk identification for SSA were carried out via literature survey. The studies could be improved via expert interviews using the Delphi method to provide a consensus of findings.

In determining suitable methods to assess these risks to provide effective mitigations in the form of policy actions, the following could be considered:

- i. Conformance to ISO 31000: Method(s) should have a holistic approach to assessing key investment risks and identifying mitigations.
- ii. SSA risk factors are multi-dimensional, and methods should be capable of assessing risks across technical, social, economic, market, policy, environmental and political perspectives. Due to the complex nature of risks and interdependencies, the method should have the capability to estimate interactions between risk factors and agents.
- iii. One of the reported barriers in SSA is the limitation in the availability of market data (27,94). In the absence of detailed data, a qualitative or semi-quantitative method is more appropriate to determine risk priorities.
- iv. and assess the potential effectiveness of mitigations, thus ensuring a holistic approach.

Table 2-4 shows a comparison of methods with their capability to conform to the considerations set out above.

MCDAs and cashflow analysis with MCS and SA have been widely used in other developing countries such as China for RE risk assessments. Apart from ANP, these methods are unable to model risk interactions. However, ANP has limitations in assessing the effectiveness of mitigations which can be tested using ABM and SD.

SD provides an alternative to the reviewed methods because it can model interactions in a complex energy system. This feedback relationship can enable analysis of risk factors and the effect of their interactions. For example, it is possible to represent the circular effect of increased electrification on productivity and income, and subsequently, the increased demand, which can lead to reduced revenue uncertainties and enhanced returns, leading to potentially more favourable investment decisions in the long term.

Although SD model development requires large data sets from both quantitative and qualitative sources, it has an advantage over ABM, which requires significantly more data in areas of model validation. SD was not used in the reviewed literature to assess social and political risks, possibly due to its limitation in representing social interactions; this can be complemented with ABM. ABM can be used to estimate the behaviours of heterogeneous agents acting independently. Such behaviours could be driven by socio-economic factors that impact revenue and investments. For instance, individual behaviour can be driven by socio-economic factors such as income seasonality, RE perceptions or availability of alternative traditional energy. These can drive demand variability, thus impacting revenue. Individual and investor behaviours can be modelled with ABM due to its capability to offer insights into emergent behaviours thereby enhancing the accuracy of predictions.

ABM and SD methodologies have been combined to support policy analysis for grid systems. Zhao et al.[75] integrated SD into the ABM framework to evaluate the potential effectiveness of policy incentives to encourage PV systems adoption by incorporating consumer behaviour. The modelling framework comprised a 2-level simulation. On the higher level, the model is comprised of an ABM to simulate the customers' behaviour on adopting PV systems, while on the lower level, ABM and SD are employed to calculate the payback period of the PV system by different types of

households (41). ABM was used to simulate household consumption at the lower level, while SD was used to model the relationship between demand, PV generation, and the local grid. The authors demonstrated that combining the two techniques resulted in more realistic outcomes. A hybrid SD and ABM methodology for risk assessment and mitigation may thus offer more advantages when ABM is deployed to complement the SD gaps.

Table 2-4 Comparative review of risk methods

Application		Method Criteria	Literature reviews *Interviews/surveys	MCDA		Cashflow/TE analysis		SD	ABM
				Fuzzy ANP	Fuzzy AHP, IT2 Fuzzy DEMATEL	TE analysis and expert interview	TE or Cashflow analysis, SA and MCS		
Risk Management	Risk Identification	Identify specific risks	•			•			
	Risk Analysis	Estimate probability and impact of risk	*•	•	•	•	•	•	
		Assess and estimate the interaction between SSA risk factors:							
		Technical, Resource		•				•	•
		Economic, Finance, Market, curtailment		•				•	•
		Social		•					•
		Political		•				NS	•

		Policy/ regulatory		•				•	•
	Risk Evaluation	Quantify risk priority		•	•	•	•	•	•
	Risk Mitigation	Estimate the effectiveness of policy actions in mitigating investment risk factors							
		Technical, Resource				•		•	•
		Economic, Finance Market				•		•	•
		Social							•
		Political						NS	NS
		Policy/ regulatory					•	•	•
Strengths			1. Relatively easy to implement	1. AHP, IT2 fuzzy & ANP are easy to understand and capable of using quantitative and qualitative data (106) 2. ANP allows for feedback and interaction for criteria. (29,106)		1. Easy to understand and simplified		1. Models complex energy systems from a cause- effect perspectiv e, rather than relying on statistically significant	1. Capability to model complex systems, host multiple actors and represent non-linear, social interaction s, and RE adoption

				relationships (109). 2. Lower amount of quantitative data needed for building a model compared to ABM (116).	patterns (116). 2. Allows for individual and non-optimal decision-making and simulates the learning behaviour of agents [81].
Limitations	<p>1. Generalised and may overlook context-specific factors.</p> <p>2. Limited to risk identification unless combined with other methods</p>	<p>1. Apart from ANP, it does not allow for feedback or interaction between risks or criteria (32).</p> <p>2. Criteria, weights & values depend on subjective expert judgements (83).</p>	<p>1. Parameter changes are typically random and do not provide a basis for decision-making [80].</p> <p>2. MCS – variables need to be statistically independent to prevent result misinterpretation.</p>	<p>1. Does not represent social interactions within social networks (115).</p> <p>2. long-term data is required for both</p>	<p>1. Significant amounts of empirical data are required to describe social interaction and for validation (81).</p>

		3. MCDA methods have not been used to determine mitigations.	Therefore, interactions and feedback relationships between variables cannot be modelled.	model development and validation (115).	2. Correct specification of realistic behaviour of agents is challenging [81].
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2.7 Conclusion

Decentralised RE systems have been identified as an enabler in improving energy access and meeting both SDG and climate change targets. Despite national targets, policy reforms and global trends of decreased capital cost, RE investments in SSA countries have been lower than required. Private investments have been identified as a key enabler to bridging the gap. However, there is a high-risk perception of investments in SSA which needs to be reduced to encourage investments (20,63).

This paper widens the scope of previous reviews of risk methods. Through a holistic lens, it provides a review of risk identification, analysis, evaluation, and mitigation methods for RE systems. It identifies the spatial and temporal distribution of studies carried out for developed, SSA and other developing countries. It is found that RE investment risks have been classified broadly according to barriers or uncertainties by focusing on location, stakeholders, or project phases. This paper has catalogued the various RE risks for developed and developing countries, including SSA based on standardised categorisation of risks (technical, economic, market, policy, social, resource, environmental, curtailment). Developing and developed countries face the same risk categories driven by different dimensions of factors. For example, social risk factors may include uncertainties in technology adoption and changes in societal attitudes in developed countries. In developing countries, these can result from resistance to change due to a lack of awareness of RE benefits. It was also found that RE risk dimensions may differ according to geographical locations within the same country across national and local levels. Consequently, in providing impactful mitigations to improve risk profiles, it is necessary to consider distinct characteristics of locations across jurisdictional boundaries, e.g., national, state, local levels or based on demography, e.g., across urban, peri-urban, or rural locations.

This paper also introduces a conceptual framework that provides a holistic approach to risk management from identification, and assessment to mitigation. The framework recognises that RE risks are complex involving multidisciplinary

perspectives and their interactions with other risks, actors, and their actions. It proposes a structured means of identifying suitable actions. Actions such as policy mitigations may have side effects and interactions with actors and other policies, leading to unintended risk impacts. It, therefore, highlights the importance of analysing the effectiveness of mitigations on risks and investment matrices given the interactions.

In the review of methods, it was found that risks were qualitatively identified primarily via literature reviews for SSA. This approach could be improved by combining literature reviews, surveys, expert interviews, and Delphi for specific locations and technologies. RA and evaluation mainly employed semi-quantitative MCDA and SD methods for developing countries excluding SSA (where limited risk assessment studies were carried out). The reviewed methods assessed technical and economic risks at a minimum, while MCDA methods were additionally used to assess social, political and policy risks. Most MCDAs had limitations in estimating interactions between risk factors. SD method was found to overcome this limitation due to its capability to conceptualise and model feedback relationships.

Qualitative methods have been used to identify risk mitigations. The effectiveness of policy actions in improving investments, and meeting climate change and national targets have been tested using quantitative (ABM, MCS and SA) and semi-quantitative (SD) methods for policy, technical and economic uncertainties. SD has been largely employed in developing (excluding SSA) countries such as China and Taiwan. Its ability to represent investment risk's dynamic interactions and complexities makes it a suitable tool for RA, evaluation, and mitigation. Its limitations in representing social interactions can be complemented with ABM. A hybrid SD-ABM method thus emerges as a powerful tool to analyse investment risks in developing countries such as SSA when applied within the framework of the ISO 31000 risk management guideline. This can provide a structured assessment of risks, identifying high-priority risks and effective mitigations towards improving risk profiles. Such mitigations may include policy actions, policy implementation strategies, incentives, and investor actions, e.g.,

aggregating a spatially diverse portfolio of projects. Risk mitigations may incur associated costs which need to be weighed against the benefits. The hybrid model can be further enhanced by determining the cost-benefit of the risk mitigation for investment decision-making. The development of such a hybrid method can provide policymakers with a tool that can be used to test and tailor location-specific policies aimed at reducing investor risks and consequently improving energy access.

3 An evaluation of multidimensional decentralised renewable energy investment risks

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Abstract

To achieve universal electricity access in Sub-Saharan African countries, it is critical to scale up private investment in Decentralised Renewable Energy (DRE, e.g., solar mini-grids) by identifying appropriate de-risking actions that consider differences in investors' risk perception. However, risk management literature offers a fragmented understanding of investor-specific DRE investment risks and their interdependencies. This study applies a holistic risk management framework for identifying, evaluating, and mitigating risks, for DRE in Nigeria. Using survey responses, the analytical hierarchy process, and interviews, 40 multidimensional risk factors were evaluated to establish their importance among four investor groups - development finance institutions (DFI), domestic finance institutions (DomFI), developers, and impact investors - and other industry stakeholders such as public sector and development agencies. The study identifies 13 additional risk factors not previously included in existing studies for Nigeria. It establishes commonalities and divergence of risk factor priorities among the investor groups and draws on interviews to suggest evidence-based mitigation measures for the common high-priority risk factors (including revenue risks, inadequate access to low-cost capital, currency risks, insecurity, and poor policy implementation). This research suggests policies enabling portfolio aggregation, diversification, and domestic financing, strengthening existing policy implementation, expanding incentives, collaboration and local capacity development can mitigate the highest priority risks. This study is a valuable reference for decision-makers to prioritise actions for catalysing DRE investment.

3.1 Introduction

The deployment of decentralised renewable energy (DRE) is crucial to attaining universal electricity access and climate change targets in Sub-Saharan African countries (SSA), where over 550 million people live without reliable electricity (5). Studies (8,126,127) have identified DRE, e.g., solar mini-grids, as economically and environmentally favourable solutions for 60% of this population. However, the deployment of DRE on the required scale in SSA has been challenged by limited private investment mobilisation (5). Whilst DRE projects may have a favourable environmental impact, such projects in developing countries are perceived as high risk which impacts costs and competitiveness (76,102). Many studies (5,23,28–30) have thus identified unattractive risk-return profiles contributing to low private investment in SSA.

Risk-return profiles can be improved through holistic risk management (RM), which entails assessing and evaluating specific multidimensional risks and their interdependencies, followed by identifying effective risk mitigations such as de-risking policy actions (23). Such mitigations have been found to induce investment or increase returns (72,128,129). However, SSA literature currently presents a fragmented approach to RM (23). Additionally, risk priorities can differ across geographical locations (28,29) and among investor types and other relevant stakeholders (30–32), highlighting the need for location-specific and investor-specific risk studies. However, there is little empirical data on diverse investor perspectives of risks in SSA countries, including Nigeria (23,28–30).

Nigeria is a relevant case study, with 95 million people lacking reliable electricity access, constituting 19% of the unconnected SSA population (130). The government aims to address this issue alongside climate commitments by targeting a 17–20% RE contribution to the electricity mix, allocating 5–12% to solar photovoltaic (PV) technology, including solar mini-grids (131). In this study, solar mini-grids will be referred to as DRE, as this is the most prominent DRE technology. Solar mini-grids represent up to 40% of DRE investment needs in Nigeria's energy transition plan (ETP) (132); nearly equivalent to Nigeria's 2022 budget, highlighting the need for increased private investment amid competing

development needs (5). Despite abundant solar irradiation, targets, and policy developments such as the 2016 mini-grid regulations providing guidelines for isolated and interconnected mini-grids (IMGs) (133), actual investment in DRE remains limited (5). In this study, solar mini-grids are referred to as DRE, due to their prominence in the country.

DRE projects, such as mini-grids, rely on diverse investment sources to secure funding. Concessional financing plays a key role, encompassing grants, equity, and concessional debt, which are offered at below-market rates to advance development or impact goals (5,134). One-off grants, primarily funded through national budget allocations, regulatory fines, development agencies, and local or international Development Finance Institutions (DFIs), contribute to project funding (135). Additionally, DFIs extend concessional debt facilities to further development objectives. Impact investors, typically international organisations pursuing both financial returns and social or climate objectives, provide critical financing in the form of equity, grants, and concessional debt. Domestic finance institutions or local banks (DomFIs) offer local currency debt financing at market rates, while project developers contribute equity capital. Considering these diverse funding sources, this study classifies DRE investors in Nigeria into four main categories: DFIs, Impact investors, DomFIs, and developers. Each investor type perceives risks differently based on their distinct objectives and mandates.

While some risk studies focusing on Nigeria exist, the studies (25–27) are fragmented and do not recognise the multidimensional perspective and interdependencies of risks. Instead, these studies mainly focus on identifying a limited set of risks and barriers impacting RE investment from the technical and policy (25–27), economic (25) or political and social (26) perspectives. Moreover, most studies have not considered factors crucial to returns, especially relevant to developing countries, such as revenue risks, collection losses, and affordability (28,29,76,89,97,98,136). Additionally, as these studies did not evaluate the risk priorities of the diverse set of investors within the DRE sector, they are unable to offer recommendations on the most essential risks to mitigate from the investor's perspective to mobilise investment activities.

This study aims to comprehensively identify, analyse, and evaluate, the multidimensional risks and mitigations as perceived by four distinct investor groups (developers, DomFI, DFI, and impact investors) and other key stakeholders in DRE investment in Nigeria. This research follows four analytical steps. First, it identifies investment risks relevant to Nigeria from the literature. Second, it analyses the importance of risks and risk factors for investors and other key stakeholders using an online survey (N=70), and third, it evaluates these using the analytical hierarchy process (AHP). Finally, it draws on the experience of investors and public-sector actors to validate the AHP risk priorities and offer insights on risk drivers, dependencies, and mitigations based on semi-structured interviews (N=17) and focus groups (N=3). This study thus addresses the following questions: (i) what are the key risks for DRE investment in Nigeria and how do they differ by investor groups and stakeholders and (ii) how can the most significant DRE investment risks be mitigated?

The paper offers three contributions to the literature. Firstly, it identifies an additional 13 risk factors previously unreported in the literature, specifically related to Nigeria (25,26). These risk factors emerge as high-priority for investors. Secondly, it addresses the limited data on diverse investor risk perspectives by offering empirical data illustrating differences in risk priorities among various investor types and other stakeholders. The analysis extends to exploring the drivers and interdependencies associated with these risks. Lastly, it proposes evidence-based mitigation strategies for the most important risk factors for investors.

The following sections present the methodology (3.2), and AHP results along with a qualitative analysis of the most important risk factors and their mitigations (3.3). Lastly, this paper offers conclusions and policy recommendations (3.4).

3.2 Methodology

3.2.1 Participants and sampling techniques

As recommended in previous studies (23,84), this study combines quantitative methods (online survey and AHP) and qualitative (interviews and focus groups).

Sampling occurred in two stages. Firstly, in the quantitative strand, purposeful sampling (137) was used to identify online survey participants (respondents) (N=79) with experience in the DRE sector in Nigeria. These individuals were identified via LinkedIn and were subsequently invited to participate. Further participants (N=59) were recruited through snowball sampling (72), by seeking recommendations from the initial respondents. The online survey sample (N=138) in this study comprised four investor groups (impact investors, developers, DFI and DomFI), public-sector actors (PI), development agencies, and others (utilities, engineering service providers and consultants). Figure 3-1 provides a cross-section of the respondents' profiles (see Appendix B for survey details).

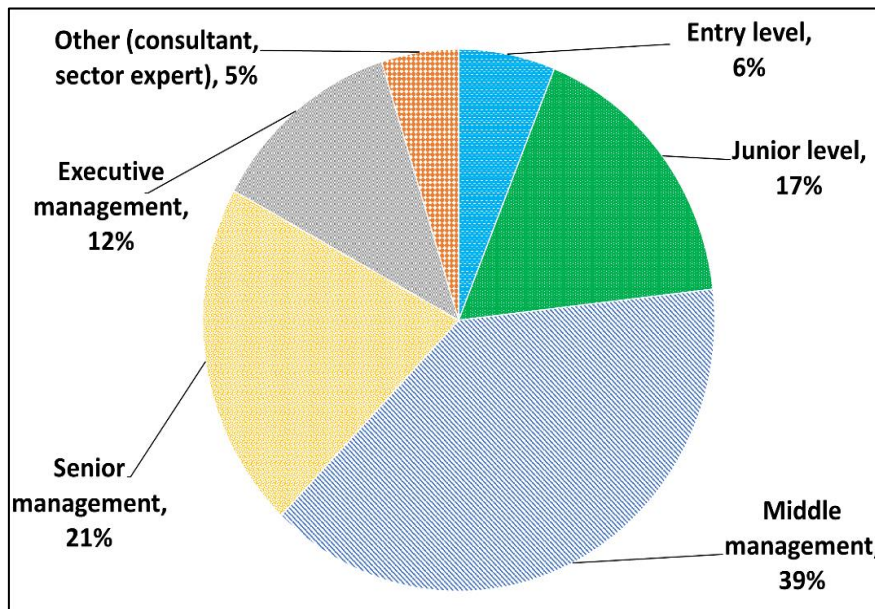


Figure 3-1 Survey respondent profile

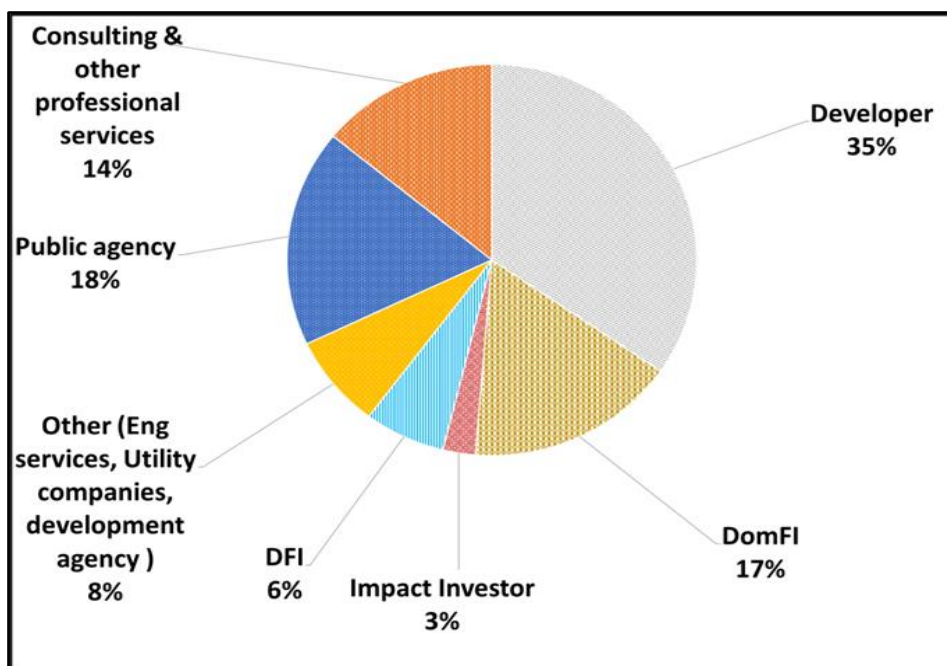


Figure 3-2 Responses by respondent groups

Secondly, in the qualitative strand, the semi-structured interviews (N=17) participants and focus groups (N=3) (Table 3-1) were drawn from willing survey respondents with a minimum of senior management level experience. Additional participants (N=3), such as the domestic development finance group (DomDFI), were recruited through snowball sampling. This approach was employed to ensure a diverse representation of the various investor groups.

Table 3-1 Classification of interview and focus group participants.

Group	Description of interviewees	Focus group participants. % (N=3)	Interview participants % (N=17)
Developer	Chief executives/founders	-	6
PI (2 groups)	Senior and management officials of public agencies for policy development, regulation, implementation	10 4	3
DFI	Senior management officials of international development finance institutions involved in	-	5

	risk management and infrastructural development		
DomDFI	Middle and Senior management officials of domestic development finance institutions involved in infrastructural development	3	
DomFI	Senior management officials of domestic finance institutions involved in RE and power financing	-	2
Impact Investor	Executive management officials of impact investment firms involved in financing RE impact investment in Nigeria	-	1

3.2.2 Methodological steps

This study follows four methodological steps, as illustrated in Figure 3-3. First, as proposed in existing frameworks (83,84), to obtain a comprehensive range of relevant investment risks, this study leveraged a previous risk literature review (Chapter 3) (23). This was complemented by further literature survey using the search terms ‘renewable energy risk OR barrier Nigeria’ in the Scopus database. The process revealed 56 risk factors, which were reviewed for relevance to DRE in Nigeria. Forty risk factors (Table 1) of which 27 were previously identified for Nigeria and 13 from other country literature were found to be relevant. Table 3-2 presents the additionally identified risk factors for Nigeria. The risk factors were categorised according to definitions in previous studies (23,58) resulting in six risk categories: technical, economic, financing, policy and political (PP), social and environmental (SE), and market risks.

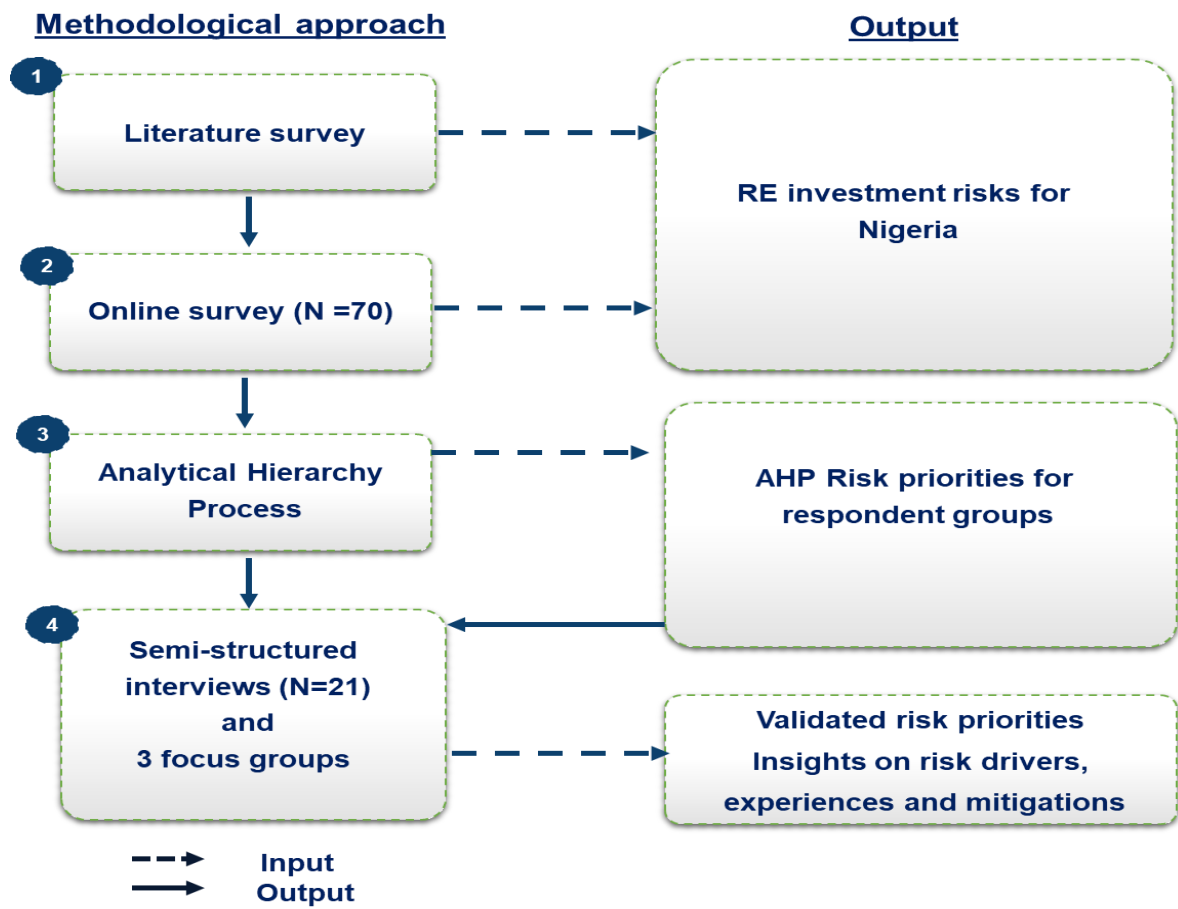


Figure 3-3 Four-step methodological approach to the study

Table 3-2 DRE investment risk factors established in this study.

	Risk Factor	Definition	Reference
E1	Revenue risk	Lower than expected revenue resulting from default by off-taker, unwillingness to pay, low affordability, seasonal income etc	(22,28,29,32,74,89)
E2	Collection losses	This could result from technical, financial, and behavioural factors that lead to non-revenue-generating consumption.	(22)
E3	Foreign exchange (FX) volatility	FX volatility results in a mismatch between revenues denominated in local currency and hard currency-denominated obligations	(28,29,76,89,97,98,136)
E4	Inability to achieve single off-taker or cluster effect	Limited creditworthy off-takers impacting project viability and revenues	(22)
F3	Short loan terms	A mismatch between short loan tenors and project lifetime.	(76)
F6	Difficulty accessing/repatriating FX	1. Inability to convert local currency into hard currency due to government action or inaction 2. restrictions to repatriate funds add uncertainty to investor	(96,97)
P5	Duplicative policy development	Impact of duplicative policies and institutions	
P7	Uncertainties in IMG regulations implementation	Uncertainties in mini-grid regulations for IMG	(77)
T3	Limitations in developer's capability	Limitations in developers' experience in executing projects	(28,62)
T5	Uncertain load profile	Poor understanding of customer needs or usage patterns leading to variability in demand	(62,96)

T6	Inadequate infrastructure	Lack of supporting infrastructure, facilities, and inadequate access to project locations	(96)
M3	Lack of competitive hardware and labour market	Limitations in the availability of competitive labour and equipment locally	
M6	Uncertain market growth potential	Uncertainty in market growth potential due to uncertain demand, market size and potential	(138)

Second, the survey was conducted in August and September 2021 where respondents were asked to assess the identified risk categories and factors on a 5-point Likert scale according to their importance (considering probability and impact) to DRE investment in Nigeria. The survey achieved a response rate of 59%. Following quality checks, N=40 responses were excluded for reasons such as incomplete surveys (N=28), not meeting the experience level criteria (N=8), and surveys with lower-than-expected survey completion times (N=4). Consequently, N=70 responses were validated and included in the analysis.

Third, the risk priorities for the respondents (N=70) were evaluated using the analytical hierarchy process (AHP). AHP is a multi-criteria decision analysis method involving pairwise comparisons of elements (risks and risk factors) to establish weighted priorities among them. This approach incorporates consistency checks to ensure the reliability of results, where a consistency ratio (CR) of $\leq 10\%$ indicates an acceptable level of consistency in judgments. This technique has been applied previously, focusing on country risk studies (31,58) and country barrier studies (1,139). A hierarchical structure of the risk factors within each category was formed (see Figure 3-4). Following the technique used by Kallas et al. (140), the Likert scale data was transformed into a collective pairwise comparison for each respondent group. The risk weightings also referred to as risk priorities in this study, were calculated following previous studies (1,31,139,141) using equations detailed in Appendix B.2.

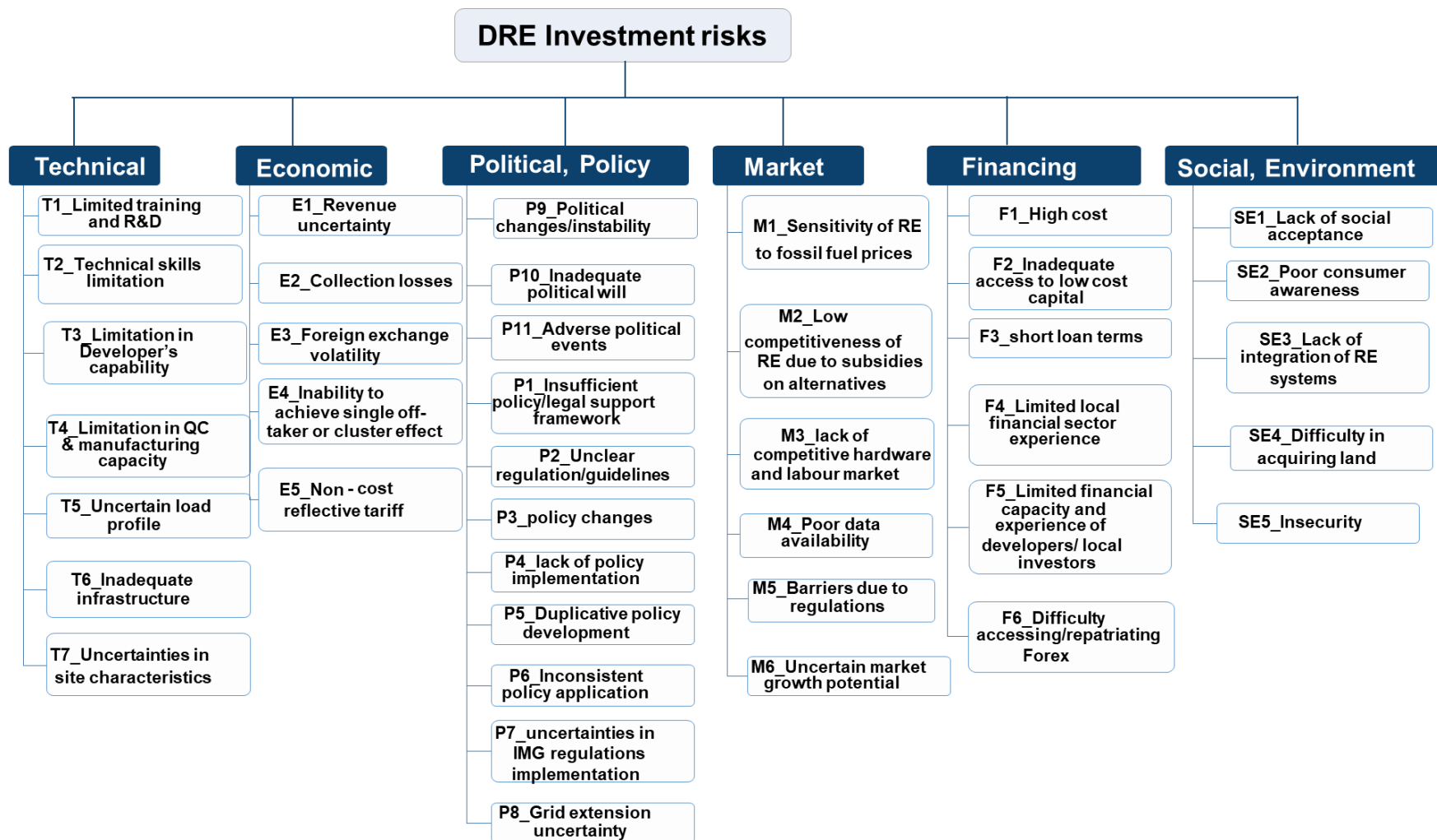


Figure 3-4 Hierarchical structure of DRE investment risks in Nigeria.

Fourth, interviews and focus groups were used to elicit insights on risk drivers and mitigations and to corroborate AHP results. While initially only focus groups were planned, some participants' unwillingness to participate in them necessitated using one-to-one interviews. The use of focus groups alongside other qualitative methods in such instances has been demonstrated in the literature (51). The focus group and interview sessions were conducted in physical and online formats in July and August 2022, lasted 1–1.5 hours each, and were audio recorded and transcribed. The participants were asked the same questions to ensure consistency and subsequent comparison of responses. The questions comprised feedback on the AHP results, exploring risk drivers, interdependencies, and mitigations. Both focus group and interview responses are termed 'interview' responses. References to interview statements were anonymised and identified by a serialised acronym of the interviewee's group (further interview details are provided in Appendix B.3).

Following a previous approach (1), data was analysed by alternating between interview transcripts and the literature to provide context to quantitative AHP results. Additionally, the mitigation actions proposed by interviewees were coded and thematically analysed. The thematic analysis of interview transcripts was conducted in accordance with the steps outlined by Braun and Clark (142). This process was initiated by an extensive review of the transcripts, focusing on risk mitigation strategies, with the aim of understanding and contextualising the responses provided by the interviewees. Following this initial review, the coding phase was executed using NVivo software version 14. The coding framework was initially informed by mitigation strategies outlined in the literature, serving as a preliminary guide. Additionally, the analysis was receptive to emergent strategies discussed by interviewees, ensuring that further codes and insights were captured. Coding involved identifying and assigning codes to texts specifically related to actionable insights for risk mitigation within the transcripts.

The subsequent phase involved the aggregation of individual codes into broader thematic categories. This process was guided by the interviewee types, the nature of the mitigation strategies proposed, and the specific risk categories

addressed. By comparing codes, identifying connections and commonalities, similar codes were grouped together to form broad themes. In the fourth stage, the emergent themes were reviewed. This involved an examination of patterns, relationships, and discrepancies within and between themes. This facilitated the refinement of themes, where similar themes were merged and appropriately renamed to reflect the underlying data. The final themes were: (i) navigating currency risks, (ii) enhancing financing mechanisms and capacity building, (iii) strategies for improving project revenues and viability, and (iv) recommendations for policy implementation and enhancements. These themes were reflective of the diverse DRE risk mitigation strategies and insights shared in the interviews and are discussed in 3.3.5.

3.2.3 Ethical considerations

This study adhered to the ethics approval process outlined by Cranfield University to mitigate research ethical risks effectively. Central to the ethical considerations of this study was safeguarding participant rights. Prior to conducting online surveys, interviews, and focus groups, authorisation was obtained from Cranfield University's Research Ethics Committee via the Cranfield University Research Ethics System (see Appendix A for the ethical approval). Prior to participation, individuals were fully informed about the study's aims, objectives, and methods, and their rights, ensuring informed consent was obtained (see Appendix B.1.2 and B.3.1). The consent also included recording, transcribing, and using anonymised information in publications. Participation was voluntary, with participants retaining the right to withdraw at any stage. Special attention was given to confidentiality and data security; responses were anonymised and securely stored, accessible only to the author and supervisory team and used solely for this study's purposes.

3.3 Results and discussions

3.3.1 Prioritisation of risk categories

This section outlines the prioritisation of risk categories for both the collective, representing the combined perspective of all respondent groups, and individual

respondent groups. The CR of <0.1 reflects consistency in the responses. From a collective standpoint, the economic (28.8%) and financing (28.8%) risk categories took precedence in DRE investment in Nigeria, followed by PP risks (17%), technical and market risks (9.8% each), and SE risks (5.9%) (Figure 3-5). The low significance of SE risks could be attributed to the advancement in the DRE landscape creating more acceptance and awareness. For example, previous studies (25,26,143,144) showed social risk factors such as low awareness and adoption as significant barriers to DRE deployment. However, the development of policies, introduction of solar standards, and implementation of programmes may have played a role in facilitating DRE awareness and implementation (145).

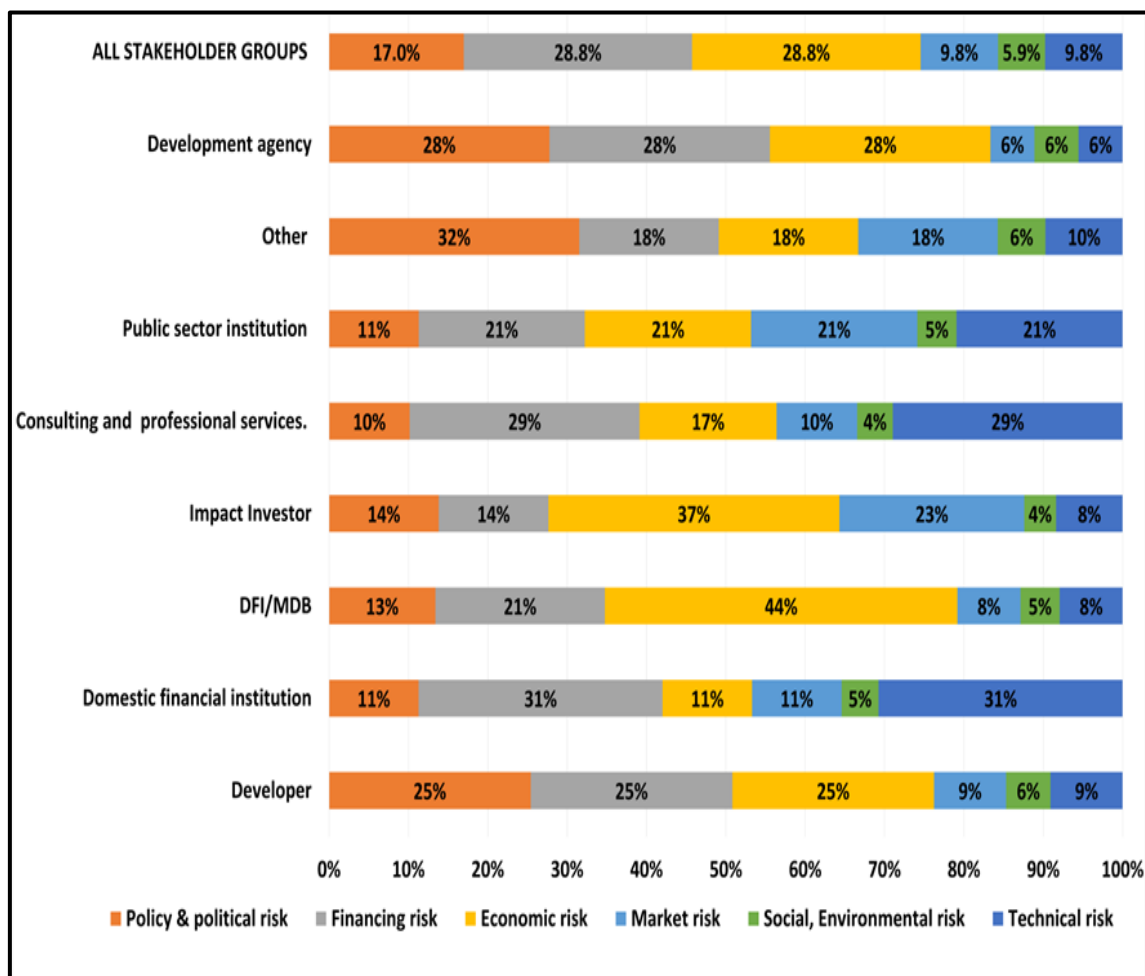


Figure 3-5 Collective and individual respondent groups' view of risk categories priorities.

While individual groups agreed on the low significance of the SE risk category, variations emerged in other categories. For example, economic risk was emphasised among investors, international investors, including DFI and impact investor groups (44% and 37%, respectively). Additionally, PP risks were highlighted by developers (25% each). In contrast, finance and technical risks (31% each) were identified as the most crucial investment risks for DomFI. Among other respondent groups, the consulting group closely aligned with DomFI risk perception (29% each), while PI identified economic, financing, technical, and market risks (21% each) as equally vital for DRE investment in Nigeria.

The collective findings depicted in Figure 3-5 contrast with results from other countries, as illustrated in Table 3-3. For instance, in Ghana, another SSA country, the primary barriers to mini-grid investment were within the political category (1). This divergence could be attributed to Ghana's mainly public sector-led approach to mini-grid deployment, contrasting with Nigeria's involvement of both public and private sectors. Furthermore, the Nigerian government's political stability, and commitment, evident through targets and advancements in RE policy development, may contribute to reduced political uncertainty, therefore interviewees didn't view see *'[PP risks] becoming a future problem'* (D1001). Notwithstanding the emphasis on political stability, the relevance of PP risks persists. Despite the presence of policy frameworks, their inconsistent and bureaucratic implementation is underscored by poor synergies between government agencies, as highlighted by:

'Policy (implementation) in Nigeria is a challenge'...agencies are rarely on the same page so it's a struggle.' (D2001).

Consequently, poor policy implementation leads to value erosion of up to *'30% of grants'* (D5001). The above highlights the need to improve policy implementation.

Furthermore, comparisons with other countries (Table 3-3) revealed disparities in findings. In Turkey, economic and market risks emerged as the most substantial

factors impacting RE investment (58). Conversely, in India, political, technical, financing, and environmental risks were highlighted as prominent (31), while in Nepal, economic and Power Purchase (PP) risks took precedence (139). These disparities in results may be attributed to distinctions in technological maturity, demographics, resource availability, and country-specific risks influenced by geopolitical factors, policy frameworks, and macroeconomic considerations (1,58,72,76,139). The identified variations in the importance of risks across countries align with other studies (1,23,28,58,139), emphasising that risks are contingent on location and necessitate location-specific mitigation strategies.

Further, while the previous studies (see Table 3-3) evaluated risks from multiple perspectives, they mainly treated investors as a singular entity. In contrast, this study broadens the scope to encompass a diverse range of investors, revealing the variations in their risk priorities. This finding aligns with a previous study (32), which evaluated solar PV investment risks in Korea from the perspectives of two investors (financial investors and private utility companies). The study revealed economic risk, encompassing financing risks, was the most significant for both investors. However, utilities found policy risks as the second most significant compared to technical factors for financial investors. This underscores the importance of policymakers considering investor-specific risk priorities when formulating policies to attract investment.

Table 3-3 Comparison with RE risk and barriers evaluation studies in the literature

Reference	Region	Overall top 3 risk /barrier categories	Number of risks/ barriers and (risk factors)	Number of groups (including investors)	Investor type covered in the study						Investor-specific risk evaluation
					Private investor type						
					Developer	DomFI	DFI	Impact investor	Type not specified	Utility (public, *public-private)	
(31)	India	Environmental (Ecological Geographical), Political, Technical	4, (17)	1						x	
(58)	Turkey	Economic, Market, PP	6, (23)	4	x						
(1)	Ghana	Political, Economic, Technical	5, (22)	6						x	
(139)	Nepal	Policy and Political, Economic, and Geographic	6, (22)	3					x		
(32)	South Korea	Economic, Policy, Technical**	3, (13)	3					x	x	x
This study	Nigeria	Economic, Finance, Policy and Political	6, (40)	8	x	x	x	x		x*	x

**Only 3 risk categories were evaluated in the study

3.3.2 Overall prioritisation of risk factors

This section presents the collective perspective on the overall relative importance of the 40 risk factors spanning all categories (Figure 3-6). Furthermore Table 3 show the risk factor priorities for both the collective and individual groups within each risk category and overall. Following precedents (1,58,139), the overall weights were derived by multiplying a category's weight by each risk factor's weight within that category.

Overall, foreign exchange (FX) volatility (9.59%) was ranked as the first most significant investment risk factor, followed closely by inadequate access to low-cost capital (8.22%). Revenue risk, collection losses, inability to achieve a single off-taker effect and non-cost reflective tariff were ranked equally in third place (4.8% each). High cost, short loan terms, limited local financial sector experience, limited financial capacity and experience of developers, and difficulty accessing/repatriation FX ranked fourth (4.11% each), followed by insecurity (2.85%). Apart from insecurity, the top five risk factors are rooted in the economic and financing categories, collectively constituting over 50% of the overall risk factor weightings.

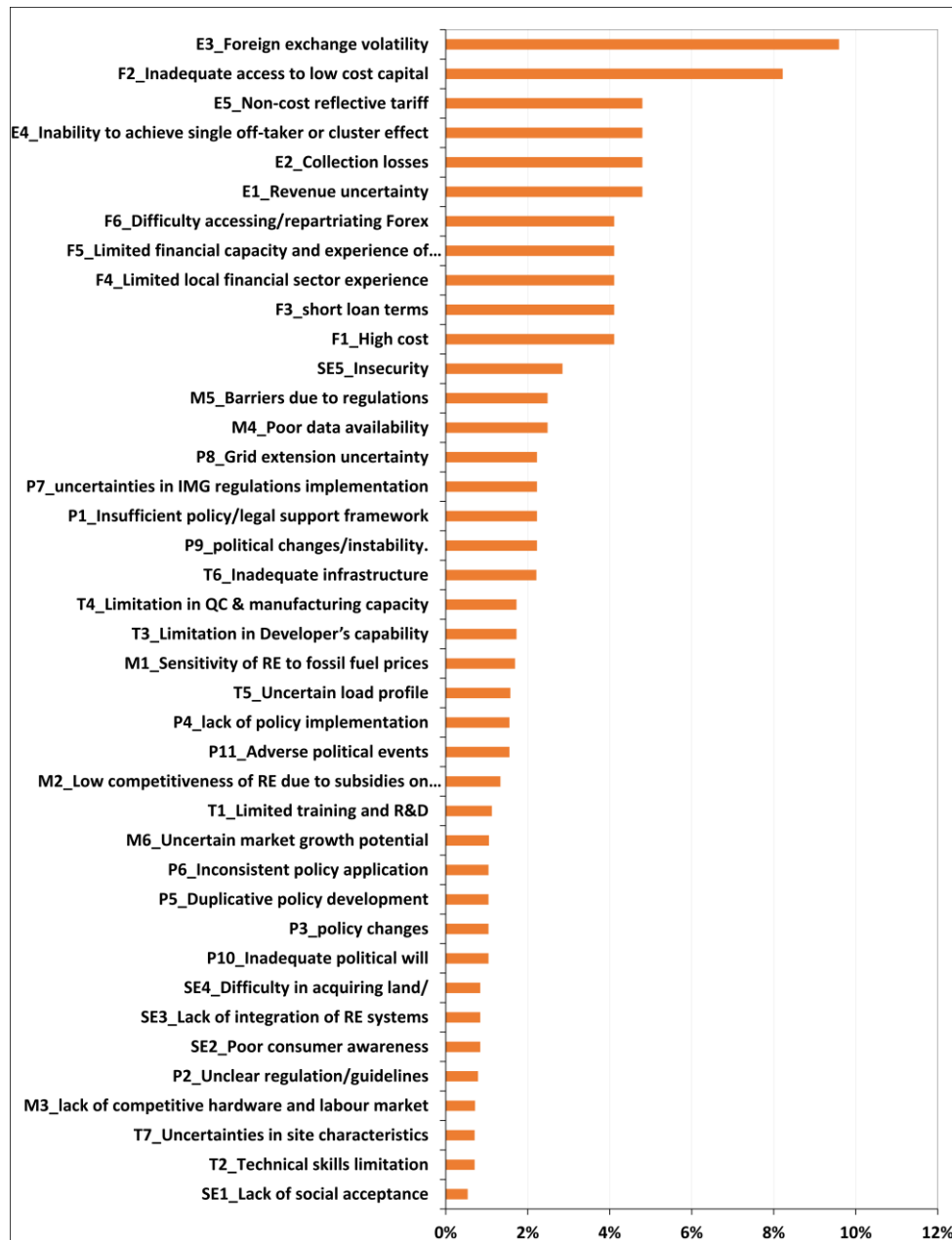


Figure 3-6 Overall and collective respondent risk factor priorities.

These findings diverge from extant literature in Nigeria (25,26,143,144), which underscores technical and social risk factors, such as limitations in quality control (QC) and manufacturing capacity (T4), limited training (T1) and technical skills, inadequate infrastructure (T6), and low adoption. The disparities can be attributed to advancement in the DRE landscape since the previous studies, such as the evolution of policies facilitating DRE, the introduction of standards for solar equipment, the removal of fossil fuel subsidies, and the impact of programs like

capacity building through technical assistance grants. These shifts highlight the necessity of re-examining the risk landscape to identify pertinent mitigations.

The following qualitative analysis of interviews and discussions reviews the top risk factors and their variations among groups, addressing risk drivers, interdependencies, and mitigations.

3.3.3 Qualitative discussion of the top 50% risk factors

3.3.3.1 FX volatility (E3)

Interviewees provided insights into the significance of E3, which emerged in the top two crucial risk factors in the economic category (Figure 3-7), and for all groups excluding DomFI (Table 3). Specifically, one interviewee suggested that E3 holds particular importance for international investment due to its role in creating a discrepancy between revenues denominated in the local currency and obligations such as hardware costs and international debts, which are priced in hard currency (HC). This effect is further amplified by the long-term nature of RE projects.

‘For a DFI, [E3] will be very important because lending dollars to an entity that earns Naira and the ability of that entity to change that Naira into foreign currency to pay back the money is important’ (DFI2001).

The procurement phase is particularly impacted by E3, as imported hardware can contribute to as much as 49% of mini-grid costs (146). This impact is notably felt by local developers *‘who import.’* (DFI3001). Furthermore, interviewees highlighted the reasons for the low importance of E3 for DomFI:

‘... if a lender is a local bank, it is somebody else's risk as to what that volatility is because you are paying them back in any case’. (DFI2001).

These findings show that the importance of E3 for investors is contingent on factors such as the type of finance source and denominated currency, and the entity assuming the risk. This could explain why E3 did not rank as the significant

factor for DomFI respondents. While increasing access to domestic financing, as proposed in the literature (76,147), may diminish exposure to E3, it specifically tackles the challenge of currency mismatch. Therefore, the residual risk of E3 linked to the cost of imported hardware remains unaddressed through domestic financing, although it is a one-time occurrence.

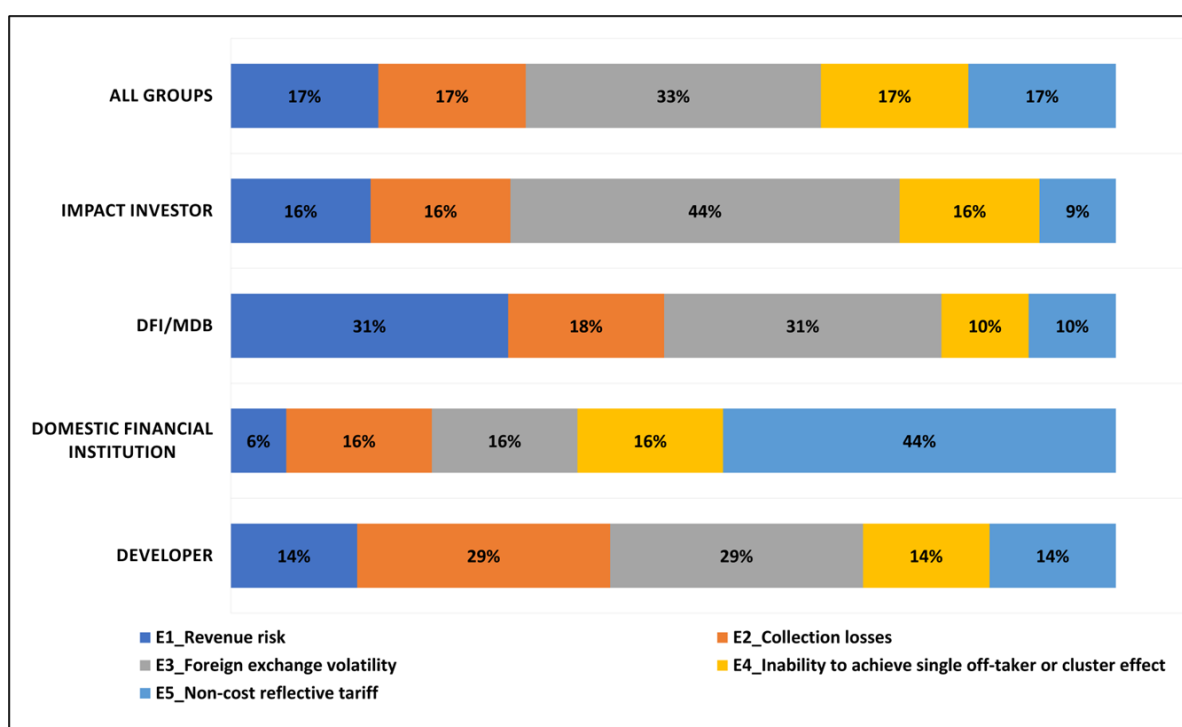


Figure 3-7 Collective and individual groups' risk priorities in the economic category.

3.3.3.2 Revenue risk (E1)

Collectively, E1 ranked as the third most crucial risk factor overall (4.8%) and second in the economic category (see Figure 3-7). E1 may arise from a low willingness to pay (WTP), collection losses (E2), the inability to achieve a single off-taker effect (E4), and an uncertain load profile (T5). This uncertainty in demand is attributed to a poor understanding of customer usage patterns, '*mainly because there isn't data enough [for] a load profile*' (DFI2001).

Moreover, while low demand may escalate project unit costs, rendering tariffs unaffordable, higher-than-anticipated demand can significantly impact a project's long-term sustainability. This is because, in the event of project failure, unmet

customer expectations may prompt them to explore alternatives, resulting in lower adoption rates (22). Additionally, T5 may be influenced by macroeconomic conditions, socioeconomic factors, behaviours, and the ability to pay (22,147). Macroeconomic factors such as high inflation rates and socioeconomic factors e.g., low commercial activities, can lead to diminished purchasing power (22,147,148). In situations of limited financial resources, households tend to prioritise more immediate needs, such as food and rent, over electricity, resulting in reduced revenues (149).

Furthermore, in rural areas, where mini-grid projects are predominantly implemented, communities often rely on *'seasonal farming and seasonal revenues'* (D2001), leading to irregular income (149) and, consequently, unsustainable revenues which can occur *'in the first one or two years [of operations]'* (D2001). Some interviewees suggested that behaviours, lifestyle, and cultural practises contributed to low electricity utilisation, resulting in reduced demand and revenues. One interviewee illustrated this point regarding rural residential customers:

'I think it is more of their lifestyle; maybe some are minimising their usage. For example, instead of using a blender, they prefer the manual means they are used to. Some have TVs, but you find that they barely use a 1-kilowatt load'. (P1001)

However, the interviews also show that the low energy use behaviour in rural consumers is not because energy is not desired but because of its affordability and low productivity as indicated below:

'they [communities] don't have a lot of commercial activity, but they have the zeal, they desire the energy solution' (D1001).

Nevertheless, an interviewee observed decreased utilisation *'as low as 20% [...] because consumers manage [ration] electricity'* (DomFi2001).

Another factor influencing E1 is WTP for electricity, which can vary across locations and is influenced by factors such as education level, income, productive activities, price of alternative sources of electricity (22,62) and conflicting

demands of greater urgency (149). Because of existing subsidies on alternative sources (grid and fossil fuels), there is low awareness of the actual cost of electricity, as *‘[customers] know the government says [grid electricity tariff] is 30–50 Naira/kWh’[...]*; they do not understand *‘why [mini-grid tariff] is 180–200 Naira/kWh’* (D2001). This preconceived notion of a low tariff can affect the WTP for electricity. Additionally, some interviewees noted that in instances where mini-grids were implemented as politically influenced constituency projects, there was an expectation within the community that *‘electricity is free’* (PF1001-1). This aligns with observations in the literature (62,150). Nevertheless, other interviewees indicated variation in this attitude as while *‘some [consumers] know that they should pay’*, others still believe it is *‘the government’s responsibility.’* (PF3001-7).

The above findings demonstrate the relevance of revenue risk and its interdependencies with T5, WTP, E4, and E2. Improving the identified interdependent factors can positively impact E1. Additionally, the results suggest that actions that target affordability and energy use behaviour while adopting energy efficiency practises could improve demand and thus revenues.

3.3.3.3 Collection losses (E2)

The survey results revealed that overall E2 ranked third (4.8%), aligning with DFI and Impact investor groups (see Table 3). Similarly, within the economic category, E2 ranked either second or third for all groups, excluding the developer group, which ranked E2 as the most significant (see Figure 3-7). However, some interviewees pointed out that *‘it used to be an issue’* (D3001), indicating disagreement and lack of awareness regarding the actual importance of E2. Moreover, E2 holds greater relevance for centralised grids and is less of a priority in the context of mini-grids because *‘of the intimate knowledge of the customer and the ability to track [...] the energy they use.’* (DFI1001).

Additionally, interviews identified factors contributing to E2. One of these factors is technical losses from the distribution system alongside ‘parasitic’ loads such as meters and service equipment. Another cause of E2 is commercial losses, which occur when projects are vulnerable to electricity theft and cash-payment handling

misappropriation because *'everything's done [in] cash'* (D2001). However, interviewees noted that the risk has improved over the years due to advancements in financial technology such as *'metering and extension of telecoms infrastructure'* (PF3001-7).

Another contributor to commercial losses is electricity theft (136). For example, developers recognised *'bypassing meters'* (PF3001). This problem is frequent as *'there was one time out of 27 connections in Benin, 20 were bypassed.'* (D1001). Nevertheless, mini-grid systems offer developers an advantage in adopting newer technology and facilitating easier system performance monitoring for prompt intervention given their smaller scale compared to the centralised grid, where electricity theft is prevalent. Despite the measures, such as *'smart meters [...] to reduce collection losses'* (D4001), the risk remains considering actions are taken retroactively. Additionally, an investor argued the relevance of E2 because of the lack of demonstration of *'willingness to pay'* and *'[the] ability to pay'* (DFI1001).

While the survey results indicate that E2 is perceived as a high priority by certain investors, developers, who execute projects and are involved with operations assert that best practices inherently integrated into the projects mitigate E2. This discrepancy suggests that other investors may be unaware of the effectiveness of existing risk reduction practises already being implemented, leading to a disproportionately higher risk perception of the projects. Therefore, historical project data is required to demonstrate the risk is adequately mitigated to investors.

3.3.3.4 Inability to achieve single off-taker effect (E4)

Overall, E4 ranked third (4.8%), equal to E1, E2, and E5 for all groups. Among the groups, only the impact investor group aligned with the overall and collective result (Table 3). In the economic category (Figure 3-7), E4 ranked second among all groups except the DFI group, which placed E4 third most important.

The creditworthiness of the off-taker, whether residential customers, businesses, utilities, or communities, can impact a project's viability (89,151). Additionally,

‘depending on whether an identified cluster, for example, has productive use of power, [...], that has a large impact on demand [and] on the ability to pay’ (DFI001). This means varied off-taker financial capacities and demand uncertainty levels, especially in rural areas, can pose significant revenue risks and diminish the attractiveness of the potential investment. Some developers have mitigated E4 risk by structuring long-term power purchase agreements (PPAs) with financially capable off-takers, such as industrial customers and public sector institutions, a practice identified in the literature (129,151) and supported by our data:

‘Our customer base is commercial clients where we sign PPAs to guarantee our revenues’ (D6001).

Thus, PPAs are perceived to have a lower risk level than the pay-as-you-go models deployed in rural communities, where limited information on customers' credit history is available. For such pay-as-you-go models, the *‘cluster effect’* (D4001) could be achieved by selecting locations with a *‘sufficient customer base, with some demonstrable ability to pay’* (DFI1001) and commercial activities that serve as anchor loads.

3.3.3.5 Non-cost reflective tariff (E5)

E5 ranked third overall (4.8%) for the collective group, but the developer group considered it a lower priority, placing it sixth overall. Interestingly, E5 took precedence for DomFI in the economic category (see Figure 3-7). This high importance of E5 by the DomFI group may be due to their experience in centralised grid financing, where non-cost reflective tariffs and low revenue collection negatively impacted performance (152). Additionally, as many projects in rural areas are subsidised by grants and concessional financing, the tariff structure of such projects may not reflect the actual cost of development and operations (148).

In striving to achieve cost-reflective electricity tariffs, investors need to balance timely cost recovery, sustainable operations and reasonable returns against customer expectations of affordable and fair electricity tariffs (22). Achieving this

balance is challenging due to factors such as high unit costs, and low intensity of use driven by low population density, demand, and affordability (22,151). Nevertheless, developers highlighted that mini-grid tariffs may compare favourably, especially for last-mile consumers *'who pay more for [alternatives] such as petrol and diesel generators'* (D3001) when considering cost and generation efficiency holistically. However, this *'benefit is not apparent to customers'*, and developers need *'to demonstrate the cost reduction opportunities'* (D3001).

Additionally, most developers considered E5 a low priority. This is because the Nigeria mini-grid regulations (133) outline *'cost-reflective tariff'* (D4001) provisions for mini-grid capacities up to 1MW. For mini-grids with capacities lower than 100kW, the regulation requires developers to sign agreements with off-takers. However, negotiating tariffs poses challenges for developers, because while *'rural communities have never heard about or negotiated tariffs' [...]* *'peri-urban [customers] are aware of the subsidised grid tariff, and it is difficult to convince them to pay more'*. (D2001).

Further, registered and permitted mini-grids of up to 1MW are subject to a multi-year tariff order (MYTO). The MYTO allows for the calculation of cost-reflective tariffs, considering up to 10% technical and non-technical losses and 6% profit. An interviewee acknowledged the benefit of the MYTO methodology, allowing *'for cost recovery'* and *'standardisation to the sector [providing] a uniform plain field for financiers, developers, government.'* (D3001). However, the regulation (133) lacks explicit details on the tariff calculation process, potentially undermining investor confidence.

3.3.3.6 Financing risk factors (F1, F2, F3, F4, and F5, and F6)

In the financing category (see Figure 3-8), collectively, inadequate access to low-cost capital (F2) ranked first while, high cost (F1), short loan terms (F3), limited local financial sector experience (F4), limited financial capacity and experience of developers/local investors (F5), and difficulty accessing or repatriation FX (F6) all ranked second. Meanwhile, overall, F2 ranked as the second (8.22%) while

F1, F3, F5 and F6 ranked as the fourth (4.11%), collectively. These risk factors are discussed together due to their interdependencies.

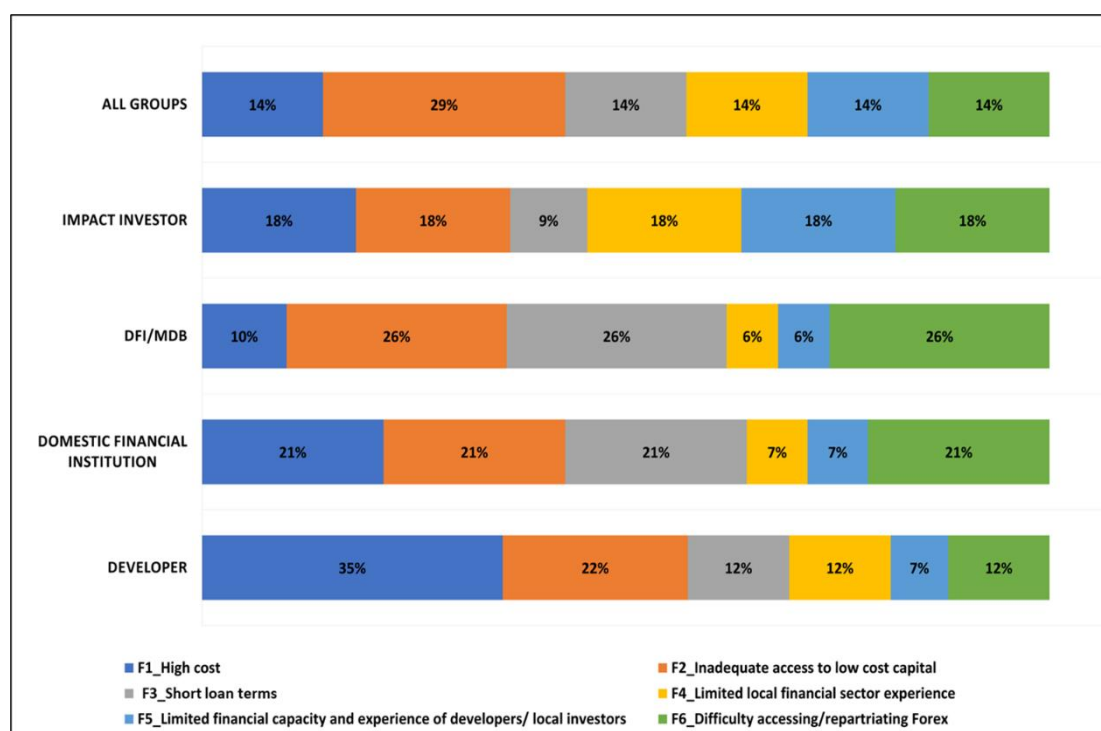


Figure 3-8 Collective and individual groups' risk priorities in the financing risk category.

Financing risks can hinder the ability to attract affordable finance or recover investment (76). DRE projects often face limited access to capital (F2), which typically comes at a high cost (F1) with short loan tenors (F3) (23,96,147,153). The importance of F2 was agreed to by interviewees. Furthermore, challenges in securing domestic and '*international capital*' were ascribed to investors' high-risk perception (D3001) and domestically prevalent low liquidity and high interest rates (22,76,154).

High costs (F1) can be attributed to high capital expenditure (CAPEX). Factors driving F1 can include inflation, financing costs, insecurity-related expenses, FX transaction costs, importation, and handling costs due to inefficiencies and bureaucracy in policy implementation, thus, '*increasing [developer] overhead costs.*' (PF3001–7).

Interviewees noted that local banks have a low willingness to invest in DRE projects and offer too short – *‘two or three years’* (P1001) – loan terms, which are unfavourable due to the longer project life cycle. However, local banks have low liquidity (76,154,155) or low *‘sleeping funds available’* (DomFI2001) and take the perspective of investment preservation by limiting their risk exposure. Furthermore, interviewees indicated barriers impacting project costs, such as *‘high [interest] rates’* (D2001) and high collateral requirements whereby *‘[developers] are unable to provide tangible collateral, and those items [mini-grid assets] do not have a secondary market for them’* (DomDFI1001). This statement also emphasises the significance of the limited financial capacity and experience of developers/local investors (F5). Limited financial and technical understanding of DRE technology can affect F4 and F5 (76,147).

According to an interviewee, *‘past negative experiences’* (DomFI2001), such as low revenue collection and an inability to recover costs, from the centralised power sector privatisation have led to a lack of interest in DRE projects. The distinction between the DRE sector and the power sector is often overlooked, with DRE projects initially perceived as power transactions and appraised accordingly. The interviewee suggested a *‘need to repackaging the DRE sector’* (DomFI2001) to garner more interest. While the literature reports the challenge of low liquidity in Nigeria’s grid sector due to revenue collection inefficiencies and non-cost reflective tariffs (152), its impact on DRE remains unreported.

Additionally, the scarcity of data on the performance of DRE projects hinders the establishment of benchmarks for mini-grid success. This lack of benchmarks leads to situations whereby financiers *‘depend on their [subjective] experiences’* (DomFI1001). Consequently, local banks may categorise DRE similarly to grid power projects, resulting in biased viability assessments. This bias results in the application of higher risk premiums, reflected in interest rates of *‘23–25%’* (DomFI2001). Such practices can impact project costs and, tariffs, subsequently affecting the affordability and sustainability of projects. This situation further underscores the influence of path dependence on the risk attitude of some investors – where historical decisions and interactions may impact the evolution

of a system e.g., investments in fossil fuel based technology may impact RE investment decisions (156,157).

Moreover, interviews underscored the importance of F6, particularly in the execution of FX conversion and transfer obligations such as importation, HC debt repayment and repatriation for international investors, *'who provide long term concessional financing'* (DFI1001). Although the DomFI group ranked F6 as among its most important risk factors, an interviewee disagreed with the result as F6 *'does not apply to local entities.'* (DFI2001). Nevertheless, local developers are affected by delays in sourcing FX, of up to *'10 months'* (D2001) in one case, from the government apex bank for obligations such as hardware importation. This risk has manifested in Nigeria's aviation sector, where funds amounting to up to US \$464 million were pending repatriation (158). This situation persists despite existing fiscal policies, such as the Nigerian Investment Promotion Commission Act No. 16 of 1995². Hence, it is recommended that the implementation of such policies be strengthened to instil confidence among investors.

3.3.3.7 Insecurity risk (SE5)

In the SE category, insecurity ranked the highest (Figure 3-9) collectively and within individual groups. However, despite its prominence in specific groups, insecurity ranked fifth overall. Some interviewees perceived *'insecurity should also have a high number'* (D1001) because of heightened insecurity at the time of the interview and its adverse impact on investor appetite. Furthermore, insecurity can affect projects from development to construction and operation, leading to escalated costs through *'additional insurance, like security insurance, [...] which was not part of our cost structure prior'* (D3001).

Developers also indicated that investment in some locations is deterred because of security concerns. For instance,

² The Nigerian Investment Promotion Commission Act No. 16 of 1995, ensures investors' free importation and unrestricted foreign currency convertibility with a certificate of capital importation (165).

‘I won't do a mini-grid in [named state with high insecurity] for example... That's where my team was ... attacked. So, for now, for me [that] state is no’ (D1001).

This suggests that, without intervention, regions marked by high insecurity and conflict may remain without investment, resulting in persistently low electricity access.

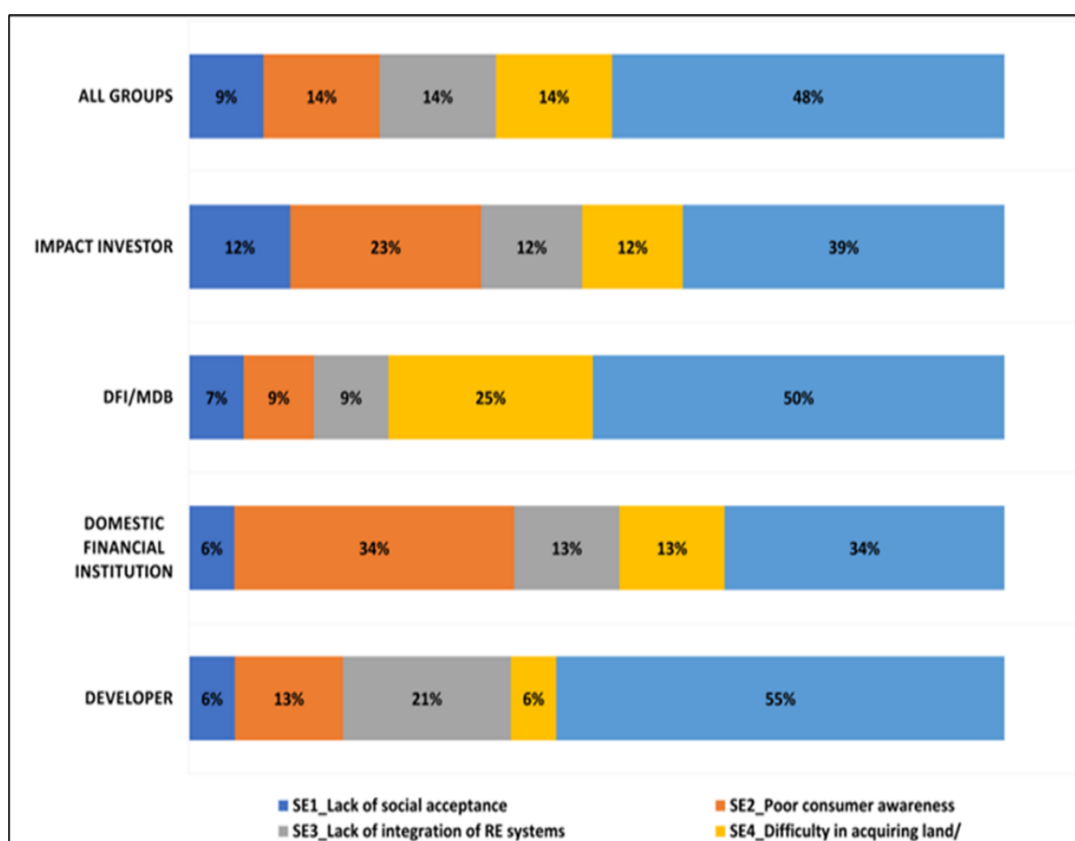


Figure 3-9 Collective and individual groups’ risk priorities in the SE risk category

3.3.4 Investors’ risk priorities – comparisons and interdependencies

To facilitate a comparison of individual group perspectives regarding the most significant risk factors overall, a normalised scale of risk weightings is presented in Table 3-4. The rankings follow a qualitative scale – very low, low, moderate, high, and very high – prioritised based on normalised AHP weightings assigned to each group. For instance, risk factors deemed very high priority have a weighting of >7.68%, while those assigned very low priority have a weighting of <1.92%.

Table 3-4 Comparison of risk factor priorities among groups

RISK FACTOR	Developer	DomFI	DFI	Impact Investor	Consulting and other professional services.	Public sector institution	Other	Development agency	ALL
E1_ Revenue risk	3.6%	0.7%	13.9%	5.8%	1.0%	6.0%	2.5%	7.6%	4.8%
E2_ Collection losses	7.3%	1.9%	7.8%	5.8%	1.5%	3.0%	2.5%	2.5%	4.8%
E3_ Foreign exchange volatility	7.3%	1.9%	13.9%	16.1%	8.5%	6.0%	9.0%	7.6%	9.6%
E4_ Inability to achieve single off-taker or cluster effect	3.6%	1.9%	4.4%	5.8%	2.4%	3.0%	2.5%	2.5%	4.8%
E5_ Non-cost reflective tariff	3.6%	5.0%	4.4%	3.2%	3.9%	3.0%	1.0%	7.6%	4.8%
F1_ High cost	9.0%	6.6%	2.1%	2.5%	11.1%	3.0%	1.9%	2.3%	4.1%
F2_ Inadequate access to low-cost capital	5.5%	6.6%	5.5%	2.5%	3.9%	6.0%	1.1%	6.9%	8.2%
F3_ Short loan terms	3.0%	6.6%	5.5%	1.3%	2.1%	3.0%	3.1%	6.9%	4.1%
F4_ Limited local financial sector experience	3.0%	2.2%	1.3%	2.5%	3.9%	3.0%	5.2%	6.9%	4.1%
F5_ Limited financial capacity and experience of developers/ local investors	1.7%	2.2%	1.3%	2.5%	3.9%	3.0%	5.2%	2.3%	4.1%
F6_ Difficulty accessing/repatriating Forex	3.0%	6.6%	5.5%	2.5%	3.9%	3.0%	1.1%	2.3%	4.1%
P1_ Insufficient policy/legal support framework	2.4%	1.7%	0.5%	1.2%	1.3%	1.2%	3.5%	2.4%	2.2%
P2_ Unclear regulation/guidelines	1.3%	0.7%	0.3%	1.2%	0.4%	1.2%	1.2%	2.4%	0.8%
P3_ Policy changes	1.3%	0.7%	0.8%	1.2%	0.7%	0.4%	5.8%	2.4%	1.0%
P4_ lack of policy implementation	2.4%	0.8%	1.5%	1.2%	1.3%	1.2%	0.8%	0.9%	1.6%
P5_ Duplicative policy development	1.3%	0.7%	0.8%	1.1%	0.7%	0.9%	3.5%	2.4%	1.0%
P6_ Inconsistent policy application	0.8%	0.7%	2.7%	2.2%	0.7%	1.1%	2.0%	0.9%	1.0%
P7_ Uncertainties in IMG regulations implementation	2.5%	2.0%	1.5%	2.1%	1.3%	1.1%	2.0%	2.4%	2.2%

P8_Grid extension uncertainty	2.4%	2.1%	1.5%	2.1%	1.3%	0.6%	5.8%	2.4%	2.2%
P9_Political changes/instability.	4.0%	0.7%	1.5%	0.7%	1.3%	1.2%	3.5%	6.7%	2.2%
P10_Inadequate political will	1.3%	0.7%	0.8%	0.3%	0.4%	1.2%	2.0%	2.4%	1.0%
P11_Adverse political events	5.9%	0.7%	1.5%	0.5%	0.7%	1.2%	1.2%	2.4%	1.6%
T1_Limited training and R&D	0.7%	6.2%	0.7%	0.4%	6.2%	4.0%	0.6%	0.5%	1.1%
T2_Technical skills limitation	1.3%	2.1%	0.4%	0.7%	2.1%	1.3%	2.3%	0.5%	0.7%
T3_Limitation in Developer's capability	1.3%	6.2%	0.7%	1.4%	3.7%	1.3%	2.3%	0.5%	1.7%
T4_Limitation in QC & manufacturing capacity	0.7%	6.2%	0.7%	1.4%	9.7%	4.0%	0.9%	1.5%	1.7%
T5_Uncertain load profile	3.3%	2.1%	2.5%	1.4%	2.1%	4.0%	0.9%	0.5%	1.6%
T6_Inadequate infrastructure	1.3%	6.2%	2.5%	2.4%	3.7%	4.0%	2.3%	1.5%	2.2%
T7_Uncertainties in site characteristics	0.4%	2.1%	0.7%	0.7%	1.3%	2.2%	0.4%	0.5%	0.7%
M1_Sensitivity of RE to fossil fuel prices	2.0%	3.4%	0.9%	3.3%	1.0%	4.8%	5.8%	1.0%	1.7%
M2_Low competitiveness of RE due to subsidies on alternatives	1.1%	1.1%	1.6%	3.3%	1.9%	4.8%	1.7%	1.0%	1.3%
M3_lack of competitive hardware and labour market	0.6%	1.1%	0.5%	3.3%	1.0%	1.5%	3.3%	1.0%	0.7%
M4_Poor data availability	1.4%	1.1%	1.6%	6.1%	3.3%	4.8%	1.7%	1.0%	2.5%
M5_Barriers due to regulations	2.8%	3.4%	1.6%	6.1%	1.0%	2.5%	3.3%	1.0%	2.5%
M6_Uncertain market growth potential	1.1%	1.1%	1.6%	1.3%	1.9%	2.5%	1.7%	0.3%	1.1%
SE1_Lack of social acceptance	0.3%	0.3%	0.3%	0.5%	0.3%	0.4%	2.2%	0.6%	0.5%
SE2_Poor consumer awareness	0.7%	1.6%	0.4%	0.9%	0.5%	1.2%	0.8%	0.6%	0.8%
SE3_Lack of integration of RE systems	1.2%	0.6%	0.5%	0.5%	0.9%	0.7%	0.5%	0.6%	0.8%
SE4_Difficulty in acquiring land	0.3%	0.6%	1.2%	0.5%	0.5%	0.7%	1.2%	0.6%	0.8%
SE5_Insecurity	3.1%	1.6%	2.5%	1.6%	2.1%	2.0%	1.3%	3.1%	2.8%

NOTE: Ranking/colour coding is defined by a normalised qualitative scale of green (very low priority <1.92%), yellow (low priority >1.93–3.84%), orange (moderate priority >3.85–5.75%), dark orange (high priority >5.76–7.67%), red (very high priority >7.68%).

Notably, as with the collective view, all groups except DomFI found FX volatility (E3) as very high to high priority. All groups attributed low priority to all SE risk factors except insecurity. Additionally, while high cost (F1) was a low priority for DFI and Impact investor groups, the developer and DomFI groups found F1 very high and high priority, respectively. This discrepancy may be explained by the association of high cost with other economic and financing risk factors such as revenue risks and loan tenors leading to variations in respondents' view of high cost.

Table 3-4 further underscores the variations in other stakeholders' views on investment risks and the need to focus on the investor-specific risks, which additionally present commonalities and differences. Therefore, in dealing with investment supported by multiple funding sources, decision-makers should address intersecting and mutually exclusive risk factors (depicted in Figure 3-10). For example, while SE5, E1, F2, F3, and E5 are important to both DomFI and DFI groups, a broader range of risk factors, which are individually important to DFI (E4, F6 and E3) and DomFI (T1, T3, T4, T6 and F1), need addressing. Notably, only DomFI found technical risk factors a high priority among the investors. This difference could be explained by experiences gained from projects over the years, and developments in the DRE sector (see 3.3.2), which DomFI may not be aware of due to their low participation in the sector.

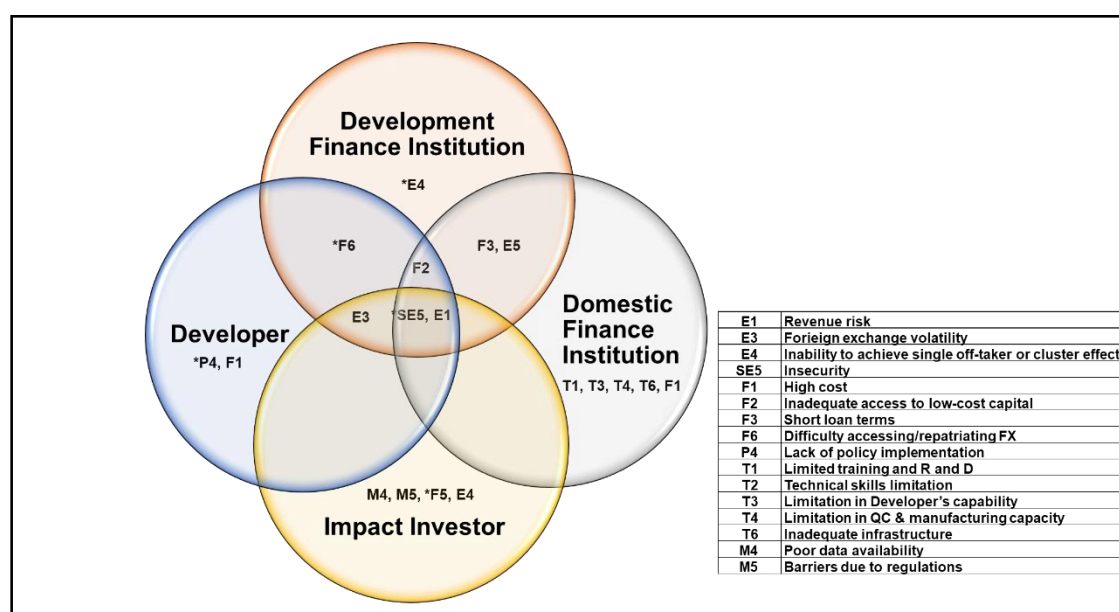


Figure 3-10: Focusing on the moderate to high-risk priorities among investors.

Although risks depend on project scope, phase, resources, and objectives, (85) additionally emphasise that psychological, behavioural, or institutional attributes and experiences can influence risk perception. Such factors contribute to diverse risk perceptions among groups. For instance, as indicated in section 3.3.3.6, previous power investment experiences have negatively impacted DomFI's

appetite for DRE projects. Moreover, the differences in risk priorities among investors emphasise the importance of considering risks not only from a collective perspective as done in previous studies (1,139) but rather, by incorporating investors' specific views. This approach can enable the identification of the most important risk to mitigate. Additionally, in analysing the importance of risks and their impacts, it is necessary to consider interactions and dependencies between risk factors which can reinforce or exacerbate them. For example, socioeconomic factors, energy use behaviour and inability to achieve cluster effect can result in uncertain load profiles and collection losses, which drive revenue risks (section 3.3.3.2).

Furthermore, the impact of feedback can reinforce risks. For instance, an increase in investment risk can increase risk premiums and consequently project costs (72). These can be further exacerbated by insecurity and ineffective policy implementation, contributing to financing risks, consequently, higher investment risk. This feedback loop, unless disrupted, can reinforce risk levels. Risk interdependencies could additionally evolve with the dynamic nature of risks. For example, the priority of social acceptance may increase in the future because of the effect of the limitation of QC, whereby unmet customer expectations can lead to lower adoption rates (22). This approach could enable more strategic identification of risk drivers, impacts and relevant mitigations, providing a more sustained impact on multiple risk factors.

3.3.5 Investor risk mitigations

This section discusses the risk mitigation actions categorised into four main themes, that emerged in the interviews and focus groups. Table 3-5 summarises the risk mitigation actions highlighting interdependencies, (identified from literature and interviews) alongside their enablers and respective potential to improve competitiveness, for the moderate to very high priority investor risk factors (identified in Figure 3-10). These risk factors comprise 37%–58% of the individual investor groups' AHP risk weightings. The following discussions focus on the mitigation actions for risks which two or more investor groups found at least moderate priority.

3.3.5.1 Navigating currency risks

In this study, currency risks comprise FX volatility (E3) and difficulty accessing and repatriating FX (F6). The impacts of E3 could be '*hedged*' (D1001) through the adoption of financing mechanisms that inherently mitigate its effects such as concessional local funding (5,126). Additionally, policies to support local manufacturing can reduce the impact of E3. Another means of mitigating E3 is through tariff indexing to hard currencies or inflation rates via PPAs (76). However, this option is typically reserved for '*commercial customers*' (D6001).

Currency hedging (76,147,151,159) via contracts and options (160) can protect against undesired exchange rate movements. Approved hedging products in Nigeria include FX options, forwards, FX swaps and cross-currency interest rate swaps (161). However, this strategy is only applicable to high-value projects such as large-scale projects (15) and in the short term. Currency risk guarantee funds are another alternative to mitigate E3 where the government covers the difference in exchange rates over a period (102,162). The government can use public funds or charge fees to participants to access guarantee funds. This approach can be used in small-scale projects but may be expensive in the event of currency depreciation (15).

F6 risk has been managed via monetary policies such as guarantees of convertibility and repatriation (102). Other means of reducing F6 include parent company cross-currency swaps (162), and cross-country portfolio diversification (163). Among the stated measures, enabling concessional local financing and local manufacturing is crucial for DRE deployment. Additionally, project aggregation may facilitate scaling and access to other identified mitigations such as hedging.

Table 3-5 Suggested mitigation measures for high priority risk factors.

Mitigation Instruments and Strategies		Impact on Risk Factor																Impact on cost competitiveness	Enablers and improvements to existing mitigations				
		Reference	Mitigation applicability to DRE	Mitigation deployed in Nigeria for MG?	E1_ Revenue Risk	E3_ Foreign exchange volatility	E4_ Inability to achieve single off-taker/cluster	E5_ Non-cost reflective tariff	F1_ High cost	F2_ Inadequate access to low-cost capital	F3_ short loan terms	F5_ Limited financial capacity and experience of developers and local investors	F6_ Difficulty accessing/repatriating FX	P4_ Lack of policy implementation	SE5_ Insecurity	M4_ Poor data availability	M5_ Barriers due to regulations			T1_ Limited training and R&D	T3_ Limitation in Developer's capability	T4_ Limitation in QC & manufacturing capacity	T6_ Inadequate infrastructure
Fiscal & financial instruments	RE Feed-in-Tariff (indexed)	1	P	N	+	+	+		+	+							+					+	Increase Mini-grid threshold and implement REFIT for IMGs
	Public Investments, concessional loans, grants, capital subsidy/rebate	3	Y	Y					+	+	+	+										+	Enable new entrants through tiering of support levels accompanied by less stringent criteria
	Guarantees, Insurance e.g., for payment and currency	1	P	N	+		+		-	+			+		+		+						Portfolio aggregation could provide the required transaction size to enable this instrument.
	Other incentives and tax reductions, e.g., VAT, import waivers	3	Y	Y-					+			+		+			+					+	Review and extend the application of tax incentives across RE components
	Currency hedging	1	N	N		+			±	+												±	Applicable to large-scale projects for short-term
	Free transferability of foreign investor returns	3	Y	Y					+	+			+	+									
Market-based	Carbon certificates/ Carbon Market	1	Y	N	+				+			+					+					+	Requires development of emissions trading framework and alignment with existing policies and institutions
	Carbon Tax	3	Y	N	+				+			+					+					+	Requires development of emissions trading framework and alignment with existing policies and institutions
Regulations	Renewable Portfolio Standards,tTradable RE certificates	1	Y-	N	+																	+	Portfolio aggregation
	Tendering	3	Y	Y	+			+	+			+										+	Spatial diversification and portfolio aggregation incorporated in tender design
	Net metering/ Virtual Net metering	1	Y-	N	+				+			+										+	Requires update in regulation and supporting infrastructure
	*Administrative/ legal provisions	2	Y	Y-										+			+						Improve implementation process and capacity.
	Tech standards	3	Y	Y					+													+	Enable procurement aggregation to reduce cost
Non-traditional financing	On-lending, local financing	3	Y	Y-					+	+		+										+	Implement priority sector loan (PSL) in RE
	Co-lending, blended finance	3	Y	Y-		+			+	+		+										+	Portfolio aggregation and diversification
	Asset-backed finance lending facility	3	Y	N					+	+		+										+	Development of a secondary market, financial sector capacity development
Other	**Capacity development	2							+					+		+	+	+	+	+	+	+	Development of technical expertise within service agencies relevant to importation. Improve manufacturing capacity, improve infrastructure
	Partnerships- community, disco-developer, financiers	2				+	+	+		+		+	+	+	+	+		+	+				Sharing performance data with public institutions, aggregation of projects and partnerships with financiers, other developers and utilities to enable risk sharing and access to financing.
	***Business models	3				+		+	+	+	+											+	
	Spatial portfolio diversification and aggregation	3				+		+	+	+	+											+	Requires update in regulation to enable aggregation
Medium-Very High risk for	Developer					*	*		*	*		*	*	*								N	
	DomFI					*	*		*	*	*	*	*	*	*		*	*	*	*	*	N	
	DFI					*	*	*	*	*	*	*	*	*	*		*	*	*	*	*	N	
	Impact Investor					*	*					*			*	*	*					N	

NOTES:

Adapted from: **1**- literature (128,164–168), **2**- interviews and focus groups, **3**- literature (128,164–168) and interviews.

Y – applicable, **P**-applicable in some instances, **N**- not available/ not applicable, **Y**- - available requires improvement

+ positive impact, **-** negative impact, **±** mixed impact, **•** applicable

*****Administrative and legal provisions e.g., regulation, licensing, grid arrival, land use,

******Capacity development- awareness, training, manufacturing, benchmarked performance data

*******Business models – Productive use, demand stimulation, robust demand estimation, anchor customers, cross-subsidy, segmentation, site and technology selection

3.3.5.2 Improving financing and capacity

Increased participation from the local finance sector could offer more affordable financing options (76,102,147,151); however, DomFIs have limited experience and appetite to finance DRE projects (3.3.3.6). This is also reflected by the Nigeria Bureau of Statistics data (169), which showed that less than 4% of loans were disbursed to the power sector in 2021, suggesting a reluctance to fund power projects. Efforts should be made to differentiate between the grid and DRE sectors, providing benchmarked performance data to instil investor confidence and eliminate bias. Furthermore, exploring initiatives such as Priority Sector Lending (PSL), as applied in India, where local banks allocate 40% of their lending to priority sectors, including RE, could be beneficial (147,160). PSL was additionally highlighted by an interviewee:

‘Government policy can help change the mindset. If we have a policy statement from CBN saying that a portion of your loan portfolio as a bank must be green’ (D4001).

Furthermore, co-lending provides an opportunity to pool funds and distribute risks among diverse financiers interested in larger-scale projects. Aggregating a spatially diverse portfolio across (78) or within (28,62) countries, coupled with document standardisation (28,76,147), can improve the risk profile by addressing financing and economic risks and diversifying finance sources. However, an interviewee noted the limitations of aggregation due to developer financial ‘capacity’ (D1001) constraints.

Portfolio aggregation combined with collaboration among developers or with distribution companies (DisCos) presents opportunities to overcome single developer capacity constraints, enabling access to a wider pool of capital and experience. Additionally, government mini-grid tenders, which allot single and aggregate sites to bidders, could be designed to aggregate projects with diverse locations and socioeconomic characteristics. This approach can facilitate regional portfolio diversification specifically aimed at reducing risks (E1, F1, F2, F5, T3, and F3).

Moreover, concessional loans and technical assistance provided by DFIs through DomFIs via on-lending structures have reduced exposure to E3 and F1 whilst building local developers' and banks' capacity (5,160). However, some interviewees indicated constraints imposed by local banks, such as '*collateral requirements*' (DomDFI1001). Collateral barriers can be mitigated by developing an asset-backed finance lending facility, where the asset or future cashflows can be used as collateral. This scheme requires the financial sector to assess the value of assets as collateral (15) and develop a '*secondary market*' (DomDFI1001) for the sale of assets. Further, to enhance increased local developers' participation, the government could reduce entry barriers for new developers by providing a special funding and technical support category while implementing monitoring and evaluating efforts to ensure compliance.

3.3.5.3 Improving revenues and project viability

Interviews revealed that revenue risk (E1), driven by low energy utilisation, could be attributed to behaviours caused by path dependence (85), cultural practices, and affordability (3.3.3.3). The implications of these behaviours, not typically quantified in cost forecasts, affect revenues. A strategy to mitigate the impact of demand uncertainty on revenues involves conducting robust analyses that consider potential variations in investment decision-making. Furthermore, developers can unlock additional revenue streams by leveraging international carbon markets, thereby mitigating revenue risks (147,170). However, realising these benefits requires the development of supporting policy actions, an institutional framework, and capacities.

Financial incentives, such as grants allocated to rural areas, enhance a project's viability and attractiveness (68,147,154). However, some interviewees raised concerns about the sustainability of grant-funded projects, noting instances of non-operational mini-grids within a few years of operation. Causal factors for a non-operational mini-grid (148) have included lack of a sustainability plan, poor maintenance, low utilisation, and consequently reduced revenues. This suggests that due to the impact of grants, a location identified as suitable for a mini-grid could be better suited for standalone systems. Therefore, in selecting

technologies, the outcome of the least-cost studies must be weighed against location attractiveness and risk factors before conducting more detailed feasibility studies. This approach could provide policymakers with data for targeted interventions and offer developers relevant site selection information.

Beyond policy actions, business strategies that enhance project viability can serve as economic and insecurity risk mitigation measures. Some developers attributed their success to site-tailored '*business development [models]*' (D2001). These could include securing anchor customers such as public facilities, industry and commercial customers, securing community partnerships to improve asset security, '*business models*' that improve adoption, productivity stimulation and '*energy efficiency practises*' (P1001), and '*training and awareness*' (PF3001-7).

3.3.5.4 Policy implementation and improvements

Inconsistent policy implementation and regulatory barriers, identified as high-priority risk factors for developers and Impact investors, respectively, can be enhanced through incentives, policy implementation improvements and enforcement. Although incentives are specified in the existing policies (135), the application is inconsistent in supporting the DRE electrification targets set by the government. For instance, under the Customs Excise Tariff Act, custom duty exemptions are limited to a few solar components (135). For example, while solar panels without diodes are exempt, solar panels with diodes are subject to import duties. To promote DRE investment, taxed components such as solar panels and batteries (with taxes of 27.5% (171)), could be further incentivised and reviewed periodically to stimulate domestic manufacturing.

Additionally, the development of technical expertise within agencies could improve policy implementation consistency. Some interviewees recommended a dedicated service desk in each agency where issues are reported, tracked, and promptly resolved to reduce bureaucracy. This approach has enhanced licencing efficiencies with the '*regulatory agency*' (D3001).

Furthermore, PIs noted that while the mini-grid (IMG) regulations (133) provide an opportunity to improve electricity access in underserved areas by leveraging

existing DisCos distribution networks, there are challenges with its implementation, as DisCos have concession rights to grant or refuse access and are hesitant *‘to deal with mini-grid developers’*. (PF3001-3)

Nevertheless, another interviewee observed the important role the DisCos can play in reducing the *‘high cost’* of investment by *‘socialising distribution cost’* (PF3001-3). Consequently, the mini-grid regulation (133) needs to be reviewed to establish better synergies between developers and DisCos. An example is the enforcement of the stipulated 50% RE target policy for DisCos and generation companies as a means of fostering partnerships. This approach has been implemented in India, where a strict renewable purchase obligation (RPO) policy resulted in 42–65MW of incremental DRE and large-scale solar capacity for every percentage point of RPO (168).

Although the mini-grid regulations allow developers to set cost-reflective tariffs, revenue risks remain. Feed-in-Tariffs (FiTs) have been used globally to ensure reasonable returns in higher-cost technologies such as RE to encourage investment (25). The RE Feed-in-Tariff 2015 (REFiT), applicable to new grid or distribution network-connected RE technologies with a capacity of 1-5MW for solar (172), guarantees grid access and purchase obligations by the bulk electricity trader (NBET) and DisCos. While the REFiT does not apply to mini-grids, policies to incorporate aggregate portfolio IMGs exceeding 1MW, making portfolio IMGs eligible for REFiT, could be explored to mitigate E3.

Nevertheless, Ozeogwu et al. (144) note that high FiT for solar is a significant encumbrance of its adoption and recommended subsidising solar FiT. However, this may not be practicable due to constrained public funds. Incorporating REFiT could be further explored under the Eligible Customer Regulations 2017 (173), which allows for a willing buyer-willing seller arrangement.

3.4 Conclusions

This study aims to holistically evaluate multidimensional risks and identify potential mitigations for DRE investment in Nigeria. It makes the following contributions: (i) it reveals 13 additional risk factors, not previously identified in

existing studies for Nigeria, (ii) provides empirical data on the multidimensional priorities of 40 risk factors within six risk categories and reveals commonalities and divergence in the priorities among four investor types (DFIs, DomFIs, developers and impact investors), and other relevant stakeholders, and (iii) suggests evidence-based mitigation measures for the common high-priority risk factors following an in-depth analysis.

The results showed that six of the 13 identified risk factors (revenue risks (E1), FX volatility (E3), inability to achieve single off-taker or cluster effect (E4), collection losses (E2), short loan terms (F3), and difficulty accessing/repatriating FX (F6)), were among the highest priority risk factors for the investors. Moreover, the results showed the divergence of risk category priorities from other country studies. While previous studies prioritised economic and market (Turkey), and political (Ghana) risk categories (1,58), economic and financing categories were the highest priority for DRE investment in Nigeria; affirming that risks are location dependent. However, the findings diverge from previous studies in Nigeria (25,26,143,144) which found technical and SE risk factors as relevant barriers. This could be explained by the lack of diversity in perspectives on risks and the advancement of DRE since the previous studies.

Further, although SE risk was the least important category for all investors, the most significant categories differed among investors. Moreover, the established risk prioritisation provides a criterion for determining the most common and significant risks for mitigation. The common high-priority risk factors were interdependent and broadly related to currency risks (E3, F6), financing and capacity (F2, F3, F1, F4, F5), revenues (E3), insecurity (SE5), and policy implementation (P4). A detailed analysis of these risk factors revealed low energy utilisation driven by behaviours caused by path dependence, cultural practices, and affordability, bias informed by past experiences in grid power sector deals as key factors influencing the risk perception.

Focusing on the top risk factors which contribute to up to 58% of risk weighting, this study suggests evidence-based mitigation measures and enablers for

policymakers towards catalysing DRE investment in Nigeria. It can be a reference point for risk studies for other SSA and developing countries.

The key policy recommendations are as follows:

- Policymakers should improve access to FX and manage the impact of FX volatility e.g., through strengthening existing FX policies, increasing concessional local funding and grants, and reducing reliance on importation.
- Policies enabling portfolio aggregation and regional diversification can unlock more options for DRE projects which are otherwise accessible to larger-scale projects. Such options include enabling currency risk guarantees, extending existing FiT instruments to IMGs and access to diverse financing sources.
- Increasing participation of domestic finance institutions through capacity building, demonstrating DRE project benchmarks and performance, and priority sector lending mandates could improve local financing.
- Strategic partnerships among developers, financiers, and communities, and policies incentivising collaboration between developers and distribution companies are likely to boost access to financing, insecurity, and developer capacity constraints.
- Actions aimed at improving revenue streams and project viability can reduce the impact of risks. These include policy frameworks leveraging carbon markets, incentives such as grants and tax reduction, and actions such as robust planning, appropriate business models, and risk-adjusted technology selection.
- Finally, policymakers should focus on improving the implementation through institutional capacity building and collaboration, and enforcement of existing policies such as RPO.

Despite the online survey's response rate of 59%, one limitation of this study is the low representation of the impact investor group. This is because the prioritisation of risks could be influenced by the number of experts involved and their subjective judgement (23,100). Nevertheless, consistency checks were

carried out to ascertain data reliability. Furthermore, while this study recognises that risks are dynamic (72), it did not establish the time and event dependencies of risk priorities. Instead, the risk priorities of investors represent the responses obtained during the survey and interviews period. This limitation could be addressed by future research to establish the impact of historical mitigation measures such as policies on the evolution of risk priority levels, thus providing further evidence-based mitigation measures. Another important area of further research is to quantify the impact of the suggested mitigation measures on electricity access targets whilst considering system interactions. This approach could provide policymakers with a tool to test the expected impacts of mitigation measures before their implementation.

4 Modelling spatial investment decisions using system dynamics and agent-based modelling.

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4.1 Introduction

The path towards achieving net zero emissions and universal electricity access for the approximately 568 million people residing in Sub-Saharan African (SSA) countries, many of whom lack dependable and clean electricity, demands a significant upscaling of renewable energy (RE) deployment (174,175). Consequently, there has been a renewed focus on the expansion of RE, particularly in the context of decentralised renewable energy (DRE). DRE involves local generation and distribution of electricity near load centres, offering a viable approach to address electricity access challenges for around 60% of the SSA population lacking access (5,126). Nevertheless, low investments have continued to hinder the deployment of DRE electrification in SSA (5,176). To boost investment in DRE, and thus electricity access in SSA, enabling policy frameworks that facilitate DRE investment planning and decisions (e.g., via improved risk-return profiles, competitiveness, and affordability) are necessary (176,177).

Several studies have examined DRE investment planning decision support, focusing on location and technology selection because DRE technologies are highly site-specific (178). These studies have used a multi-criteria decision approach (MCDM) to identify the optimal allocation of DRE technologies across locations (13,175,179). Some studies additionally incorporate a geographic information system (GIS) approach to explore the implications of spatially explicit factors such as resource potential and socio-economic factors (8,179,180) and environmental factors alongside techno-economic factors (12,179) on the optimal selection of technologies in specific locations. While these studies are useful in planning DRE systems, they do not consider the additional complexity presented

by heterogeneous private investor preferences, their interactions and feedback, which can drive the evolution of spatial investment decisions in liberalised electricity markets, such as is the case in many SSA countries (176).

Investment decisions in liberalised electricity markets can be complex due to interactions between multiple interconnected components, agents, and their emergent behaviours (33,34). As a result, the liberalised DRE market structure can be considered a complex adaptive system (CAS). CAS is characterised by interacting heterogeneous agents with individual behaviours that evolve (156). The agents exhibit attributes of bounded rationality, imperfect information, diverse risk preferences and goals ranging from profit maximisation to environmental impact (181,182). Their interactions occur within networks governed by rules according to their institutional, market, and policy structures, influencing behaviours and reactions to the environment (156). For DRE, the complexity of investment decisions is increased by the diverse technology options and spatial variability in location factors (e.g., resource potential, demand, socio-economic characteristics) which drive investment attractiveness and risk (14,35).

Current approaches to analyse investment in such complex electricity systems include agent-based modelling (ABM) and system dynamics (SD). ABM is well-suited to depict investment decisions among diverse agents (115) and has been used to explore investment decisions in heterogeneous firms in electricity markets (37,38,183,184). Meanwhile, SD enables the modelling of complex systems from a cause-effect perspective at a macro level (34). SD approach has been utilised to explore spatiotemporal investment patterns based on location attractiveness (35) and supply-demand dynamics (185).

However, SD and ABM applications in investment decisions predominantly represent grid-connected liberalised market structures and present some limitations for their application to DRE. Firstly, the ABM and SD models do not fully account for factors relevant to DRE's site-specificity, especially in the context of investment in SSA, such as investment risk (5,14,162,176), location factors that drive attractiveness (14,35,36), willingness to pay (13,176) and

competitiveness among other electricity generation alternatives (13,14,186), which in turn have implications on investment decisions. Secondly, as ABMs focus on micro-level interactions and aggregation of agent decisions, they do not incorporate macro-level interactions and feedback to establish the dynamic spatial effect of investors' decisions and their consequences on the overall system's supply-demand dynamics. On the contrary, while the SD approach can establish this macro-level perspective, it can ignore interactions between agents leading to the low resolution of representation of complex investor behaviours (115,187). Consequently, the complementary benefits of integrating ABM and SD approaches have been applied in the context of solar PV adoption (41) and RE investment trends (40), albeit in a centralised grid system. Therefore, factors relevant to DRE and in the SSA context were not considered in the studies. This study thus aims to introduce and validate an SD-ABM model that can analyse the spatial evolution of DRE investment considering interactions between heterogeneous investors, their preferences and attributes and location attractiveness attributes. The model is validated for a case study of Nigeria. The research addresses the question: *How can a holistic risk management approach, which accounts for these complex interactions, be integrated into a spatially explicit model to improve investment planning and decision-making, thereby identifying actions for catalysing DRE investment?*

This study contributes to the need for improving electricity access via DRE investment in three ways. Firstly, this study develops an SD-ABM model to address the absence of a unified framework for DRE investment planning and decision support in a liberalised market structure which can inform spatial investment decisions of diverse investors. As shown in Figure 4-1, the model improves on existing methods by leveraging SD and ABM approaches to (i) explicitly incorporate location-specific attributes, individual investor agents' decisions and their interactions at a micro level for each modelled location, (ii) establish feedback mechanisms that aggregate individual investor decisions into a unified system perspective; facilitating a spatial perspective of DRE development over time and (iii) incorporate investment risk considerations. These features enable decision-makers to identify conditions and policy actions

conducive to promoting investments, aligned with electricity access targets. Additionally, potential investors can identify locations that suit their investment profiles. Secondly, we demonstrate the model capability by applying and validating it for a case study of Nigeria and by comparing its output to one that does not consider investor heterogeneity against historical data. Lastly, we conduct a sensitivity analysis to explore the sensitivities of model parameters on investment and investor types.

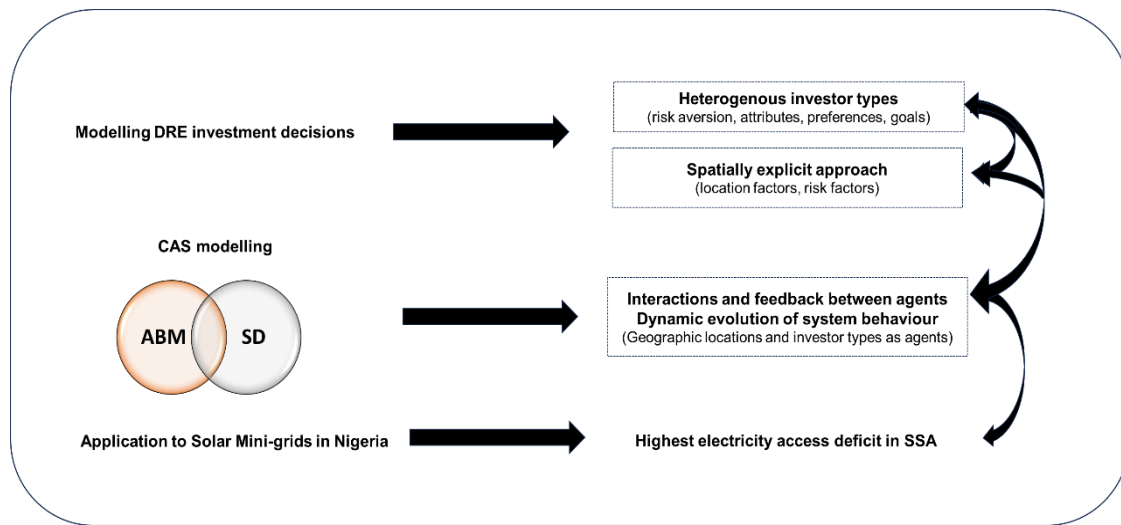


Figure 4-1 Integrating complex system modelling with DRE investments in the SSA context.

The following sections compare the features of the developed model to existing planning and decision support models (section 4.2). Subsequently, a detailed description of the methodology is presented (section 4.3), followed by the results of the validation and sensitivity analysis (section 4.4). The discussions follow (section 4.5), and finally, conclusions are offered (section 4.6).

4.2 Literature review

This section compares the developed model with existing approaches for electricity system investment planning and decision support established in the literature (see Table 4-1). The comparison is made by highlighting key features relevant to DRE investment modelling (see Table 4-1) that distinguish the developed from the existing approaches identified in the literature. The features

include applicability to DRE investment, consideration for spatial and investor heterogeneity, micro-level interactions and decision-making, supply-demand dynamics and macro-level feedback.

Table 4-1 A comparison of this study against existing relevant models

Reference	Methodology (Region)	DRE application	Consideration for heterogeneity								Consideration for complexity	Applicati on			
			Spatial differentiation in location factors					Heterogeneity in investors							
			Technical	Economic	Environmental	Social	Political	Multiple Investor types	Differentiation in financial attributes	Investment decision goals/ criteria	Risk preference	Supply-demand dynamics	Feedback	Interactions and emergent decision making	Policy analysis
(179)	MCDM, optimisation (China)	•	•	•	•					Cost and efficiency optimisation					•
(8)	MCDM GIS (SSA)		•	•										•	•
(12)	MCDM, GIS (Colombia)		•	•	•		•			LCOE, environmental criteria				•	•
(117)	ABM (Malaysia)	•						•*	Income/ expenditure	Affordability		•	•		•
(35)	SD (UK)		•	•	•			**		LCOE, CO2 emission		•	•		•

(185)	SD, game interface (Turkey)							•	Expected IRR, profitability, discount rate	NPV	•1	•	•		•	•
(40)	SD, ABM, Game Theory (Iran)							•***		ROI and share of the total investment profit		•	•		•	
(188)	ABM, game theory (NS)									IRR threshold				•	•	•
(189)	ABM (UK)							•	Maximum build rate	NPV, ROI		•	•	• market share	•	
(37)	ABM (NS)							•	Discount rates, resource constraint	Positive cashflow and maximum EU,	•2	NS	•	•	•	•
(190)	ABM (Australia)			•						Positive cashflow		•	N S		•	•
(52)	ABM (China)							•	Technology preference	Maximum EU	•	•	•	•		
This study	SD-ABM (SSA)	•	•	•	•	•	•	•	Discount rates, financing mix, investment	LCOE, CO ₂ emissions avoidance, positive cashflow and	•2, 3	•	•	• market share-peer effect	•	•

									threshold and goals	EU, IRR, payback time, consumer WTP, IRR,						
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* - residential investors, ** investment goals simulated as scenarios, *** - RE and non-RE companies

1-Risks taken at levels of aggression, 2- varying degrees of risk-averse behaviour incorporated using expected utility theory (EUT)

3 - Explicit risk levels. NS – Not stated in the study.

4.2.1 Spatial and temporal differentiation in location factors

Within the same country, heterogeneity exists in the capacity to attract investment due to location-specific factors (14). These location factors are categorised into technical (resource potential, accessibility), economic (LCOE, supply-demand, income), political (conflict), environmental (potential for emission avoidance or reduction, impact — physical, cultural, and economic) and social (affordability) factors. As shown in Table 4-1, MCDM and SD approaches have incorporated mainly technical, economic, and environmental location factors. However, apart from the authors of (190), whom considered economic factors in the spatial allocation of generation capacity, the reviewed ABMs have not incorporated this spatial approach.

Further, Falchetta et al. (14) identified five location attractiveness factors in the economic, social, and political categories as strong drivers of RE investment by private investors in SSA. These include historical conflict propensity, poverty rate, urban/rural prevalence, travel time to the nearest city and excluded ethnic groups. Additionally, Allen et al. (35) recognised stress level — a measure of the supply-demand gap and resource potential as differentiators of location attractiveness for investments. These factors have been adopted in this study to provide a holistic representation of a location's attractiveness factors to investors considering the SSA context.

Another location factor considered in the developed model is willingness to pay (WTP) for electricity by consumers. Low WTP can impact latent demand, revenues and, thus, the sustainability of an investment. In the reviewed models, revenue risks were not a concern as the electricity tariffs may be guaranteed, cost-reflective or could be subject to feed-in-tariff subsidies. However, in the case of DRE where one of the key risks is related to revenue, low affordability and low WTP of consumers need to be considered. Affordability can depend on the socio-economic condition of a consumer (36). Therefore, in this study, poverty level is used as a proxy for affordability as in SSA literature (14,36). Along with cost and return expectations, investors weigh the potential tariff against the consumer's WTP in making decisions (191). For example, WTP could be established through

customer engagement during site surveys (13) or by benchmarking potential tariffs against the cost of alternate electricity sources (such as kerosene lanterns, petrol, or diesel generators) in the customer location (191). This study adopts the latter and incorporates WTP as an investment criterion.

Furthermore, the model incorporates the temporal variability of factors that can impact the cost and competitiveness of DRE and consequently investment decisions. One factor included in the model is the estimated 5% annual cost reduction in solar components because of evolving technology maturity (192). Additionally, the model incorporates the impact of inflation and exchange rate volatility as these are key financial risks and cost drivers for investment. The location factors considered in the model are further discussed in the methodology section.

4.2.2 Heterogeneity in investor agents

The liberalised DRE electricity sector consists of investor types with diverse characteristics including financial attributes (35,37), decision criteria (37,193,194) and individual investment goals (35). Such goals could be cost minimisation, profit maximisation, social impact, or environmental impact (35,193). These goals can impact decisions on spatial technology selection and capacity allocation (35).

Further, investors can have different risk attributes (37,194) comprising risk aversion and risk priorities. The degrees of risk aversion correspond to their attitudes towards risk under uncertainty (37). For example, risk-averse investors may prefer more established technologies or markets with lower risk levels to more profitable higher-risk investments. Thus, incorporating investor risk aversion into ABMs can improve the outcomes of decision modelling (37,38). Additionally, investors prioritise risks differently due to their different experiences, objectives, and perceptions, resulting in diverse risk levels and consequently, diverse discount rates — which impact capital costs and cost competitiveness against alternative technologies. The impact of risk mitigation actions on risk levels, and discount rates can thus differ (14,102). However, this implication was not considered in the reviewed models.

Moreover, investors may use different decision criteria to make investment choices such as return on investments (ROI), Net present value (NPV), Internal Rate of Return (IRR), expected utility (EU) and levelised cost of electricity (LCOE). Additionally, some models stylised investors with different financial attributes such as source of funding, capital cost, and investment thresholds. These heterogeneous attributes, preferences and goals of investors can influence investment decisions and, consequently, the spatial development of DRE.

4.2.3 Dynamic interactions and feedback

Investment capacity additions are influenced by interactions and feedback between investor behaviours and supply-demand dynamics (39). For instance, the supply-demand gap determines a location's potential generation capacity requirements, which is considered in establishing electricity prices and, consequently, the economics that drive investment decisions towards bridging the supply gap (53). Such dependencies and interactions at the macro-level are better modelled with SD (34,115). Meanwhile, ABMs have been used to model micro-level interactions and aggregation of investor decisions. While ABMs do not consider this macro level of dynamic interactions and feedback between supply, demand and investment decisions, some studies have integrated ABM with SD. For example, (40) developed a hybrid model that integrates SD, ABM, and game theory to analyse RE trends and policymaking while considering its competition with conventional electricity generation. The model incorporates an endogenous determination of demand at the macro level via SD and ABM for micro-level interactions. However, the model is not spatially explicit in representing demand and investment choices, which is relevant to decentralised systems. Such an approach can improve the visibility of regions with supply-demand gaps and enable a tailored approach to policy intervention.

This study further considers emergent behaviours such as peer effect, which refers to an investor acting in response to the actions of its peers. Firms follow industry peers in making investment decisions (195). This effect is stronger in certain instances such as financially constrained firms in a competitive

environment (196) and under high economic policy uncertainty (197). It is thus hypothesised in this study that a location with existing investors is likely to attract further investments due to peer effects resulting from market familiarity.

The following section explains the conceptual framework guiding the SD-ABM model followed by the methodology.

4.2.4 Conceptual framework

This study leverages complex systems theory and considers that the process and outcomes of investment decisions are CAS-characterised by investors with bounded rationality and heterogeneous attributes (see section 4.2). The concept of bounded rationality can be applied when agents lack perfect information for optimal decision-making (198). This model framework considers DRE investors to have imperfect information and, therefore, only consider a subset of choices (31).

Further, the framework establishes investor agent decision-making in the SSA context (i) by aggregating investor agent characteristics (such as funding sources and risk attributes) (37,52) to yield representative decision-making agents, (ii) recognising spatial differences — in supply-demand dynamics (35,185), location attractiveness factors (14,35), and investment risk factors (9,23,102), and (iii) using goals and decision strategies (35,193) and analysis tools (expected utility) (37,52,193). In establishing their investment choices, investors seek to maximise their expected utilities (EU) by considering probabilities and outcomes (52,199,200).

Moreover, the framework integrates ABM and SD modelling approaches. Three levels of SD-ABM integration have been applied in the literature (201) (i) independent SD and ABM models, (ii) connected models with partial inputs/output exchanges between SD and ABM models such as implemented in (40) and (iii) intertwined models SD and ABMs with alternating inputs and outputs. The conceptual model architecture used in this study is the latter. The framework follows the structure for SD in (201), whereby emergent agent behaviour from the decision-making process is distinguished from the system structure.

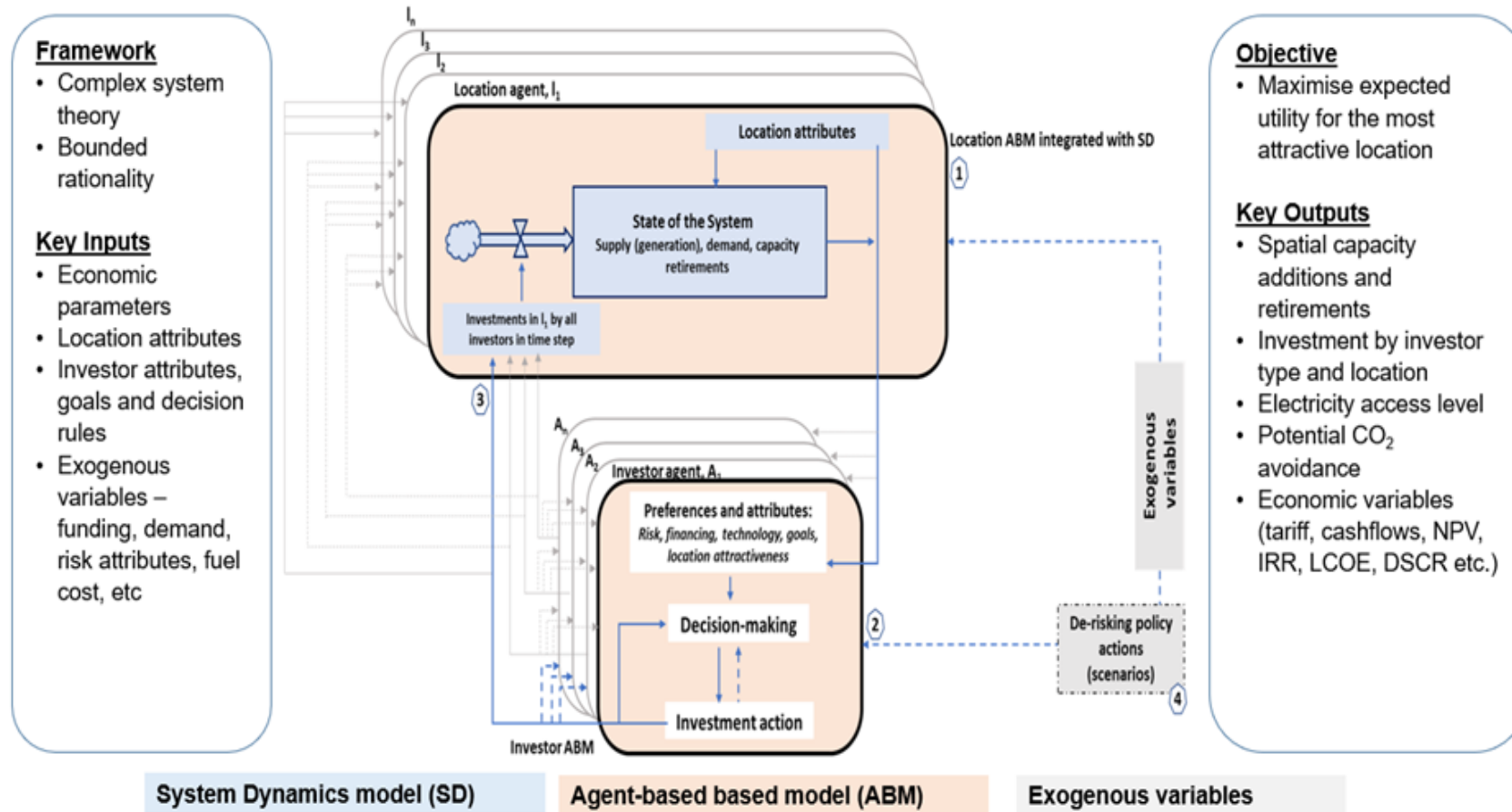


Figure 4-2 A unified conceptual framework for DRE investment decision

The framework illustrated in Figure 4-2 builds on structures and concepts in the literature (35) and integrates ABM and SD in the following manner. Firstly, potential DRE locations (representing unelectrified population clusters) are modelled as non-autonomous location agents, each with its dynamic supply-demand structure and location attributes. The system's dynamic state is determined within the SD model based on location attributes, exogenous, and endogenous variables and information transferred to and from decision-making agents through feedback mechanisms. Secondly, the decision-making of heterogeneous investor agents is modelled in ABM. Investor agents make decisions based on their preferences, attributes, decision rules, interactions with other investors, exogenous variables such as alternate fuel costs, exchange rates, total demand, risk mitigation scenarios etc, and information from the SD model regarding the system's state. Through the interactions, the decision-making agents are informed of their past choices and those of other investors. Thirdly, the interactions result in investment actions that can alter the system's state (supply-demand) over time. Fourthly, risk mitigation and policy scenarios are exogenous parameters that may be tested to evaluate their impact on emergent behaviour and supply dynamics.

4.3 Methodology

This section presents a background of the case study used for validating the model, followed by the methodological approach for the model development. Next, an overview and detailed description of the model are provided along with relevant case study parameters.

4.3.1 Case study background

Planning models such as the Nigeria Integrated Energy planning tool (57) have identified solar PV as one of the least cost paths to achieving electricity access targets. While these tools determine several potential locations for solar PV investment, they do not assess the relative investment potentials of the identified sites, i.e., which locations are the most viable for a given investor profile considering location attractiveness and investment risk. This understanding is

relevant because Nigeria has set targets to achieve 90% electrification by 2030, universal electricity access by 2040, and net zero by 2060 (202,203). These targets require a significant scale-up in private investment of up to US\$35 billion for solar mini-grids alone as estimated by the government (132). A spatially explicit approach to analysing the development of DRE investment decisions whilst considering location attractiveness, investor heterogeneity and preferences and interactions could provide insights into actions that can improve investment. The following sections describe the model along with the relevant case study parameters.

4.3.2 Methodological approach

This study followed five main methodological steps (illustrated in Figure 4-3) adapted from established literature (204,205). The first step was to define the problem and aim of the model, while the second step involved model conceptualisation. In this step, the primary conceptual causal relationships, system boundaries, parameters and variables were established. The third step was model development, which involved mathematical model development by formulating equations and agent rules and creating stock and flow diagrams. The operational model was built using Anylogic software version 8.8.3, and the intermediate results were validated. The fourth step was the final validation. Validation is the process of determining if the model is representative of the real system being depicted. The real system refers to the expected or historically observed behaviour of a system. Validation was carried out in two ways; (i) iteratively and at different stages of the model development process and (ii) through expert feedback to improve the confidence level in the model (55,118,204,206). Expert feedback was sought at two stages: during the model development phase from academics, and subsequently, at the final validation stage, by involving a diverse group of expert stakeholders. This group comprised domestic finance investors, impact investors, development finance institution investors, developers, policymakers, and regulators (see Table 3-1). The stakeholders participated in interviews and focus group sessions, as detailed in part 3 of Appendix B.3.2. During the sessions, the model and its underlying

assumptions were discussed, enabling stakeholders to provide invaluable feedback. The validation process involved adjusting assumptions, system boundaries and structure of the conceptual or mathematical model and re-testing when model output did not conform to the expected system behaviour. In this step, the following (54,55) structural and behavioural validation were carried out for the case study of Nigeria (see section 4.4 and Appendix C.4). Whilst the validation tests were originally developed for SD models in the literature, (118) argued the applicability of the tests for ABMs. Finally, a sensitivity test was carried out to analyse the implication of changes in selected variables on investment. Although the model was developed and tested for the case study of solar mini-grids in Nigeria, it can be adapted to incorporate other technologies and countries.

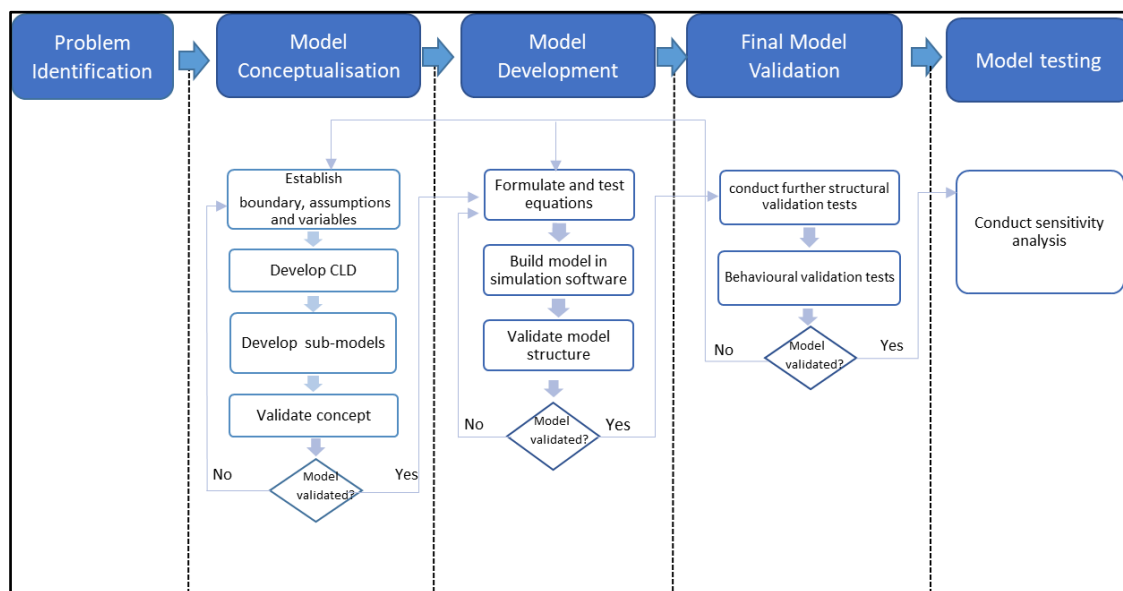


Figure 4-3 Modelling approach.

Source: Adapted from (204)

4.3.3 Model description

The model description follows the overview, design concepts, and details protocol (207). This protocol was adopted to improve model acceptability by decision-makers, transparency, and replicability, which have been highlighted as limitations of ABMs.

4.3.4 Overview of agents

The model includes two agent types: investors and locations, which are described specifically for the case study in the following sections. The principal agents are the investors. These are heterogeneous decision-making agents with CAS characteristics of learning and bounded rationality. Investors compete to meet demand in a location based on attractiveness and rules that meet their decision criteria. The non-autonomous location agents are potential locations suitable for DRE deployment with their supply-demand dynamics and location attributes. Geographical coordinates, population, population growth and death rates, current generation capacity, resource potential, and socio-economic characteristics define the location's attributes. Investment decisions by investors lead to a change in the state of the supply-demand dynamics of each location.

4.3.4.1 Investor agents

As a result of the operationalisation of policies, and regulations and enabling development agency programmes, DRE investment in Nigeria has evolved from public funding provided by the government, impact investors, and development agencies in the form of concessional capital such as concessional debt and grants to mixed funding from mainly public and private sources (134). Private capital can comprise non-concessional debt from institutions such as domestic and international development finance institutions/multilateral agencies (DomDFI and DFI), domestic finance institutions (DomFI), and private equity e.g., from developers and impact investors. One of the enabling regulations for private capital is the mini-grid regulation (133) which allows investors to charge cost-reflective electricity tariffs that are acceptable to at least 60% of consumers in a location. This means electricity tariffs can vary by investor and location.

This study categorises DRE investors into broadly four types primarily based on their finance sources in Nigeria — concessional debt and grant, equity, commercial (non-concessional) debt and DFI debt³. Investment can represent a

³ *Investor type definitions:*

Type 1: represents investment financed mainly from concessional debt and grants.

Type 2: represents investment financed mainly from private equity.

blend of these finance sources. Therefore, in this study, investor agent heterogeneity is depicted by a stylised representation of the four main funding types referred to as investor types. These include Type 1 (concessional), Type 2 (Equity), Type 3 (DFI debt) and Type 4 (DomFI debt) investors. The investor type categories are further decomposed into nine sub-categories as defined in Table 4-2 according to variation in the financing blend. The model can be adapted to portray other investor profiles.

The investor types are further differentiated by their risk attributes (from high-risk aversion to low-risk aversion), measured by the Arrow-Pratt coefficient (37), investment criteria of equity IRR, investment threshold, payback time for debt component, discount rate, and investment goals as shown Table 4-2.

Type 3: represents investment financed mainly from DFI debt.

Type 4: represents investment financed mainly from non-concessional DomFI debt.

Additionally, these stylised categories have varied financing blends comprising debt, grants and equity represented in the sub-categories.

Table 4-2 Stylised heterogenous investor attributes.

	Investor types ³		Financing	Investor goal		Investment threshold		Risk attribute	Expected payback time (years)
	Type	Sub-type		Economic (LCOE)	Environmental (CO ₂ emission reduction)	Minimum (kW)	Maximum (MW)	Risk aversion (arrow Pratt coefficient)	
1.	Type I (Mainly Equity)	Equity (E)	100% E	0.9	0.1	10	1	High (1e ⁻⁵)	-
		Equity (EG)	95% E, 5% G	0.8	0.2	10	1	High (1e ⁻⁵)	-
2.	Type II (Primarily DomFI Debt)	DomFI (DEG)	65% D, 30% E, 5% G	0.8	0.2	10	1	High (1e ⁻⁵)	5
		DomFI (DE)	70% D, 30% E	0.8	0.2	10	1	High (1e ⁻⁵)	5
		DomFI (DG)	80% D, 20% G	0.8	0.2	10	1	High (1e ⁻⁵)	5
3.	Type III (Primarily Concessional debt)	Conc (DEG)	50% D _c , 30% E, 20% G	0.4	0.6	10	1	Low (1e ⁻⁷)	10
		Conc (DE)	11% D _c	0.5	0.5	10	1	Low (1e ⁻⁷)	10

			39% E, 50% G						
4.	Type IV (Primarily DFI debt)	DFI (DEG)	60% D, 30% E,10% G	0.4	0.6	10	1	Moderate (1e ⁻⁶)	10
		DFI (DE)	70% D, 30% E	0.5	0.5	10	1	Moderate (1e ⁻⁶)	10
	Reference		Actual project (208)	Actual project (208)	Actual project (208)	(133)	(133)	(37)	Actual project (208)

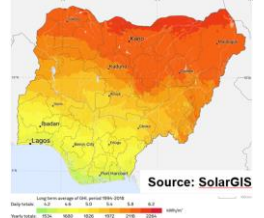
NOTE: E-Equity, D- Debt, G- Grant

4.3.4.2 Location agents

The location agents in the model represent 10 geographical locations with existing mini-grids commissioned between 2012–2018 (209). This dataset is used for model validation and sensitivity analysis. The model can be adapted to include additional locations by updating the relevant location parameters. Each location has defined parameters such as geographical coordinates obtained from the government database and actual project information, initial population, growth, and death rates (130) and household demand based on the World Bank demand classification (210).

Furthermore, some location parameters are dynamic for example, the model calculates the total demand in each model time-step following population system dynamics. Additionally, in the case study, petrol generation LCOE is used as a proxy for WTP. This is because petrol generators are considered as alternate electricity generation sources in the locations. As petrol cost (169) varies across time scales and spatially, so does WTP. The model thus calculates the WTP for each location in each time step. Similarly, dynamic stress levels are established per location in a time step. Furthermore, Table 4-3 presents spatial factors that are considered predictors of the propensity to attract private investment in the literature (13,14,35,195,210).

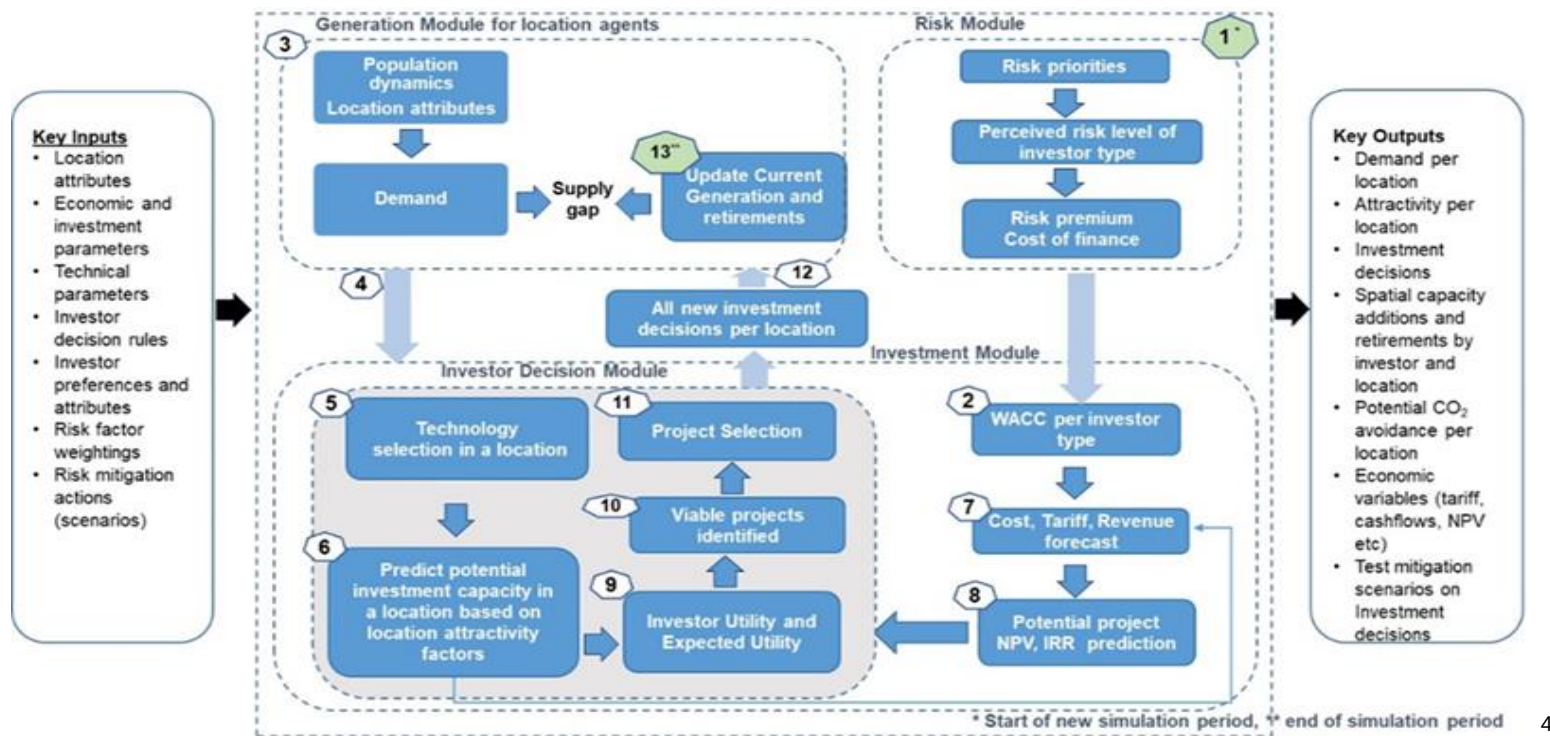
Table 4-3 Spatial input data used in the model.

Factor	Variable	Data transformation	Spatial resolution	Temporal resolution	Data source	
Conflict (209)	Count of conflict events in the state (211)	Conflict data for each state was normalised on a scale of 0–1	By state	Yearly, 2013–2018	ACLED (212)	
Poverty (209)	The proportion of people living below the poverty threshold (211)	Poverty data for each state was normalised on a scale of 0–1	1 km	-	WorldPop dataset (213)	
Distance to the nearest city/ town (209)	Cities or towns with a 25km radius (211)	Identification of the number of towns and cities within a 25km radius of each location. Output was normalised	1 km	-	ArcGIS Pro 2.9, Open Street maps (214) (The methodology is provided in Appendix C.1)	
Solar potential (213)	Global Horizontal Irradiation (GHI) (215)	GHI for each state was normalised on a scale of 0–1	1 km	-	SolarGis (216)	

Population	Population	Dynamically calculated in SD	100m	Yearly time-step	Initial values WorldPop dataset (217) Subsequent data was model generated.		
Stress level (215)	Generation capacity and demand (215)	Dynamically calculated in SD	Location (population cluster)	Yearly time-step	Model generated		
Peer effect (195)	Investments in each location(195)	Dynamically calculated in SD-ABM	Location (population cluster)	Yearly time-step	Model generated		
Willingness to pay (191)	Alternative fuel - petrol generation cost(191)	Dynamically calculated with input from the average yearly petrol cost in a location	By state	Yearly, 2013–2018	NBS (169)		

4.3.5 Overview of the model structure

Figure 4-4 presents the model structure. At the start of the yearly investment time step, the model calculates each investor agent's financing source's risk level, risk premium, and cost of financing. This information determines the weighted average cost of capital (WACC) for each investor type in the investment module. The WACC may change based on the likely effectiveness of risk mitigations, which can be evaluated as scenarios in the model. Next, the model determines each geographic location's current demand, generation (supply), and stress level. Each investor's current potential generation capacity (the potential capacity an investor may be considering investing in) for a technology option and location is then determined based on a location's stress level, attractivity factors and investors' goals. Considering the potential generation capacity, WACC, and investment cost, investors make predictions of economic variables namely capital expenditure (CAPEX), operating expenditure (OPEX), electricity tariff, cashflow, payback time, internal rate of return (IRR), net present value (NPV) and expected utility (EU) of a potential investment. The investors do not share their plans within each time step to capture the impacts of imperfect information on competitors' strategies (37). The outcomes of economic predictions, guided by investor constraints, decision rules and consumers' WTP in a location, are used to make investment decisions. The investment decisions are passed on to the SD models within the location agents. In the SD model, the investments progress from the investment decision phase through to the construction, operation, and retirement phases (see section 4.3.6.1). Once a new project enters the operation phase or retires at the end of its life, the model updates the current generation stock to reflect the available electricity supply and starts a new time step. The steps are repeated until the investment horizon is reached. A more detailed description is provided in the following section.



Note: Numbers in Figure 4-4 indicate the sequence of calculations in the model.

Figure 4-4 Modelling An overview of the model structure and sub-systems interaction

⁴ As part of my manuscript publication, I am committed to publishing the details of the model in an open access platform such as Github.

4.3.6 Model sub-systems

The model framework presented in Figure 4-4 consists of three modules: generation, risk, and investment modules. Each module and the guiding equations are described in the following sections (see C.2.2 for further details). The equations and constructs are adapted for DRE application from existing literature (14,35,37,52,102).

4.3.6.1 Generation module

In this module, demand, current generation and stress level are calculated yearly until the investment horizon is reached. Demand in a location, D_l , (4-1) is determined based on population dynamics using the World Bank tier classification (210) and population growth forecasts. Meanwhile, the current generation $Gen_l^{current}$, (4-2) is updated based on (i) capacity retirements at the end of a facility's life and (ii) feedback from the investment module. Following investment decisions in the investment module, projects selected by all investors in a location are placed on a queue to account for the time lag between investment decision-making, construction and the start of operation (as reflected in Figure 4-5). The project life is assumed to be 20 years after which the project is retired. The stress level in a location (4-3) is calculated by comparing the demand in two years, $Demand_l(t + 2)$ and current generation.

$$D_l(t) = \left(\frac{P_l * (1 + r_g)^{(t-1)}}{n} \right) * Dh \quad (4-1)$$

Where n is the number of households, Dh is the household demand, r_g is the growth rate, t is the model year, and P_l is the population in location l

$$Gen_l^{current}(t) = \quad (4-2)$$

$$Gen_l^{current}(t-1) + \sum_i Gen_{i,l}^{investedOnstream}(t) - Gen_l^{retired}(t)$$

Where $Gen_{i,l}^{investedOnstream}(t)$ is the on streamed generation location l and year t .

$Gen_i^{retired}(t)$ represents the generation facility retirements in location l and year t .

$$Stress\ level_l(t) = \left(\frac{Demand_l(t+2)}{Gen_i^{current}} \right) \quad (4-3)$$

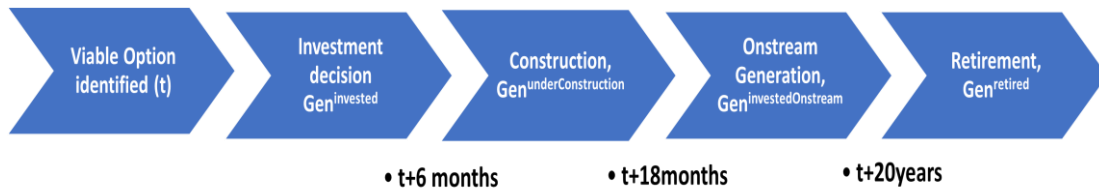


Figure 4-5 Project lifecycle and timeline from selection to retirement

4.3.6.2 Risk module

The key output from the risk module is the risk premium calculation for various sources of financing, which serves as an input to the investment module for determining the WACC. Following Waissbein et al. (41), the risk premium recognises that higher financing costs in developing countries are reflective of actual or perceived investment risk priority levels. This is defined by the survey of DRE investors' (N=70) risk priority levels (see Chapter 3 for details of the risk survey). Six risk categories are considered: political and policy (R_p), technical (R_T), economic (R_E), financial (R_F), market (R_M), and social and environment risks (R_{SE}), each with five to eleven risk factors. Overtime, risk priority levels may change when a mitigation is applied depending on its effectiveness. This change is expected to reflect on the risk premium, $riskPremium_i$, cost of debt R_i^{debt} , (4-4) cost of equity, R_i^{equity} , (4-5) and consequently, WACC. For example, a risk mitigation policy of long-term subsidies to reduce market risks could lead to lower risk premiums overtime depending on the importance of the risk factor to the investor, i and its effectiveness. Other equations are provided in Appendix C

$$R_i^{debt} = baseCost_i^{debt} + riskPremium_i^{debt}(t) \quad (4-4)$$

$$R_i^{equity} = baseCost_i^{equity} + riskPremium_i^{equity}(t) \quad (4-5)$$

4.3.6.3 Investment module

The Investment module calculates economic variables for potential projects and determines which projects are selected in the investment decision sub-module. Firstly, the WACC, $WACC_i$, (4-6) for each investor type is calculated based on input from the risk module as investor agents may have different financing structures and risk priorities. Secondly, the outcome of the investment decision sub-module (section 4.3.6.3.1), and WACC are used to calculate the economic variables (see section 4.3.5) required to determine the economic viability of the potential projects and make investment decisions. The model additionally assumes a 5% annual decline in the cost of solar equipment due to technological development and scale of adoption (218). It further considers revenue risks by incorporating the revenue collection rate and currency risk by incorporating the impact of historical exchange rate depreciation and inflation in the cashflow calculations.

$$WACC_i = \frac{R_i^{debt}(t) * F_i^{debt} * (1 - \tau_c) + R_i^{equity}(t) * F_i^{equity}}{1 - F_i^{grant}} \quad (4-6)$$

4.3.6.3.1 Investment decision sub-module

The key output from this sub-module is a decision by an investor agent, i , regarding their potential total capacity investment in a technology, Y , $Gen_{total,i,Y}^{potentialcapacity}$, followed by a decision on the potential total investment capacity in a location, l , $Gen_{i,l}^{potentialcapacity}$. Finally, investment decisions on projects are made based on investor-specific criteria that follow.

In each time step, the sub-module first calculates the $Gen_{total,i,Y}^{potentialcapacity}$ (4-7) based on the total demand and the investor's relative attractiveness to the technology, Y , $RelativeAttractiveness_{i,Y}$ which informs how much an investor could be willing to invest in a technology relative to other technologies (35).

Technology attractiveness is dependent on the investor's preference for economic benefit against environmental benefit, measured as LCOE and CO₂ emission avoidance respectively. The model can calculate $Gen_{total,i,Y}^{potentialcapacity}$ of five decentralised technology types (onshore wind, combined cycle gas turbine, small hydro, petrol generator and solar PV mini-grid) for each investor agent. However, as the technologies available to the population in the case study are solar PV and the alternative of petrol generators, the next section detailing investment decisions considers these two technologies.

Second, the model determines the total investment by investor, I in location, l , $Gen_{i,l}^{potentialcapacity}$ (4-8) in each technology, by distributing the calculated $Gen_{total,i,Y}^{potentialcapacity}$ across the locations according to the relative attractiveness of each location to an investor, $Relative\ Attractiveness_l$. The location attractiveness (see Appendix C) is determined from the location's attributes identified in Table 4-3.

$$Gen_{total,i,Y}^{potentialcapacity} = FutureDemand^{total}(t) * Relative\ Attractiveness_{i,Y} - Gen_i^{current}(t) \quad (4-7)$$

$$Gen_{i,l}^{potentialcapacity} = Gen_{total,i,Y}^{potentialcapacity} * Relative\ Attractiveness_l \quad (4-8)$$

4.3.6.3.2 Investment decision process

After the model determines the investor's potential total capacities to invest in a technology and location, it makes investment decisions. The investment decision process encompasses three main phases (as illustrated in the flow chart in Figure 4-6): determination of (i) potential investment (project) size, (ii) viable projects, and (iii) the selection of projects for investments.

Potential project size, $P_n^{i,l}$

First, the model determines the size(s) of potential project(s), $P_{i,l}^n$, an investor may consider in each location based on investment capacity thresholds.

Thresholds are investor-dependent and assumed to be constant. For an investment to be considered, the potential investment capacity of an investor in a location must exceed the investor's minimum generation threshold i.e. $Gen_{i,l}^{potentialcapacity}(t) > InvestorThreshold_i^{minGeneration}$. If the $Gen_{i,l}^{potentialcapacity}(t)$ is above an investor's maximum threshold, another project, $P_{i,l}^n$ with an incremental size of up to $InvestorThreshold_i^{maxGeneration}$ is considered by the investor in the same time-step. It is assumed that each incremental project by an investor in a location has a different capital cost structure and thus, new economic variables. This reflects the relatively inelastic supply of labour and hardware in a location whilst ensuring that none of the locations is unrealistically dominated by one investor type (37).

Viable projects

Second, investors determine the viable projects, $viableProjects_i$ amongst their potential projects' portfolio, $P_{i,l}^n$. One key risk factor impacting DRE investment in Nigeria is revenue risk stemming from collection losses. As this can affect economic variables such as NPV, this study incorporates the impact of collection losses through project scenarios applied to predict the expected NPV outcomes for each potential project scenario $TNPV_{i,l}^{pn,s}$ (4-9). A project scenario, s , is thus defined to reflect historical revenue collection rate ranges (219). Subsequently, the utility for each potential project scenario, $U_{i,l,s,pn}^{invest}$ (4-10) is determined using a standard utility function which incorporates an Arrow-Pratt coefficient, α_i indicating the risk attribute of investors. Next, the EU of each $P_{i,l}^n$ is calculated (4-11). A viable project must meet the constraints of positive EU, positive cashflow, WTP and investor-specific preferences of payback time and IRR (see Table 4-2, Figure 4-6).

$$TNPV_{i,l}^{pn,s} = \sum_t^{projectLife} \frac{(Cost_{i,l}^{pn,s} - Benefit_{i,l}^{pn,s})}{(1 + WACC_{i,l})^t} \quad (4-9)$$

Where $Cost_{i,l}^{pn,s}$ and $Benefit_{i,l}^{pn,s}$ are respectively, the total cost and benefit for a potential project scenario of an investor i in location l .

$$U_{i,l,s,pn}^{invest}(t) = 1 - e^{(-\alpha_i(t)*TNPV_{i,l,pn,s}(t))} \quad (4-10)$$

$$EU_{i,l}^{invest}(t) = \sum_s \theta_s * U_{s,i,l,p}^{invest}(t) \quad (4-11)$$

Investment decision

Third, all *viableProjects_i* are sorted and the projects with the highest EU up to $P_{max,i}$ (where $P_{max,i}$ is the investment threshold of an investor) are considered for an investment decision. Viable projects considered for investment decisions in a location by all investors are combined and sorted. If the sum of investment is less than the supply gap in a location, then, all the projects are promoted to the investment queue ($Gen_{i,l}^{invested}$) in each location agent. Otherwise, projects with the smallest size and then the least EUs are removed from the list until the projects meet the supply gap requirement. Finally, following the time delays in decision-making to the construction and operation phases (Figure 4-5), the generation module is updated with all the projects meeting the selection criteria.

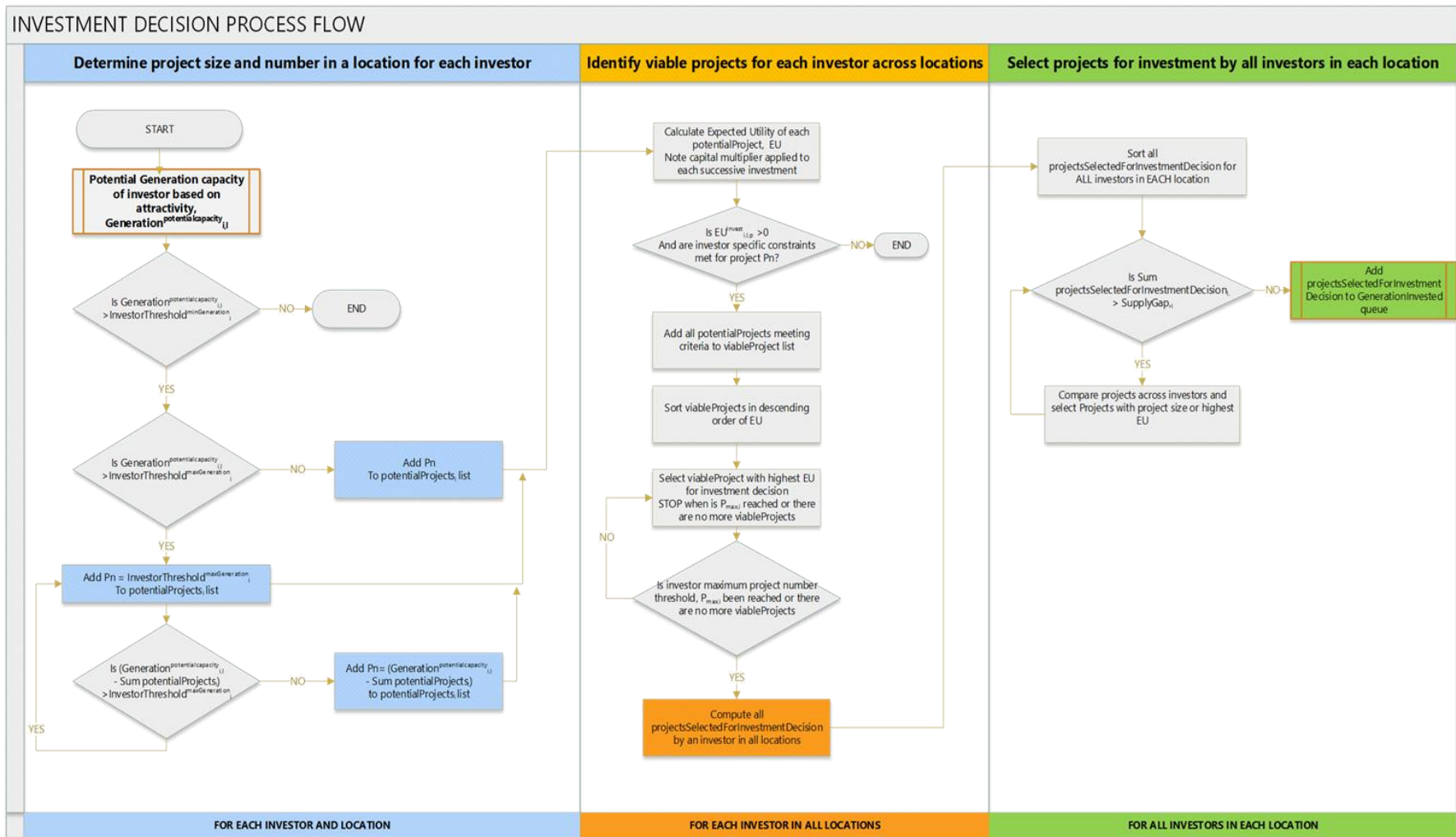


Figure 4-6 Investment decision process flow chart

4.4 Results

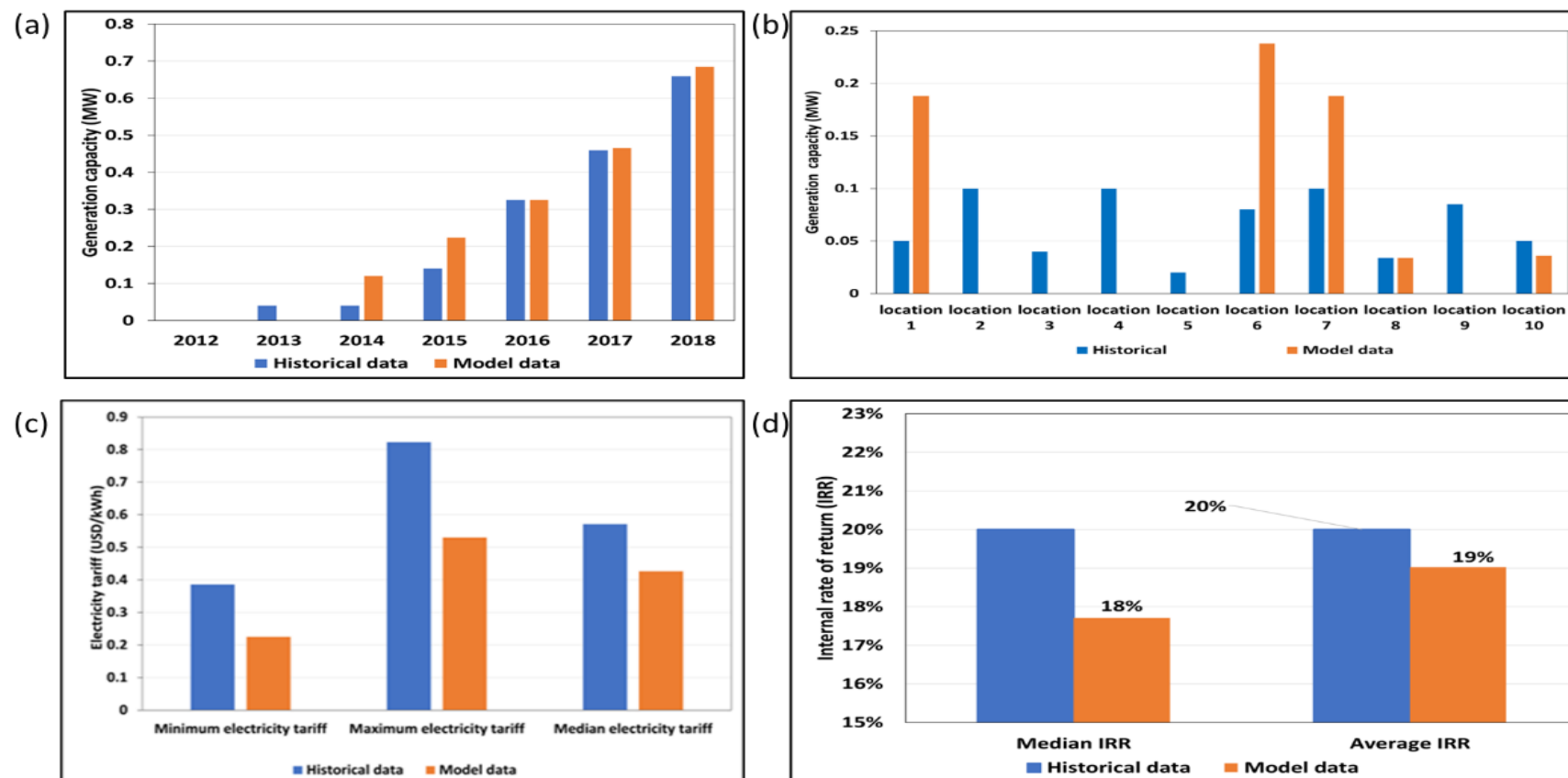
Three types of model outputs are presented. First are the model validation results based on historical solar PV mini-grid installations between 2012 - 2018 in Nigeria (219) and following the approach of other scholars (54,55,118). Second is the demonstration of the model's capability by comparison to a model without investor heterogeneity features, and third is the sensitivity analysis to establish impact of selected variables on investment.

4.4.1 Model validation

This section presents the behaviour validation tests conducted to test the model's robustness and fit with the historical data. Whilst the tests are not exhaustive, they collectively provide confidence in the model. Further validation conducted are presented in Appendix C.4.

Figure 4-7(a, b) compare the model-generated total and spatial solar PV mini-grid installed generation capacity, to the historical data. The model results showed an upward trend in the total installed generation capacity, which aligned with the historical trends; however, there were deviations in the yearly total installed generation capacities. For instance, deviations were observed between 2013–2015, while 2016–2018 results were closer to historical data.

Although the model can produce electricity tariffs and IRR for each location, the historical data at the location level was not available to enable a comparison. Therefore, electricity tariff ranges, and expected IRR ranges are compared to aggregate historical data ranges in Figure 4-7(c, d). The results aligned with historical IRR range.



Note: A historical range for IRR was not available. A typical value for projects in the literature was used for comparison.

Figure 4-7 Comparison of simulated and historical (a) total installed generation capacity, (b) distribution of generation capacity, (c) electricity tariff range and (d) IRR range

An error analysis (see Table 4-4) was conducted to analyse the model fit with historical data from the mean-square error (MSE), the root mean squared per cent error (RMSPE) and the Theil inequality statistics. The Theil inequality statistics decompose sources of error into Bias (U_M), unequal variance (U_S), and unequal covariance (U_C). A large error, considered as impacting the model validity, is typically depicted by high RMSPE and U_M values (54,220). The error analysis showed a 2% RMPSE for the IRR range, indicating an excellent historical fit. Furthermore, the low MSE and RMSPE of 10% for total installed generation capacity suggests good replication of the actual behaviour. A decomposition of the 10% RMSPE indicated that 78% of the error resulted from U_C . The high U_C component suggests that some point-by-point values of the simulated and historical data do not match, even though the model represents overall trends that align with historical data. This is because the model underpredicted investment trends, particularly in the first two years (Figure 4-7a) and in five locations (Figure 4-7b), as indicated by the RMPSE of 35% for spatial generation capacity.

The spatial generation capacity error analysis indicated $U_M = 0$. At the same time, the U_S and U_C had an almost equal distribution, which can be interpreted as an indicator of unsystematic error in a way which does not compromise the model (54). However, as one of the model's objectives is to explore the spatial allocation of investment; it is essential to note and explain the discrepancy. The difference likely arises because of the earlier investments being primarily funded through grants (5,7) with different investment criteria from the model, which considers the more profit-driven investment criteria of private investors. Moreover, since the timing of the actual investment decision and construction duration are also unknown for most locations, it was thus not feasible to match the historical location data exactly. Nevertheless, the overall trend of low MSE provides confidence that the model structure and behaviour capture the fundamentals of the system for the intended purpose.

Furthermore, a comparison of the average electricity tariff showed an RMSPE of 27%, indicating variability in the model versus actual data. This variation can be explained based on the model assumptions as follows. Firstly, the electricity tariff calculated in the model is the minimum tariff that makes an investment attractive, considering supply, demand, location, investor attributes, project economics, and consumer WTP. Secondly, it is noted that the spatial resolution of variation in WTP in the model is regional (at the state level) and not location-specific due to data limitations. Lastly, the electricity tariff can be influenced by other variables such as market factors, availability of additional grants, presence of industries with higher purchasing power, and attributes of other investor types not captured in the model. The discrepancy in the results could be due to any of these factors. As the model focuses on the comparison of the minimum electricity tariffs investors can charge in separate locations, as opposed to predicting electricity tariffs in each location, further work may address the sources of this discrepancy. Overall, it can be concluded that the model has a good historical fit for its purpose.

Table 4-4 Error analysis of the model results

Variable	MSE (units ²)	RMPSE (%)	Henry Theil's inequality statistics		
			Um	Us	Uc
Aggregate Generation capacity (MW), $Gen_{total}^{current}$	0.002	9.7%	0.221	0.001	0.779
Spatial Generation capacity (MW), $Gen_t^{current}$	0.008	35.1%	0.00	0.48	0.52
Electricity tariff range (USD/kWh)	0.0044	27.3%	0.901	0.062	0.037
IRR range	0.00007	1.84%	0.979	0.021	0

4.4.2 Assessment of model capability

The model capability was demonstrated by comparing the results (generation capacity, investment, and electricity tariff) of the validated model, termed the base model, with a homogeneous model, where heterogeneity features such as investor technology preference, financing attributes, risk preferences, risk considerations, and dynamic peer effect were disabled from the base model while location attributes were retained. Where feasible, the model results were also compared to the historical data.

As shown in Figure 4-8(a), which compares the temporal evolution of total installed generation capacities of the base model to the homogeneous model and historical data, the total installed generation capacities for both models were underestimated in the first two years. However, from 2014, the homogeneous model overestimated the total generation capacity. This discrepancy arose because the homogeneous model assumes that investment is made to meet the electricity demand once the profitability criteria are met. Additionally, the calculations do not account for risks such as exchange rate volatility, revenue collection, and investor heterogeneous attributes such as discount rates and risk aversion, making locations appear more profitable than in the base model. As such, 90% of investment in the homogeneous model (in Figure 4-8(b)) was made in the first two years, while electricity generation began in 2015, and no new investment was made after 2015. In contrast, accounting for heterogeneity in the base model provided generation capacity results that gradually tracked the historical data. This result provides confidence in the model's performance against historical data and further indicates that the model can better capture the evolution of DRE investment.

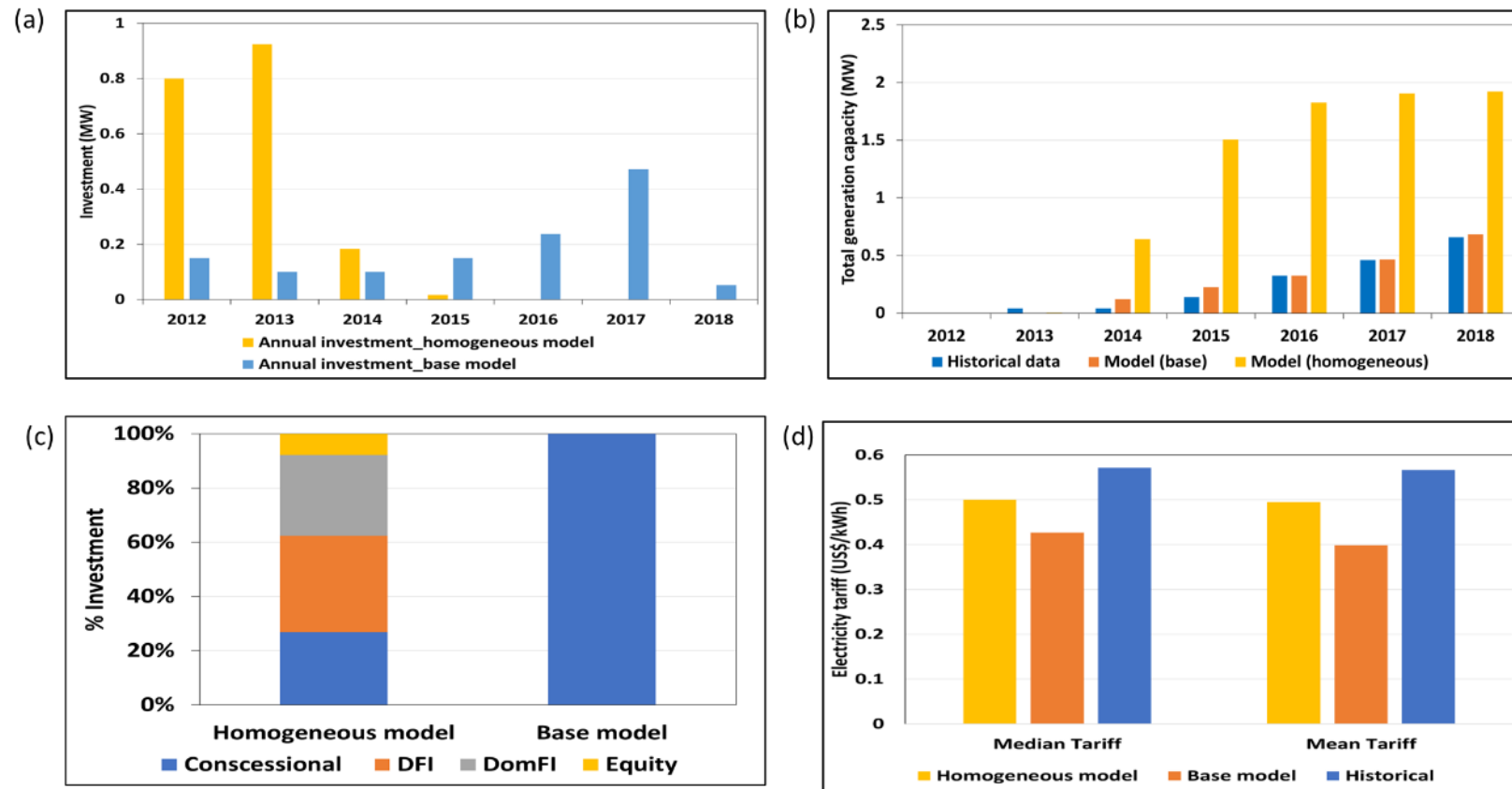


Figure 4-8 Comparison of historical, base model, and homogeneous model (a) temporal evolution of total installed generation capacity, (b) total annual investment capacity, (c) Investor mix (d) potential tariff

Moreover, Figure 4-8c compares investment at the end of the model horizon for both models. In the homogeneous case, investors made almost equal capacity additions, apart from the equity investor type. This is because, aside from the financing mix that distinguished the homogeneous investor types, investors had similar attributes, investment decision criteria and access to the same debt discount rate. Meanwhile, the equity investor had a lower capacity addition, contributing to 8% of the total investment because of their higher equity discount rate. In contrast to the homogeneous model, only the concessional investor type made investment decisions in the base case. This can be explained by their access to lower discount rates, longer debt tenure and lower-risk aversion, which enable the concessional investor to invest at higher capacity and profit. Meanwhile, investors with higher-risk aversion and discount rates, such as the equity investors, had lower profits and no capacity additions in the base model. The lack of investment by other investor types, aside from concessional investors aligns with the literature, which has found that favourable financial characteristics can increase profitability and investment capacity (37,52). Therefore, capturing the impact of investor attributes can inform policy and regulatory decisions about improving investment, in addition to decisions about the best financing mix for a project (11,12).

Furthermore, a comparison of electricity tariffs in Figure 4-8(d) shows that the homogeneous model better matches historical tariffs, while the base model moderately underestimated the historical electricity tariff. As discussed in section 4.4.1, the variance is attributed to the model assumptions. Yet, the minimum electricity tariff calculated in the base model is aligned with the 0.55–0.60 \$/kWh LCOE as reported in the mini-grids literature (221). This indicates that the base model could offer insights into the actions that could offer more affordable investment for consumers.

The above results find that the assumptions about investor attributes yield close approximations to the historical data for investment additions, investor type, and potential electricity tariffs. This suggests that defining investor heterogeneity alongside location attributes can improve model output in support of investment

planning and decisions. This approach can provide a helpful approach to explore the implications of policy actions towards reducing investment barriers. Further, it indicates that the preferences of investor agents are dynamic, and their decision-making is affected by location attributes as well as investor characteristics, risk attributes, prior decisions, and the decisions of other investors. While location models (as represented by the homogeneous model) can identify feasible locations for investment, such an approach can also overlook the evolution of decision-making of different investors and the actual investment potential of locations for a given set of investor profiles. This leads to the discrepancies observed between historical and homogeneous models and demonstrates the capabilities of the developed base model.

4.4.3 Sensitivity analysis

This section assesses the sensitivity of the model behaviour to a given parameter and the consistency of the observation with the expected behaviour (55,118,206). Three exogenous parameters considered important to investment were varied against the base model parameters to analyse the impact of the changes on investment. The parameters include: (i) investors' risk aversion (ii) discount rate, and (iii) funding, available to an investor.

4.4.4 Impact of risk aversion

The impact of risk aversion on investment was examined by comparing the base case results with three cases where all investors were high, low-risk averse and risk-neutral — this means the investors' utility is equivalent to NPV. The base case investor risk aversions are described in section 4.3.4.1, whereby risk aversion is represented by the arrow Pratt coefficient. In the base model, the non-concessional investors (DomFI and equity investor types) have high risk aversion while concessional investors such as impact investors and DFI investor types have low to medium risk aversion. Figure 4-9(a-d) illustrates the impact of the differences in risk aversion attributes on investment capacity, minimum electricity tariff, unit profitability, investor mix, and spatial and temporal distribution of investment. It was established that investment was significantly reduced at higher risk aversion; for instance, when all investors were highly risk averse, investment

capacity was reduced by 91% of the base case result (Figure 4-9(a)). Conversely, the low-risk aversion and risk-neutral cases showed up to 47% increased investment. Furthermore, risk aversion can impact the investor mix where it was found that at higher risk aversion, investment decisions were made only by concessional investors supported by grants due to their lower capital cost, compared to the base case where a mix of (73%) and non-grant (27%) supported concessional investment were made (Figure 4-9(b)). Conversely, the investor mix was widely distributed in the low-risk aversion and risk-neutral cases. These results suggest that assumption on risk aversion has a significant impact on the investment decisions whereby a high population of highly-risk averse investors could increase requirements for higher government subsidies and yet, yield lower electrification outcomes.

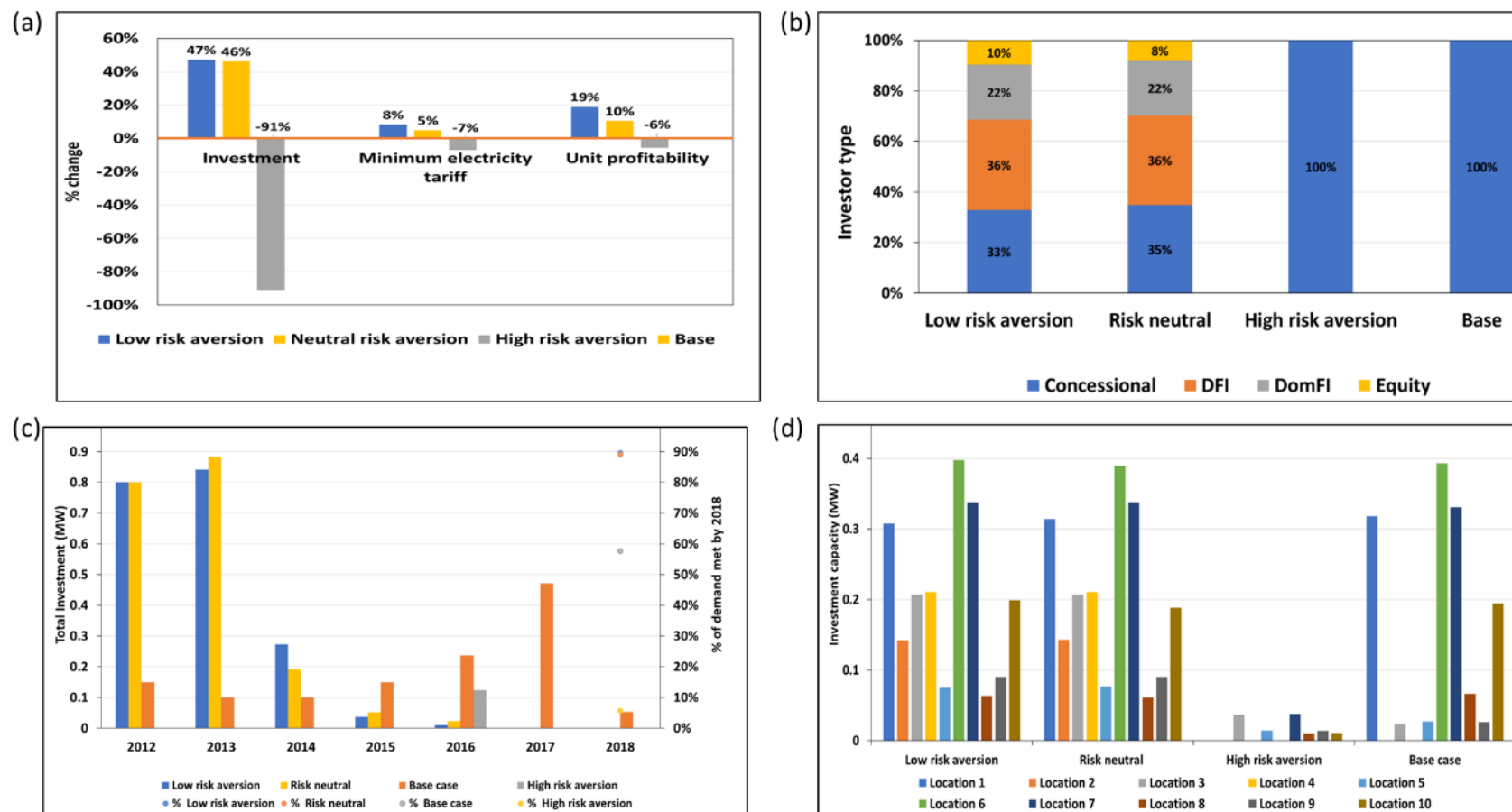


Figure 4-9 Comparison The impact of risk aversion on: (a) investment, unit profitability and tariff (b) investor mix (c) temporal variation in investment (d) spatial distribution of investment

Additionally, the results show that assumptions about risk aversion can significantly impact unit profitability. The unit profitability is the percentage change in total NPV per unit investment and is compared across the risk aversion cases. This approach enables a fairer comparison of actual profits; for instance, simply comparing total NPV showed a significant variation of 90% with the high-risk aversion case, where fewer investment decisions were made, than in the base case. However, the actual variation of unit profitability was -6%. Figure 4-9(a) further demonstrates how assumptions on risk attributes can affect investment outlook. For instance, at the end of the model horizon, the unit profitability in the risk-neutral case was 9% lower than in the low-risk aversion case, suggesting that some level of risk aversion can benefit profitability, as reported in previous studies (37). This difference can be explained by the fact that the low-risk aversion case had a higher proportion of equity and non-concessional investors (Figure 4-9(b)), which demanded higher discount rates and NPV than in the risk-neutral case.

Consequently, assuming risk neutrality could underestimate the profitability of projects and allocate funding towards investment where risk neutrality holds. While increased risk aversion resulting in higher NPV is reported in literature (37,222), we find a similar outcome in the low-risk aversion case. In the high-risk aversion case, there was an 11fold decrease in investment compared to the base case, leading to a significant reduction in the unit profitability Figure 4-9(a). The reduction can be explained by the limited investment made by the high-risk averse concessional investors who required higher NPV projections to meet maximum utility expectations and make investment decisions. The result is supported by findings in the literature (52) that suggest risk aversion significantly impacts capacity investment decisions. It is thus vital to incorporate risk aversion level of investors into investment planning and decision modelling. The results additionally demonstrate the model's capability in the quantification of the impact of these changes on different investor types.

In considering the impact of risk aversion on the minimum electricity tariff, we find that higher risk aversion showed a favourable impact on electricity tariff, with a

7% reduction from the base case (Figure 4-9(a)). This can be explained by the investor mix across the cases. As shown in Figure 4-9(b), at high-risk aversion, investment was made only by concessional investors with grant support making tariffs more affordable. However, an 8% increase in the electricity tariff from the base case was observed in the low-risk aversion case, which had a more varied mix of investors requiring higher revenues to cover higher costs. The results suggest that risk aversion assumptions impact investor mix and, consequently, the expected electricity tariff. Thus, the benefits of improved risk aversion (such as more diverse investor mix, lower grant requirements, and improved investment capacity) may affect consumer affordability, because of higher tariffs.

The impact of risk aversion is further portrayed in the spatial and temporal distribution of investment. Figure 4-9(c) shows the differences in investment timing in the risk aversion cases and the base case. In the risk-neutral and low-risk averse investor cases, up to 96% of investment occurred in the first three years (2012–2014), compared to no investment and 28% investment in the high-risk aversion and base cases, respectively, in the same period. By 2018, up to 90% of the demand was met in the low-risk aversion case compared to 6% and 60% in the high-risk aversion and base case, respectively. The observed higher investment was because the investors' expected utility was met in the lower-risk aversion and risk-neutral cases in the earlier modelled years.

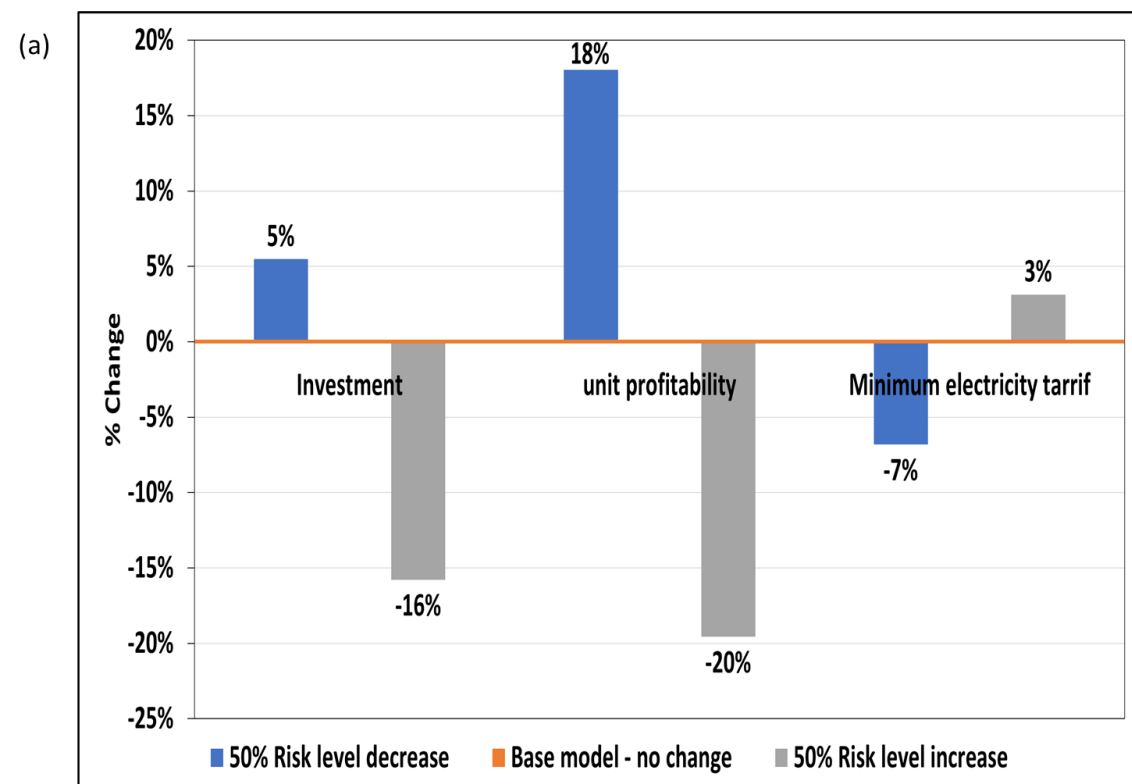
Additionally, Figure 4-9(d) shows that low-risk aversion improved investment capacity and spatial distribution of investment across locations. In contrast, the investment capacity and extent are limited at higher-risk aversion. These results suggest that assumptions on risk aversion can impact the spatial allocation and timing of attaining electricity access goals. Furthermore, less risk-averse investors need to be encouraged to enable earlier achievement of electrification targets.

4.4.5 Impact of discount rate changes

As investors have heterogeneous risk priorities, changes in risk levels, e.g., due to risk mitigations, can impact risk premium, discount rates and consequently investment cost. The impact of risk levels on investment was assessed by

implementing a $\pm 50\%$ variation in base case risk levels, equivalent to a 24% average change in discount rate.

Figure 4-10(a) shows the impact of changes in risk levels on investment capacity, unit profitability, and minimum electricity tariff, and investor mix. The results show that a 50% risk reduction had a moderate impact on unit profitability of 18%, increasing total investment by 5% compared to the base case. The observed investment increment was attributed to concessional investors, characterised by lower discount rates and risk aversion. Additionally, as shown in Figure 4-10(b), a more than 50% risk reduction was needed to boost investment from other investor types beyond 0.1% of the total investment. This result aligns with findings in the literature (14), where improvements in discount rates did not lead to significant penetration of mini-grids and standalone systems. Nevertheless, as shown by the 14% decrease in concessional investment supported by grants in Figure 4-10 (a), lower risk level reduces reliance on grants which would otherwise be required to ensure investment viability.



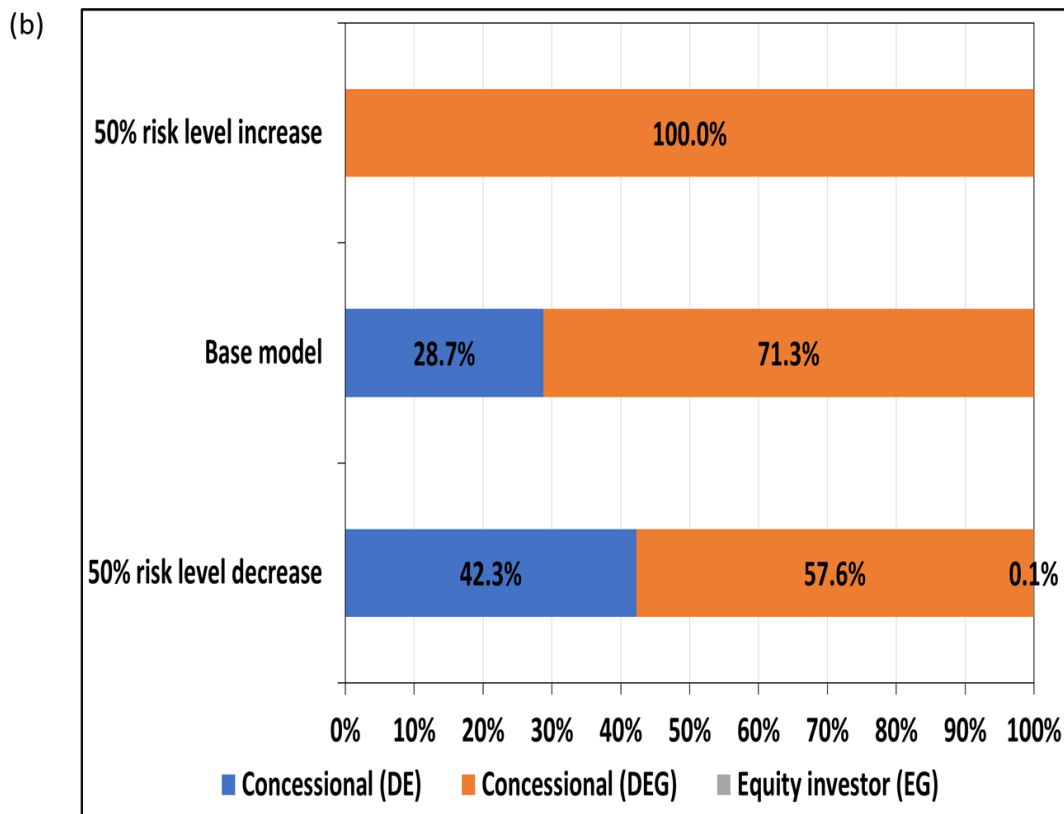


Figure 4-10 Impact of changes in risk levels on (a) investment, unit profitability, and electricity tariff (b) investor mix

The impact of increased risk level is demonstrated in the 20% reduction in unit profitability and, consequently, 16% lower investment. In the risk level increase case, only grant-supported concessional investments were viable. This result suggests that more public funding would be required to support electrification projects in a scenario where risk premiums are increased due to higher perceived investment risks. Therefore, in addition to mitigating risks, it is essential for policymakers to take action to prevent risk escalation that may cause detrimental impacts on investment from less risk-averse investors. Furthermore, the decrease in risk levels presented a 7% decrease in the average minimum electricity tariff, while there was a 3% increase at higher risk levels. This outcome illustrates that electricity tariffs could be more affordable under effective risk mitigation. However, the impact of risk level on investor profit is more significant than that on electricity tariff.

4.4.6 Impact of funding availability

In this scenario, the funding available to investors based on their calibrated investment threshold was varied by $\pm 50\%$ and compared to the base case results. Figure 4-11(a-d) show the impact of changes in funding on investment capacity, unit profitability, and minimum electricity tariff, investor mix, and spatial, and temporal distribution of investment.

The results indicate that funding significantly affects investment capacity. As shown in Figure 4-11(a), a 50% reduction in available funding across investors resulted in 93% reduction in investment capacity compared the base case. When funding was increased by 50% across investors, investment increased by 36% from the base case improving the electricity supply from 60% to meet 83% of demand. Additionally increased funding was found to improve unit profitability to 10%, while profitability was reduced to -6% of the base case when funding was halved. The reduction in profitability can be explained by the increased proportion of grant-supported investment as shown in Figure 4-11(b). The same reason can explain the positive impact of reduced funding on the minimum electricity tariff, where electricity tariff was 11% lower than the base case.

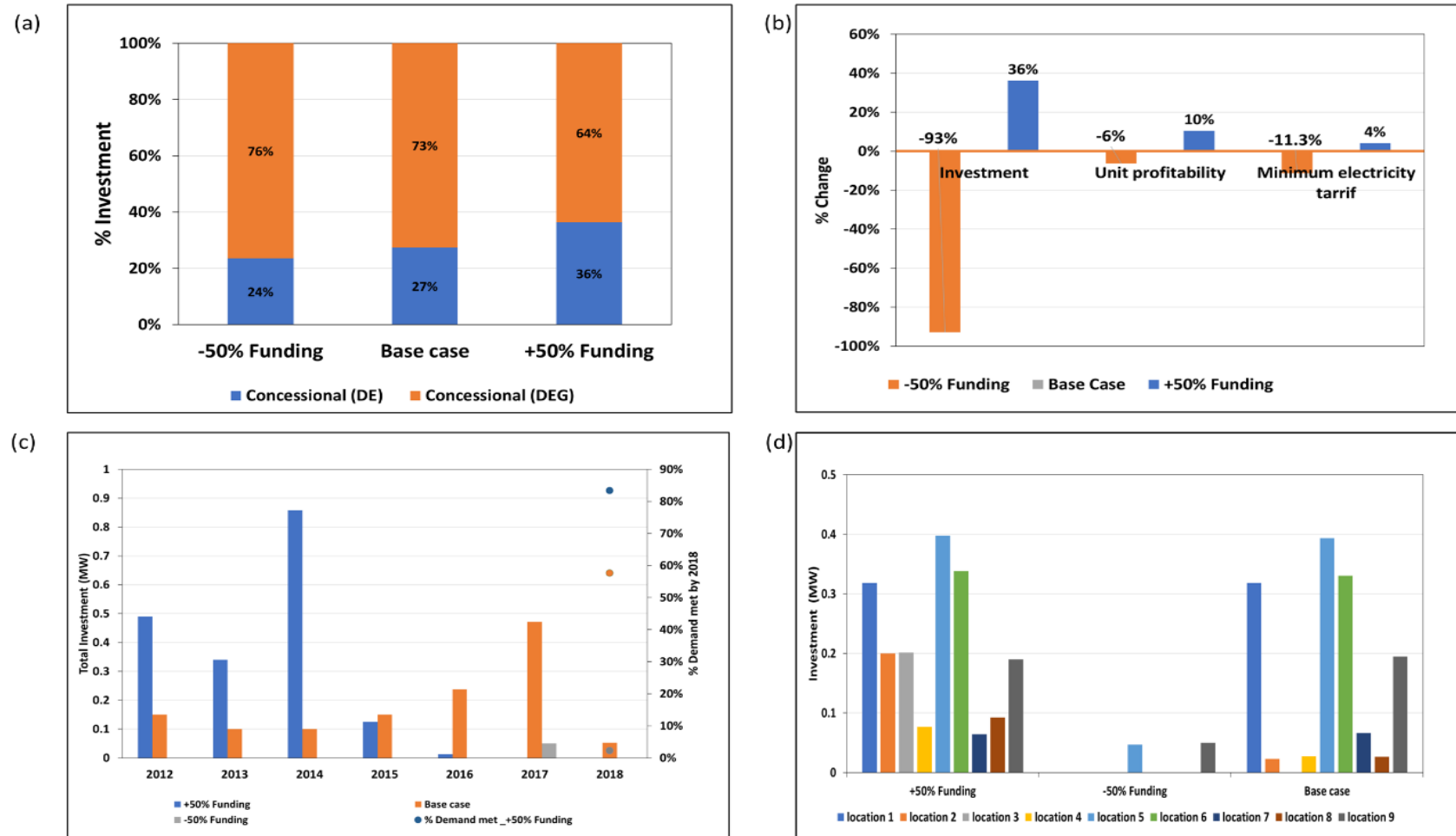


Figure 4-11 The impact of funding on: (a) investment, unit profitability and minimum electricity tariff (b) investor mix (c) temporal variation in investment (d) spatial distribution of investment

Furthermore, the increase in funding significantly improved the temporal and spatial allocation of investment. As shown in Figure 4-11(c), in the case of a 50% improvement in the availability of funding, 93% of investment occurred in the first 3 years whereas investment was delayed to year 7 in a 50% funding reduction scenario. This was because investors preferred to wait until the cost of solar and WTP were sufficient to meet investment criteria. Moreover, analysing the spatial distribution of investment at the end of the model horizon, Figure 4-11(d) indicates an increase in funding improved the spatial allocation of investment capacity compared to the base case, whereas, only two locations received investment in the 50% reduced funding case.

The results align with the literature (5) that increased funding can accelerate access to electricity across locations. Interestingly, while the variation in funding did not change the diversity of investor type (see Figure 4-11(b)), the proportion of grant and non-grant investment varied. We find that the increase in funding reduced the reliance grant-supported concessional investment by 9%.

4.5 Discussion and implications

This study highlights the importance of incorporating investor heterogeneity alongside risk and location attributes in assessing the spatial evolution of DRE investment decisions and consequent electricity supply. The results demonstrate that planning and decision support models must consider investors' heterogeneity to avoid overestimating the potential for investment, leading to unrealistic expectations of achieving access targets. For example, in the homogeneous scenario (where investor heterogeneity was not applied), over 95% of demand was met by the end of the investment horizon. However, when investor heterogeneity and risk factors such as exchange rate volatility, WTP and revenue risks were considered in the base model, the investment made by 2018 satisfied only 34% of demand. This result aligned with the historical value of 32% (section 4.4.1). Our results confirm (37) that including investor heterogeneity and risk considerations in an ABM model reveal more realistic investment profiles than those from a homogeneous model.

Table 4-5 Summary of sensitivity analysis for impact of change in risk aversion, funding availability and risk level on investment

Sensitivity % change in	Investor Risk Aversion			Funding Availability		Risk level	
	Low Risk Aversion	Risk Neutral	Risk High Risk Aversion	+50%	−50%	+50%	−50%
Investment	47%	46%	−91%	36%	−93%	−16%	5%
Unit profitability	19%	10%	−6%	10%	−6%	−20%	18%
Electricity tariff	8%	5%	−7%	4%	−11%	3%	−7%

The sensitivity analysis has implications for decision-makers. The model sensitivity results summarised in Table 4-5 highlight that assumptions about investor attributes can impact investment outlook. For example, sensitivities of risk aversion attributes highlighted an 11fold decrease in investment in the high-risk aversion case. While this outcome is supported by the findings (11) that suggest risk aversion significantly impacts capacity investment decisions, we find that some level of risk aversion is beneficial. When compared to the other cases, the low-risk aversion case presented higher increments in investment and unit profitability. Furthermore, the results indicate risk aversion influenced the investor mix and the reliance on grants. When all investors were high-risk averse, only concessional investors with grant support were willing to invest while the low risk-aversion and risk-neutrality cases had a diverse investor mix. The benefit of low-risk aversion over risk neutrality was represented by its higher unit profitability and 5% less grant-supported concessional investment. These results suggest that incorporating the risk attributes of investors can have a significant impact on more realistically projecting electrification estimates and grant requirements. More specifically, policymakers could encourage investment from low-risk averse investors, however, the impact on the affordability of electricity tariff should be

considered. The results thus demonstrate the model's capability in the quantification of the impact of changes on different investor types.

Moreover, many studies assume risk neutral investors whereby utility is equivalent to NPV (117). Such an assumption could underrepresent the profitability of the potential investment where risk neutrality may not hold such as DRE projects and thus limit investment decisions. This is because investors may prefer more profitable infrastructure projects where risk neutrality holds. The approach can thus provide a more realistic decision-support in selecting projects.

Comparing the three sensitivities, the level of investment is increased most by low-risk aversion, followed by an increase in funding (see Table 4-5). The results indicate that electrification can be enhanced significantly by improving investor risk perception; thereby unlocking financing from traditionally risk averse investors, such as domestic finance investors such as local banks. Additionally, results highlighted that unit profitability was highest when risk mitigations improved risk aversion and reduced risk levels and consequently the discount rate. Reducing risk levels provided the benefits of lower minimum electricity tariff and reduced the level of grant-supported investment, indicating that more projects were viable without grants in a risk-reduction scenario.

Furthermore, the results showed the impact of the sensitivities on the temporal and spatial allocation of investment. The temporal results indicated a four-year delay in investment decisions in the high-risk aversion case; whereby only 6% of demand was met by the end of 2018 compared to 90% in the low-risk aversion case. Additionally, the spatial extent of investment was limited in the high-risk aversion case compared to the other cases where investment occurred in more locations and at higher capacity. These spatial differences are not explored in existing studies (8,12); instead, the outcomes are binary, where locations are found to be either viable or not for specific technologies. This study contributes by representing the spatial extent and evolution of investment. This approach could enable policymakers and impact-oriented investors identify locations unlikely to receive investment and channel bespoke actions while more profit-driven investors can identify potentially bankable locations.

This study supports previous literature (5,147,176) that calls for increased funding accelerate investment to meet SDG targets. For example, when funding increased by 50%, in addition to the improved spatial extent of investment, 83% of demand was met compared to 60% in the base case. Nevertheless, we find that it is necessary to address the type of funding that can accelerate access. In the case of a 50% increase in funding, all the investment was made by grant-supported concessional investors. This outcome can be interpreted in two ways (i) the cheaper funds from these investors contributed to higher NPVs, therefore higher utility to invest compared to the other investor types, and (ii) the other investor types were not incentivised to invest. Indeed, the previous trends in DRE investment have shown investment has been mainly from public sources (5,134,176). However, the result highlight that it may not be sufficient to increase funding alone. Thus, government must ensure other types of financing are encouraged. Encouraging non-concessional investors requires exploring de-risking actions and incentives that could improve revenues such as leveraging carbon markets, demand stimulation and tax exemptions. The impact of these need to be quantified with respect to achieving targets.

The model developed in this study has some limitations. Firstly, the results of this study are specific to the investor and location attributes employed in the model. Although the investor profiles used in the model was applied based on actual DRE projects, certain distinct characteristics of investors such as risk aversion were generalised for the investor types. It is conceivable that investors within the same category might possess diverse goals and attributes, potentially leading to varying outcomes for electrification. Nevertheless, the model structure can be adapted to other contexts, and different investor types. Secondly, this study made assumptions regarding some location attributes due to data limitations. These include, economic potential, the ability to pay was and willingness to pay, which were represented by proxies of accessibility to towns and cities, poverty level, and the cost of alternative electricity sources respectively. While these proxies have been applied in the literature, they are estimations of the location factors in the model. Actual measured data could better inform model outcomes. Furthermore, the data was only available at the state level, while the locations in

the model were at the administrative level. A higher resolution of this data could enable improved parametrisation of these factors.

4.6 Conclusion

Despite the importance of DRE in achieving SDG targets of clean and affordable electricity access, low investment has hindered its development in SSA. According to IRENA (5), only 25% of SSA investment need was met in 2021. Policy frameworks that facilitate DRE investment planning and decisions are necessary to boost DRE investment. As DRE, such as solar mini-grids, is highly location-specific, existing planning and decision approaches focus on location and technology selection applications. While these studies are helpful in planning DRE systems, they need to consider the additional complexity of heterogeneous private investor attributes and preferences, which can drive investment decisions. Furthermore, they need to consider the dynamic feedback and interactions in the complex electricity system to understand the evolution of investment. Such an approach can help explore the key actions required to enhance DRE investment.

This study contributes to the need for improving DRE investment by developing and validating an SD-ABM model to address the absence of a unified framework for DRE investment planning decision support in a liberalised market structure. The SD-ABM model aims to capture the spatial development of DRE investment considering the differentiation in location attractiveness factors, investor heterogeneity, risk attributes, and dynamic feedback and interactions. The model was validated with historical data from mini-grids in Nigeria.

The validation results show that the model adequately captured the historical trends in the total generation capacity resulting from investment decisions. In contrast, the spatial generation capacity was moderately underpredicted. The variance was attributed to assumptions on investor characteristics and investment decision timings, which could not be verified due to data limitations. Yet, a comparison of the validated base model and a homogenous case, which did not account for investor heterogeneity, demonstrated the model's capability and provided confidence in the validity of the model. The outcome demonstrates that planning and decision support models must consider investors' heterogeneity

to avoid overestimating the potential for investment, leading to unrealistic expectations of achieving access targets.

The sensitivity analysis showed variations in system parameters — investor risk aversion, risk level, and funding carried implications on investment. This study contributes to existing DRE investment planning and decision modelling by representing the impact of changes in system parameters on the spatial extent and evolution of investment. The results revealed that the temporal investment and spatial distribution of investment across locations were significantly improved at lower-risk aversion and higher funding availability. However, they also indicated that lower-risk aversion could negatively impact electricity tariffs and present implications for affordability to consumers. This is because at low-risk aversion, investment was from a more diverse mix of investors requiring higher revenues to cover higher costs. Additionally, results indicated that the assumption of risk neutrality made in other studies could underestimate the profitability outlook of DRE projects and lead to allocating funding to investment such as large-scale infrastructure projects where risk neutrality holds. This further highlights the significance of incorporating investor heterogeneity.

This study additionally demonstrates the model's capability in the quantification of the impact of changes on different investor types. The results further reveal that aside from risk aversion, variations in funding and discount rate did not significantly improve the potential for other investor types to invest. This suggests that improving investor risk aversion can unlock further investment. One approach to which is the implementation of mitigation actions that enhance investor risk perception. In future work, it would be beneficial to quantify the implications of various de-risking policy actions and incentives on investment decisions and spatial development of electricity access. This could for example include application of performance-based grants, demand stimulation, leveraging on carbon markets, tax exemptions and priority sector mandates (5,76,147,176,223).

Furthermore, the spatial perspective of investment can suggest the most attractive, risk-adjusted locations for a given investor profile; for example, the

model may be applied as an early-stage tool to identify suitable locations for a given investor type. While the intent of this application may appear investor-biased, it can identify investment-ready projects to potential investors whilst alerting policymakers of potential locations likely to be left behind because they are relatively less attractive. Policymakers can proffer suitable location-based policies for these areas, such as aggregation of projects, cross-subsidies, mandates, and financial incentives. Future studies can explore the likely impact of such policies on informing investment outcomes and improving electricity access.

5 Insights on risk mitigation strategies for spatial investment and improved electricity access

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5.1 Introduction

The scarcity of reliable electricity access has significant implications for economic development of a society (224). Approximately 550 million people worldwide lack access to reliable electricity, many of whom reside in sub-Saharan African countries (SSA). Many countries have committed to net zero targets and adopted the Sustainable Development Goals (SDGs). SDG 7 is specifically relevant to electrification, which aims to ensure 'universal access to affordable, reliable, sustainable and modern energy for all' by 2030. Decentralised renewable energy (DRE), including solar mini-grids, has been identified as a key enabler to meet both SDG7 and climate targets especially in rural and peri-urban areas, where grid connection is uneconomical (8,9).

According to IRENA (5), investment in DRE is not of a scale required to achieve the SDG agenda especially in SSA countries. Low investment has been attributed to factors such as investor risk aversion and high-risk perception (5,225). Additionally, inadequate supportive policy and a regulatory environment to address investment risks, leading to unattractive risk-return profiles and low competitiveness are further investment limiting factors. Risk factors limiting investment in SSA countries such as Nigeria include foreign exchange volatility, revenue risks, low access to affordable financing, difficulty in accessing and repatriating foreign exchange, insecurity, inadequate policy support, and poor policy implementation (see Chapters 2 and 3). To achieve the electrification targets, implementation of mitigation actions that improve risk-return profiles, affordability, and competitiveness are necessary.

Risks can be mitigated through various options. These could be achieved by removing underlying barriers through policy and regulatory support such as regulations, transferring risks using financial and economic derisking instruments such as concessional loans and loan guarantees, eliminating or transferring risks through direct financial incentives e.g., tax reduction, grants and feed-in-tariffs and market-based instruments such as carbon taxes (147,226). Additionally, actions taken to improve attractiveness and competitiveness such as productive use stimulation can improve risk profiles (128). However, the optimal combination of mitigation actions to promote private investment decisions needs further clarification (37,181). The identification of effective mitigation actions for DRE projects requires a holistic approach to understanding the complexity of the liberalised DRE market, comprising its interactions, and feedback between technical components, location and investor attributes and associated risks, that influence spatial investment decisions and ultimately impact electricity supply dynamics (5,174,181). Such an approach can be used to evaluate effect of mitigations on spatial investment decisions.

Previous DRE planning and investment decision models primarily employ least-cost considerations (8,12,36) and location attributes to evaluate the economic viability of DRE in specific locations (57,225). The studies lack details regarding the types of investors, the locations, or the conditions under which investment decisions may occur. They do not account for heterogeneity, complex interactions and feedback presented by DRE, which can impact the spatial evolution of investment decisions (7,25). Current methodologies (35,37–39) for analysing investment decisions in complex systems include system dynamics (SD) and Agent-based models (ABM). However, these models predominantly represent grid-connected liberalised market structures and pose limitations in their application to DRE. This is because the models neglect factors relevant to DRE's site-specificity, especially in the context of investment in SSA. Such factors include investment risk (5,14,162,176), location-specific factors that drive attractiveness (14,35,36), willingness to pay (13,176) and competitiveness among other electricity generation alternatives (13,14,186). These factors, in turn, impact investment decisions. Consequently, existing DRE investment

planning and decision models have limitations in informing spatial and temporal investment decisions. Moreover, there is a lack of research on the impact of mitigation options in influencing spatial investment decisions that ultimately lead to changes in SDG indicators, such as generation capacity and electricity access, within a liberalised DRE market (23,41,187,194,227).

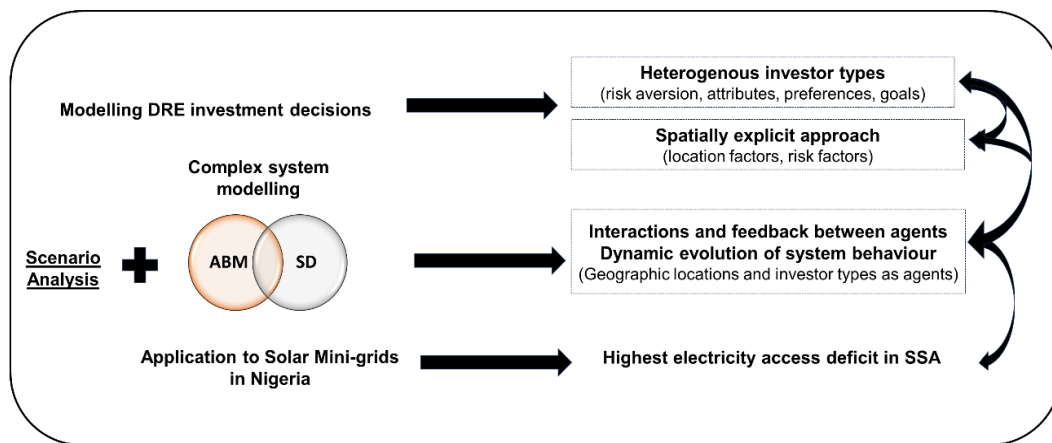


Figure 5-1 A unified framework for the application of SD-ABM approach in modelling spatial DRE investment patterns.

This study aims to address these gaps (see Figure 5-1) by applying the developed SD-ABM model in Chapter 4 to inform spatial investment decisions for DRE and evaluate the impact of mitigation actions on the spatial investment capacity additions and electricity access levels. The novelty of this study lies in the methodological and policy contributions. Methodologically, it implements the SD-ABM model and evaluates future spatially explicit investment patterns for 65 modelled locations for a baseline case and six mitigation actions. More specifically, it applies factors relevant to DRE investment planning and decisions in developing countries namely, location specificity, the heterogeneity of investors, and risk considerations in complex systems modelling which are largely unaccounted for in existing studies (8,9,14). Furthermore, it offers insights on the impact of six mitigation actions on spatial investment decision of different investor type and electricity access. This can be useful in informing appropriate risk mitigating actions and identifying bankable projects for specific investor profiles.

The following sections provide an overview of the status of electrification in Nigeria (5.2), describe the methodology, including scenario setting (5.3), present

the results and discussions for the baseline and scenario analysis (section 5.4), and offers conclusions on policy implications (5.5).

5.2 Background on Nigeria's electricity sector

5.2.1 Electricity access status and targets

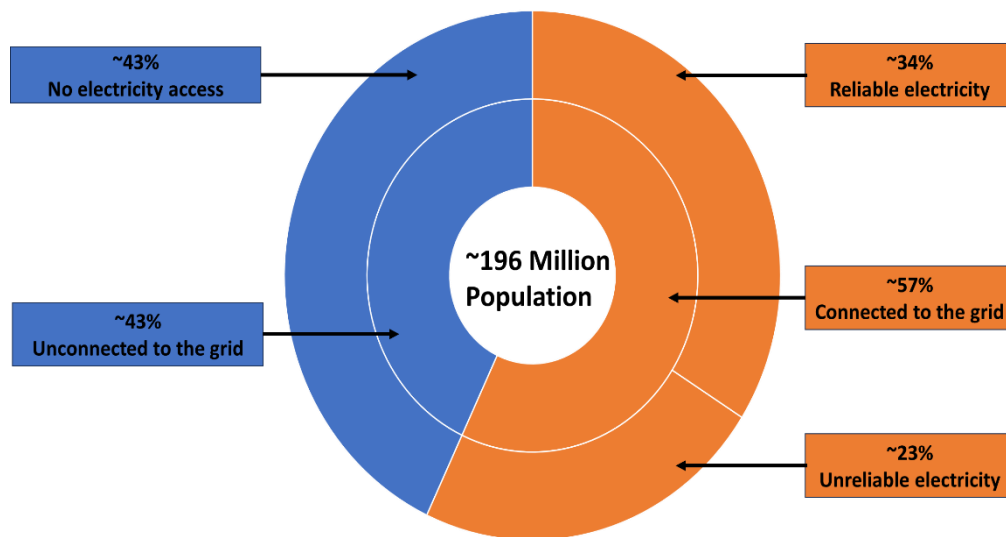


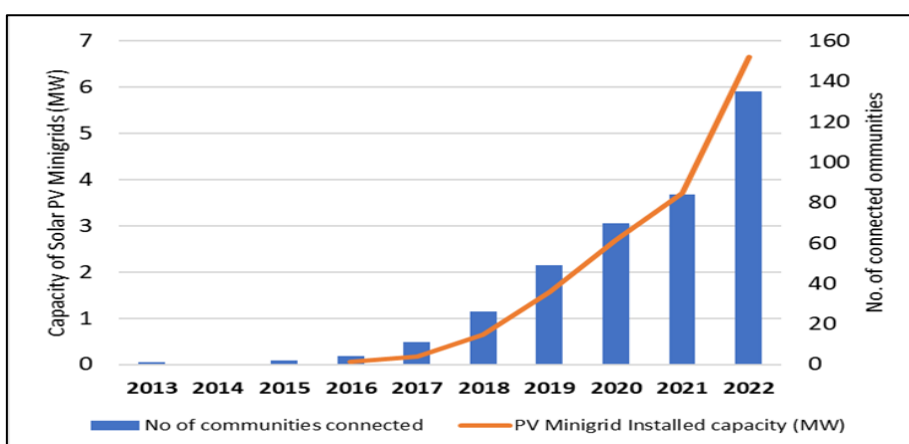
Figure 5-2 Electricity Access Status in Nigeria (data source World Bank (130)).

Nigeria is home to one in six of the SSA population without reliable electricity access. About 127 million people —66% of Nigeria's population (see Figure 5-2), mainly in remote rural and peri-urban areas, live without (43%) or with unreliable (23%) access to electricity. With annual average population growth rates of 4.5% and 1.1% in urban and rural areas respectively (130), electricity deficits could remain without a significant increase in electricity infrastructure investment. Additionally, the unelectrified locations tend to be in remote locations with dispersed population clusters making DRE a viable solution to bridging the electricity access gap (8,18). DRE electrification is the off-grid RE generation and distribution of electricity, close to the load centres. DRE systems in Nigeria are in the form of isolated mini-grids, interconnected mini-grids (IMG), and standalone systems such as street lighting and solar home systems. Isolated mini-grids operate primarily in unserved rural areas, while IMGs operate in underserved

areas, typically peri-urban locations with existing but unreliable grid connections. In this study, isolated mini-grids and IMGs are referred to as mini-grids (MG).

Nigeria's grid electricity supply mix is 79% thermal and 21% hydro supplied electricity generation (202,228). Out of an installed 13GW grid generation capacity, only 4–6GW is supplied mainly due to constraints in gas supply, transmission and distribution infrastructure and revenue collection (152,228). Meanwhile, the estimated peak electricity demand of 24GW is expected to increase about five folds by 2030 (131). To bridge the electrification deficit, private standalone diesel or petrol power generators are estimated to provide around 10–15 GW of back-up electrification annually in Nigeria (43,202). This electricity deficit is estimated to account for a GDP loss of US\$29 billion per annum (56,228) while negatively impacting the drive towards net zero.

The contribution of DRE to the electricity mix is currently marginal. Nonetheless, there has been a notable rise in the deployment of mini-grids and standalone solar systems, facilitated by RE financing instruments in the form grants and concessional loan. This trend is evident in the increasing capacity of solar PV mini-grids, as illustrated in Figure 5-3. Despite this increase, it falls short of the scale needed to meet the connection estimated demand of 600,000 new households annually, to achieve the electricity access target (43). Achieving the target requires actions that catalyse diversified investment.



*Capacity excludes SAS such as SHS, solar street lighting, irrigation pumps

Figure 5-3 Solar mini-grid development trend in Nigeria (Source: SE4All (208))

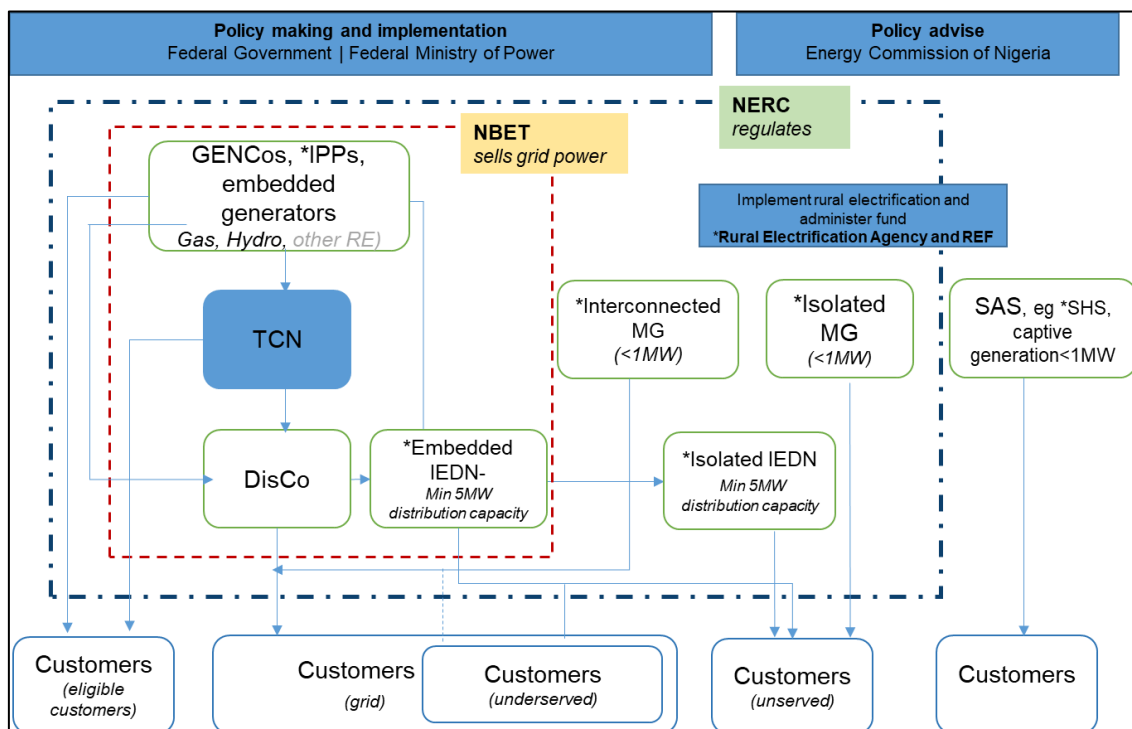
The Nigerian government has set ambitious targets for electrification in the Energy Transition Plan (ETP) (132). This plan outlines steps to close the energy access gap and achieve the goal of 90% electricity access by 2030, and universal access by 2040. The ETP is designed to accomplish a dual purpose: facilitating a clean energy transition towards carbon neutrality by 2060 and ensuring universal energy access (SDG7) in conjunction with sustainable economic growth. Within the ETP framework, one identified strategy to meet the electrification target involves deploying 6.3GW DRE by 2030. This includes allocating 2.6GW for mini-grids, equivalent to electrifying approximately 600,000 new households annually. The implementation of this plan requires a private investment of approximately US\$82 billion, with US\$35 billion earmarked specifically for solar PV mini-grids. Although Nigeria is endowed with RE resources such as wind, hydro, solar and biomass, solar PV is the most prominent DRE technology in Nigeria (25,144,152,229). This is primarily due to the abundance of solar radiation, with an annual average of 12.6 MJ/m²–day to 25.2 MJ/m²–day (131). Additionally, decentralised solar PV technology maturity, trending reduction in cost, modularity, and relatively shorter project implementation durations compared with grid generation make it a preferred technology (25,131,225).

5.2.2 Policy and reforms evolution

The unbundling and consequent privatisation of the Nigeria power sector were initiated by the National Electric Power Policy of 2001 and the Electric Power Sector Reform Act of 2005 (EPSRA). These actions led to the establishment of a new administrative structure (Figure D-1, Figure 5-4), along with policies, regulations, and programmes relevant to RE as illustrated in the policy evolution timeline in Figure 5-5. Specifically, the EPSRA established the Rural Electrification Agency (REA) with the goal of promoting rural electrification such as through the utilisation of RE technologies. This is facilitated by providing technical and financial assistance through the Rural Electrification Fund (REF). The REA aims to achieve its objectives through grid extension, mini-grid

development, and the implementation of standalone systems in unserved and underserved communities.

Following the establishment of the REA, RE policies and plans were implemented (Figure 5-5) notably, the 2016 mini-grid regulations, which paved the way for private off-grid generation. The regulation makes provision for off-grid generation up to 1MW and distribution capacity for embedded power generation of up to 100kW of electricity (25). The regulations also provide guidelines that address investor concerns such as licensing, consumer and investor protection, and compensatory terms for grid arrival and cost-reflective tariffs (133,219). In 2017, the REF guidelines were operationalised, offering partial one-off capital subsidies and technical assistance through competitive tenders for the least-cost technologies in the on-grid and off-grid sectors.



Colour code: blue: Government agency, white with green outline: private or public-private partnership, white with blue outline: customers

NERC: Nigerian electricity regulation commission (regulator), NBET: Nigeria Bulk Electricity trader (grid market settlement), TCN: Transmission Company, REF: Rural Electrification Fund, IEDN: independent electricity distribution, GenCo: Generation Company, IPP: Independent power producer, DisCo: Distribution company, MG: Mini-grid, SAS: Stand-alone system, SHS: Solar

home system, * Financial assistance provided by REF., **Generation >1MW requires NERC license.

Figure 5-4 Nigeria's power system structure, adapted from (230).

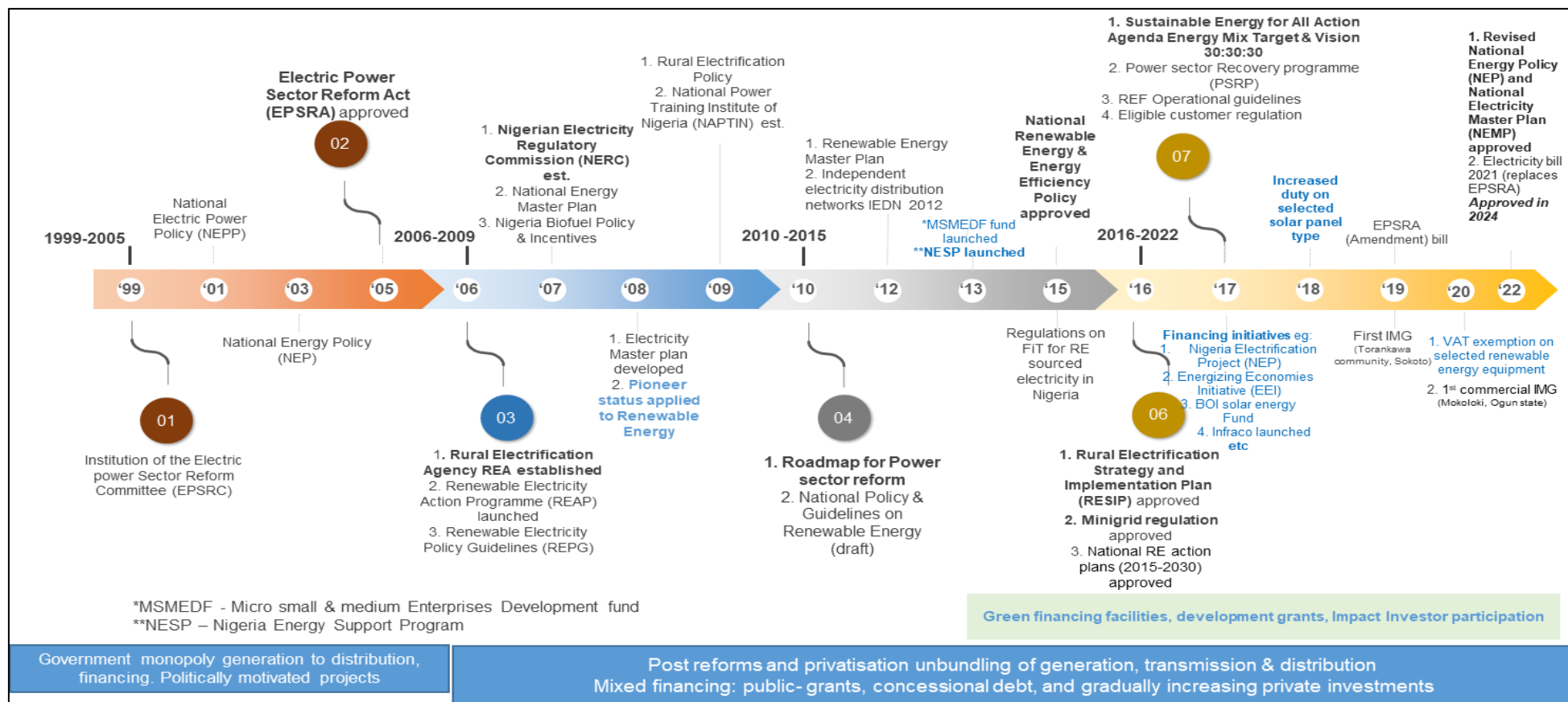


Figure 5-5 Nigeria renewable energy related policy, programmes & incentives timeline

(developed by Author)

5.2.3 Decentralised renewable energy investment in Nigeria.

Before 2005, power projects were primarily government-funded and politically motivated (134,231). However, the operationalisation of policies and donor agency programmes has led to the evolution of mini-grid funding sources from public grants (via REF) to mixed funding from public and private sources. Public sources include grants, equity, and concessional debt from the government, development agencies, development finance institutions (DFIs) e.g., Africa Development Bank, and domestic development finance institutions (DomDFIs) e.g., Bank of Industry. Private investment includes concessional and non-concessional financial instruments mainly comprising (i) equity financing from corporations, developers, (ii) non-concessional debt from commercial financial institutions such as domestic finance institutions (DomFI) or local banks, and DFIs, and (iii) concessional debt and equity from impact investors (5,134).

Concessional instruments, such as concessional debt, play a pivotal role in advancing sustainable development by offering low-cost funding and extended tenors, thereby enhancing the financial viability of projects. This form of financing is particularly instrumental in supporting development projects in developing countries where securing funding can be challenging due to elevated risks. Concessional instruments are generally supplied by public sources and impact investors (5). On the other hand, non-concessional instruments, exemplified by commercial debt, provide financing at market-based rates and terms, including shorter loan tenors and collateral requirements. Typically, this type of financing is directed towards projects with a primary focus on profitability and is sourced from private entities, such as banks (5,176). In this study, the non-concessional investors are defined to have high risk aversion while concessional investors such as impact investors are defined to have low risk aversion.

Mini-grid project financing can be a blend of these sources. However, a significant portion of mini-grid funding is from concessional debt and grant facilities (5,134). One-off grants from the Rural Electrification Fund cover up to 75% of project costs, funded from national budget allocations, regulatory fines, and concessional debt facilities from DFIs (135). Some DFIs provide non-concessional financing

mainly for utility-scale projects, while domestic DomDFIs such as the Bank of Industry provide concessional local currency-based debt financing. Additionally, impact investment in the form of equity, grants, and concessional debt is provided by international organisations such as All On. Some domestic financial institutions provide local currency debt financing through partnerships with DFIs or at market rates. In securing debt financing, the developer is usually required to contribute equity for the project. Based on the foregoing, this study broadly categorises DRE investment into four finance sources which may be accompanied by grants — concessional debt, equity, non-concessional commercial debt and DFI debt.

5.3 Methodology

The unified SD-ABM model developed in chapter 4 is implemented to explore the potential effectiveness of mitigation options on investment decisions and consequently improvement in electricity access in 65 locations population clusters in Nigeria. Section 5.3.1 provides an overview of the model, input, and output parameters — a more detailed description of the model and its validation are provided in chapter 4. Section 5.3.2 provides the scenario descriptions.

5.3.1 Model description

The SD-ABM model is a spatially explicit model that simulates the dynamic investment decisions of diverse investor types, considering their attributes, goals, preferences, and interactions with location attributes and investment risks, as well as system-level feedback. This model incorporates four investor types — Type 1 (concessional), Type 2 (Equity), Type 3 (DFI debt) and Type 4 (DomFI debt) investors. The categories are further decomposed into a total of nine sub-categories as presented in Table 5-1.

Table 5-1 Investor types in the model³

	Investor types			Investor goal		Investment threshold		Risk attribute	Expected payback time (years)
	Type	Sub-type	Financing	Economic (LCOE)	Environmental (CO ₂ emission reduction)	Min. (kW)	Max (MW)	Risk aversion (arrow pratt coefficient)	
1.	Type I (Mainly Equity)	Equity (E)	100% E	0.9	0.1	10	0.05-1	High (1e ⁻⁵)	-
		Equity (EG)	95% E, 5% G	0.8	0.2	10	0.05-1	High (1e ⁻⁵)	-
2.	Type II (Primarily DomFI Debt)	DomFI (DEG)	65% D, 30% E, 5% G	0.8	0.2	10	0.05-1	High (1e ⁻⁵)	5
		DomFI (DE)	70% D, 30% E	0.8	0.2	10	0.05-1	High (1e ⁻⁵)	5
		DomFI (DG)	80% D, 20% G	0.8	0.2	10	0.05-1	High (1e ⁻⁵)	5
3.	Type III (Primarily Concessional debt)	Conc (DEG)	50% D _c 30% E, 20% G	0.4	0.6	10	0.05-1	Low (1e ⁻⁷)	10
		Conc (DE)	11% D _c 39% E, 50% G	0.5	0.5	10	0.05-1	Low (1e ⁻⁷)	10
4.	Type IV	DFI (DEG)	60% D, 30% E, 10% G	0.4	0.6	10	0.05-1	Moderate (1e ⁻⁶)	10

	(Primarily DFI debt)	DFI (DE)	70% D, 30% E	0.5	0.5	10	0.05-1	Moderate (1e ⁻⁶)	10
	Reference		Actual project (208)	Actual project (208)	Actual project (208)	(133)	(133)	(37)	Actual project (208)

NOTE: E–Equity, D– Debt, G– Grant, Conc– Concessional

Additionally, the model features 65 unelectrified population clusters in Nigeria that are represented by location agents in Figure 5-6 and specific location attributes (see Table D-1). These clusters have been identified through literature (56) and government databases (57) as potential sites for solar PV mini-grids based on least-cost electricity analysis.

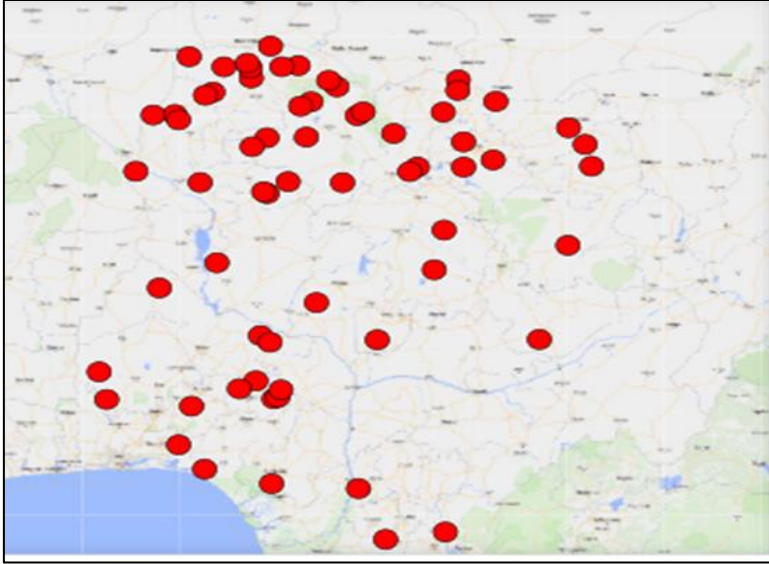


Figure 5-6 Location agents representing 65 location clusters in the model.

Furthermore, the model forecasts some future location attributes. Firstly, the dynamic yearly population and demand, $D_l(t)$, are forecast using historical birth and death rates. Secondly, the stress level is calculated based on the dynamic demand in two years, $D_l(t + 2)$, and supply, $Gen_l^{current}(t)$, where the supply is determined by the system feedback on aggregate investor decisions in a specific location. Thirdly, the cost of alternative sources of electricity, such as petrol-based electricity generation, is assumed to influence the customers' willingness to pay for mini-grid connection. This cost is influenced by the volatility in the cost of petrol due to inflation and exchange rate volatility, as well as spatial variations in the fuel cost. The model forecasts future volatilities and inflation using historical data.

$$D_l(t) = \left(\frac{P_l * (1 + r_g)^{(t-1)}}{n} \right) * Dh \quad (4-1)$$

Where n is the number of households, Dh is the household demand, r_g is the growth rate, t is the model year, and P_l is the population in location l

$$Stress\ level_l(t) = \left(\frac{D_l(t+2)}{Gen_l^{current}} \right) \quad (4-2)$$

The objective of the SD-ABM model is to determine which locations will be invested in, the investment capacity, and the investor type responsible for the investment. As represented in the model overview Figure 5-7, this is accomplished by first determining the potential generation capacity, $Gen_{total,i,Y}^{potentialcapacity}(t)$, an investor can allocate to solar PV mini-grids in a location based on cost optimisation (least-cost) or emission reduction goals (CO₂ emission avoidance), and the capacity threshold. Secondly, the model determines the potential generation capacity, $Gen_{i,l}^{potentialcapacity}(t)$ each investor could invest in based on the location factors that drive its attractiveness, and the capacity threshold. Lastly, the model selects the potential investment that offers the maximum positive expected utility, $EU_{i,l}^{invest}(t)$, for the investor and meets the NPV, IRR, payback time, and consumer willingness to pay criteria. Details of economic variables calculations are provided Chapter 3. Investment decisions are made on an annual basis from 2024–2040. The investment choices are aggregated for each location and overall, annually. Further details of the model and its validation has been discussed extensively in Chapter 4.

$$\begin{aligned} Gen_{total,i,Y}^{potentialcapacity} &= FutureDemand^{total}(t) * Relative\ Attractivity_{i,Y} \\ &- Gen_i^{current}(t) \end{aligned} \quad (4-7)$$

$$Gen_{i,l}^{potentialcapacity} = Gen_{total,i,Y}^{potentialcapacity} * Relative\ Attractiveness_l \quad (4-8)$$

Where $Gen_{i,l}^{investedOnstream}(t)$ is the on streamed generation location l and year t .

$Gen_l^{retired}(t)$ represents the generation facility retirements in location l and year t .

$$U_{i,l,s,pn}^{invest}(t) = 1 - e^{(-\alpha_i(t)*TNPV_{i,l,pn,s}(t))}EU \quad (4-10)$$

$$EU_{i,l}^{invest}(t) = \sum_s \theta_s * U_{s,i,l,p}^{invest}(t) \quad (4-11)$$

Where $U_{i,l,s,pn}^{invest}$ is the utility for each potential project scenario.

$TNPV_{l,l}^{pn,s}$ is the expected NPV outcomes for each potential project scenario s , reflecting historical revenue collection rate ranges (219) and their probability θ_s .

α_i is the Arrow-Pratt coefficient, indicating the risk attribute of investors.

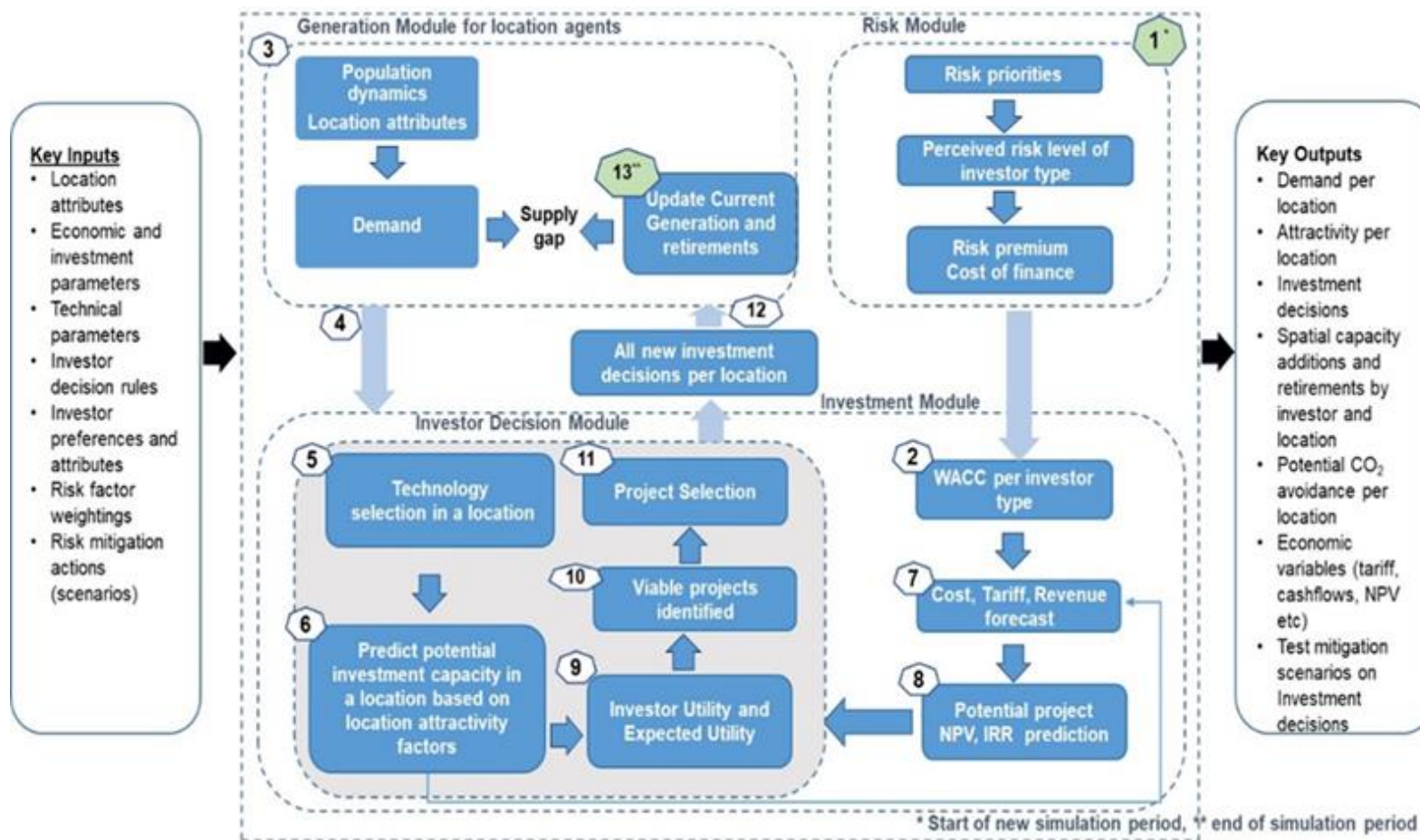
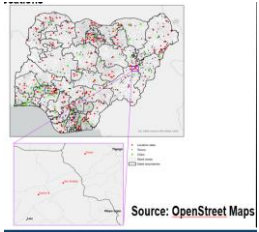
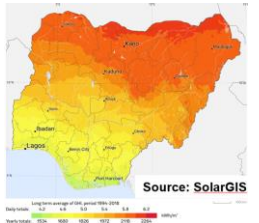


Figure 5-7 Model process overview

(adopted from Chapter 4).

The primary inputs to the model include the geographical coordinates of the locations agents, location and investor attributes, initial population, birth and death rates, demand, initial generation capacity, technology costs, inflation rates, risk levels, discount rates. Additional input parameters for the mitigation scenarios are explained in section 5.3.2. The primary outputs include the aggregate and spatial investment capacities by investor type and overall, spatial and aggregate electricity access level, economic variables — minimum potential electricity tariff, NPV, and profitability. Profitability is defined as NPV per unit investment capacity (US\$/MW) and allows for comparison of investments regardless of capacity and investor type. The model was implemented using Anylogic version 8.8.4 software, utilising spatial data from ArcGIS, Open Street Maps, and the Worldpop database.

Table 5-2 Spatial input data used in the model.

Factor	Variable	Data transformation	Spatial resolution	Temporal resolution	Data source	
Conflict (211)	(211)	Conflict data for each state was normalised on a scale of 0–1	By state	2022 data	ACLED (212)	 <p>Source: ACLED</p>
Poverty level (211)	(211)	Poverty data for each state was normalised on a scale of 0–1	1 km	-	WorldPop dataset (213)	 <p>Source: WorldPop</p>
Distance to the nearest city/ town (211)	(211)	Identification of the number of towns and cities within a 25km radius of each location. Output was normalised	1 km	-	ArcGIS Pro 2.9, Open Street maps (214) (The methodology is provided in Appendix C.1)	 <p>Source: OpenStreet Maps</p>
Solar potential (215)	(215)	GHI for each state was normalised on a scale of 0–1	1km	-	SolarGis (216)	 <p>Source: SolarGIS</p>

Population	Population	Dynamically calculated in SD	100m	Yearly time-step	Initial values WorldPop dataset (217) Subsequent data was model generated.		
Stress level (215)	(215)	Dynamically calculated in SD	Location (population cluster)	Yearly time-step	Model generated		
Peer effect (195)	(195)	Dynamically calculated in SD-ABM	Location (population cluster)	Yearly time-step	Model generated		
Willingness to pay (191)	(191)	Dynamically calculated with input from the average yearly petrol cost in a location	Model forecast. by state based on historical data	Yearly, forecast is based of 2013–2018 data	NBS (169)		

5.3.2 Scenario Setting

A baseline model, incorporating heterogeneous investor agent types and 65 locations was established as the business as usual (BAU) case. Subsequently, mitigation options that decision-makers could implement were simulated as scenarios. Risk mitigation actions have the potential to alter key economic variables, influencing investment viability. For instance, the literature (128,226) showed a positive but short-term impact of grants and subsidies because of its impact of reducing financing constraints and improving project viability. The selection of scenarios aimed to replicate recommended actions proposed in Chapter 3. Scenarios 1, 3, 4, and 5 were identified in interviews and confirmed in the literature while Scenarios 2 and 6 were identified from the literature. Furthermore, certain align with ongoing initiatives being implemented on a smaller scale by government and development agency programmes (scenarios 5 and 6). Others draw from strategies and interventions implemented by other countries (163,223) (scenarios 3 and 4). The scenarios are described in Table 5-3.

Table 5-3 Scenario Setting

Category	Scenario	Mitigation Action	Description
Funding	Scenario 1 (S1)	Increased funding	Represents the call for increased funding in emerging economies to support the energy transition. Funding assumed to be available to all investor types in the BAU case is doubled.
	Scenario 2 (S2)	Substantial risk (discount rate) reduction	Represents substantial improvements in investor-perceived risk levels which can result from e.g., regulatory or market reforms investors perceive as effective. The effectiveness of the risk mitigation strategies is expected to potentially reduce the highest priority risks and,

			consequently, reduce discount rates. In this scenario, a 50% risk reduction of the BAU highest priority risks (identified in chapter 3) is assumed, resulting in an average discount rate reduction of 24% for investor types.
Policy	Scenario 3 (S3)	RE Priority sector lending mandate for local banks (DomFI)	Assumes the DomFI investor type is less risk-averse than in the BAU case because of a policy requirement for local banks to invest in RE projects. The strategy is implemented by applying a medium-risk aversion coefficient to DomFI investors compared to a high-risk aversion coefficient in the BAU case.
	Scenario 4 (S4)	Carbon Mechanism CDM	This scenario leverages carbon markets to establish a revenue stream from the implementation of a project. The scenario assumes an additional revenue of 8 USD/tonne CO ₂ e of avoided emission.
	Scenario 5 (S5)	Demand stimulation	Represents adoption of demand stimulation and productivity improvement schemes such as appliance financing to stimulate electricity use. The base case demand of tier 3 is increased to tier 4 ⁵ for all locations.
Incentive	Scenario 6 (S6)	Performance based grants (PBG)	Represents the application of performance-based grants (PBG) across all locations irrespective of investor type or location. PBG of 350USD per connection have been awarded to selected eligible projects by the government, after one year of project operation (230). This scenario

			considers that the existing is scaled-up.
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5.4 Results and discussions

In this section, the outputs of the BAU case are presented first, followed by the impact of the scenarios on the BAU results. For each case, the model yields indicators applicable to sustainable development goals (SDG), the Nigeria Energy Transition Plan, and profit. These include investment capacities determined by the yearly investment decisions, profits (NPV/unit investment), minimum electricity tariff, and electricity access levels, which last compare the annual electricity generation to the demand in each location. By analysing and comparing the scenarios, this study aims to quantify the efficacy of the scenarios in boosting DRE investor decisions and the likely attainment of electricity access goals in the years 2030 and 2040, which represent 90% and 100% (universal) electricity access targets respectively. Subsequently, the implications of the findings are discussed.

5.4.1 Business as usual (BAU) case

Prior to presenting the scenario results, it is important to analyse the baseline business-as-usual case (BAU) output as produced by the model. In the BAU case, heterogeneous investors make annual decisions regarding investment in the 65 modelled locations. Figure 5-8 presents the total investment, demand, electricity access level, and investor mix for the BAU case by the target years 2030 and 2040. The results reveal that while there is an investment need in solar PV mini-grids of 95MW and 113MW by 2030 and 2040 based on the total demand, 51% investment deficit is predicted by 2040 in the BAU case. As a result, the electricity access levels (19% and 43% respectively) do not meet the 2030 and 2040 targets.

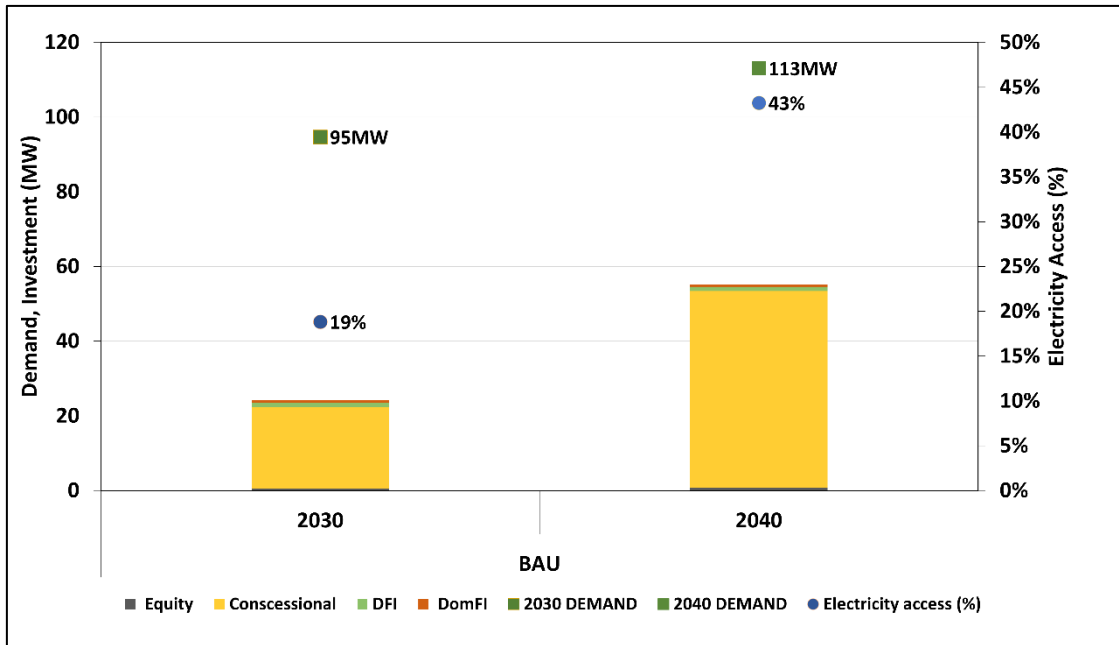


Figure 5-8 BAU total investment by investor type and electricity access levels in 2030 and 2040.

Figure 5-9 presents the investment allocation and resultant electricity access of each location by 2030 and 2040. The results indicate that only 9% of the modelled locations achieve 90% access by 2040, meaning none attain the electricity access targets. This result suggests that while a few locations can attract investment decisions within the BAU case, all the locations will require specific interventions to attain targets. Interestingly, most of the locations that achieved 90% electricity access by 2040 were in the Northern region, which have the highest solar potential (Figure D-3). While this regional affinity aligns with the view in the literature (232) that the northern region is more attractive for solar PV projects than the southern regions, there are other explanations for the investment pattern. For instance, investors made decisions on locations that offered the highest expected utilities (EUs). The high EU could be explained by the larger population clusters in the areas with higher investment, and thus higher demand.

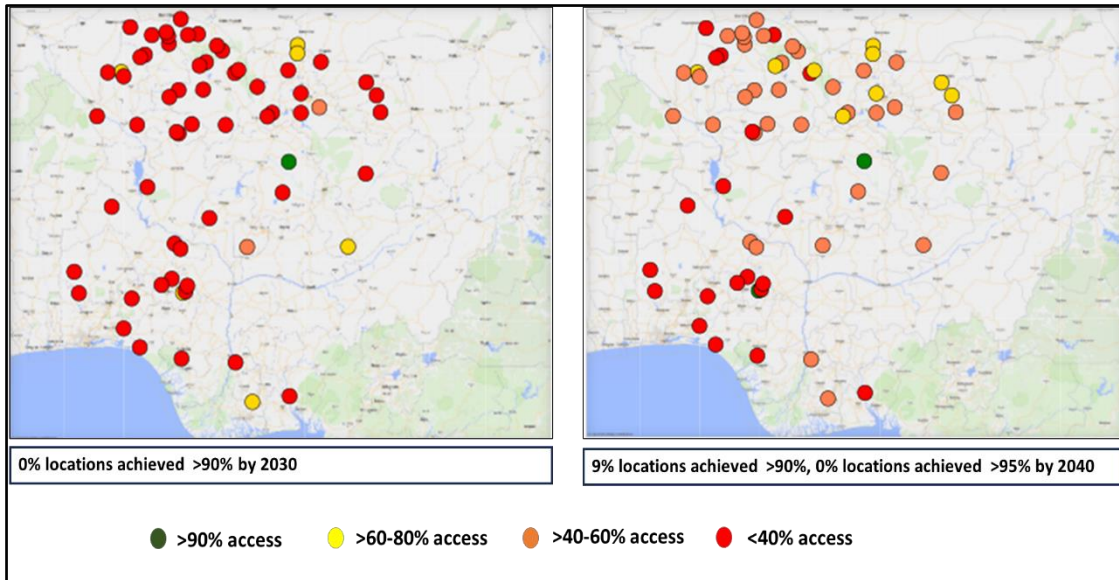


Figure 5-9 Spatial investment allocation in 2030 and 20140 pre-2030

Moreover, as shown in Figure 5-10, the EUs decline over time. A view of EUs for investment pre-2030 and post-2030–2040 in each location as presented in Figure 5-11 show that the pre-2030 EUs are, on average, 28% higher than the post-2030 EUs. This difference can be explained by the reduction in post-2030 revenues being driven by lower dynamic stress levels (or higher electricity access levels) and model assumptions of exchange rate depreciation. However, there are exceptions, such as location 52, where the average expected utility (EU) was 58% higher post-2030 compared with pre-2030 EU. The increase is because the EU is driven by larger project sizes of 200kW, which has lower unit costs than the pre-2030 average-sized 100kW projects. The result suggests that aggregating projects in the same location cluster could improve EU even at relatively lower revenues.

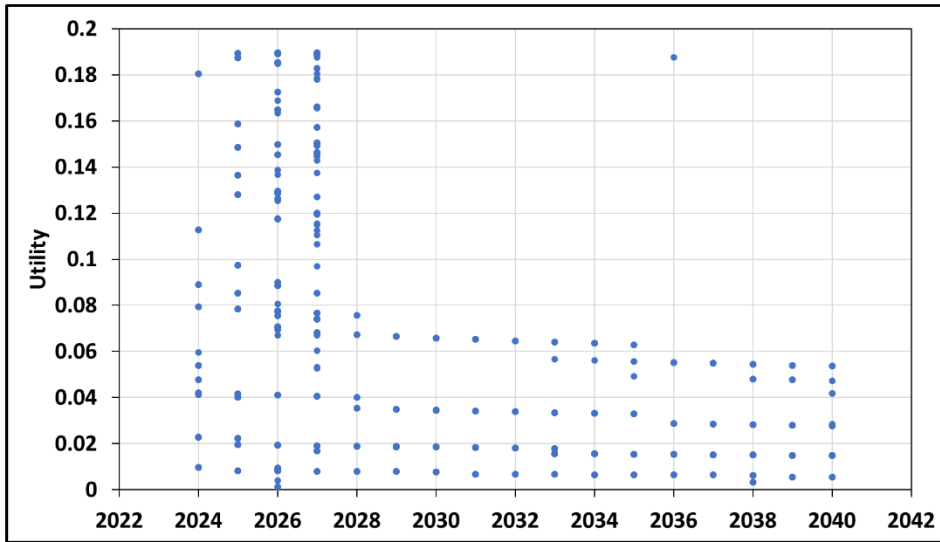


Figure 5-10 Temporal expected utility ranges for investment up to 2040

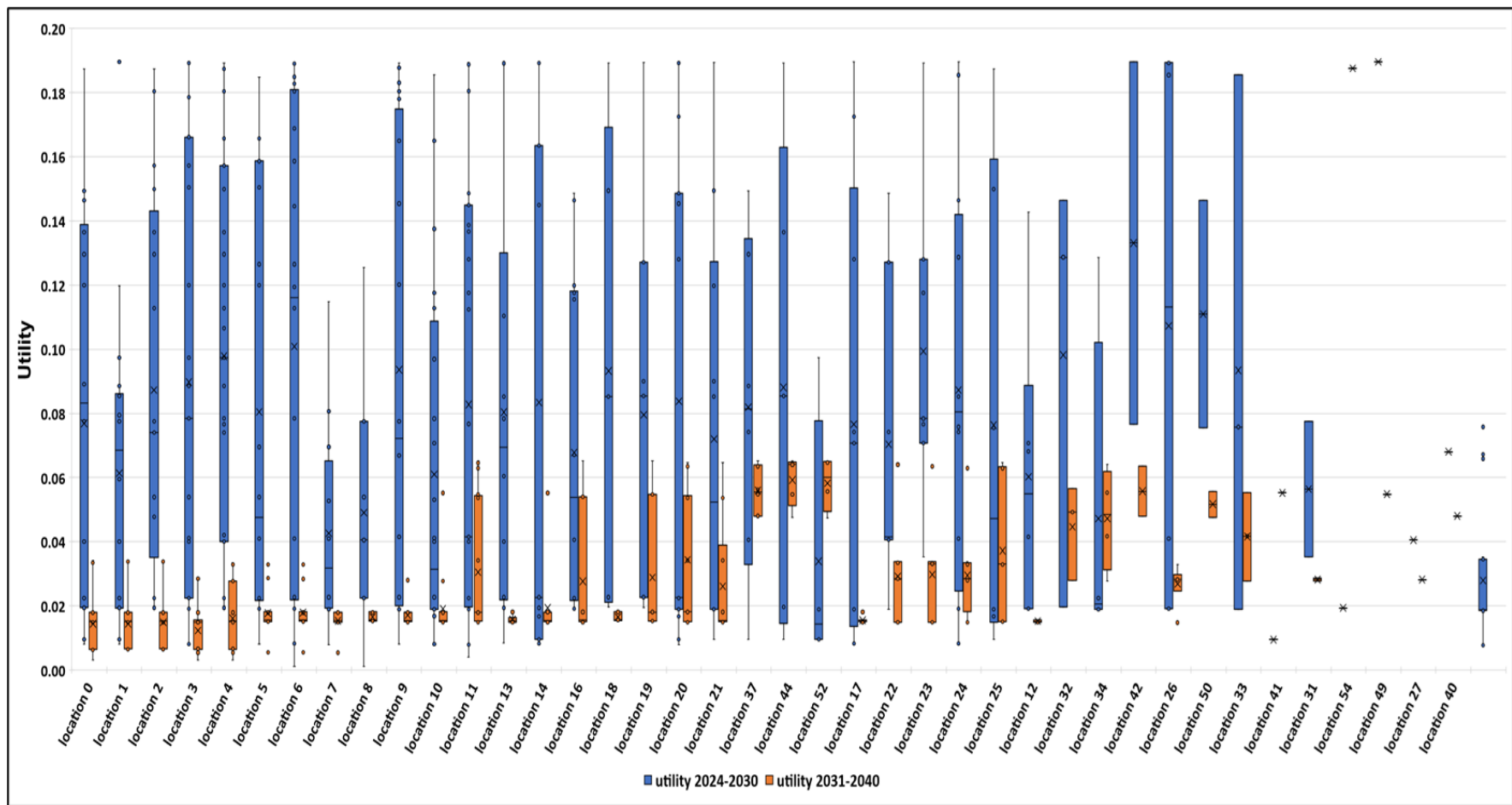


Figure 5-11 Spatial expected utility ranges for locations with investment by 2030 and 2040

An analysis of the investor types shows that in the BAU case, investment (see Figure 5-12a) is mainly from the concessional investor groups (Concessional DE and DEG), who invest 45 times more capacity than other investors. This finding corroborates literature findings (5,233) which established that investment in SSA countries are skewed towards concessional investment. Additionally, concessional investors make a sevenfold higher investment in larger capacity projects on average compared to other investors, as shown in Figure 5-12b. The predominance of concessional investors can be ascribed to their lower discount rates and low risk aversion attribute. This is supported by the literature (2) which finds that firms with access to lower financing tend to dominate investment.

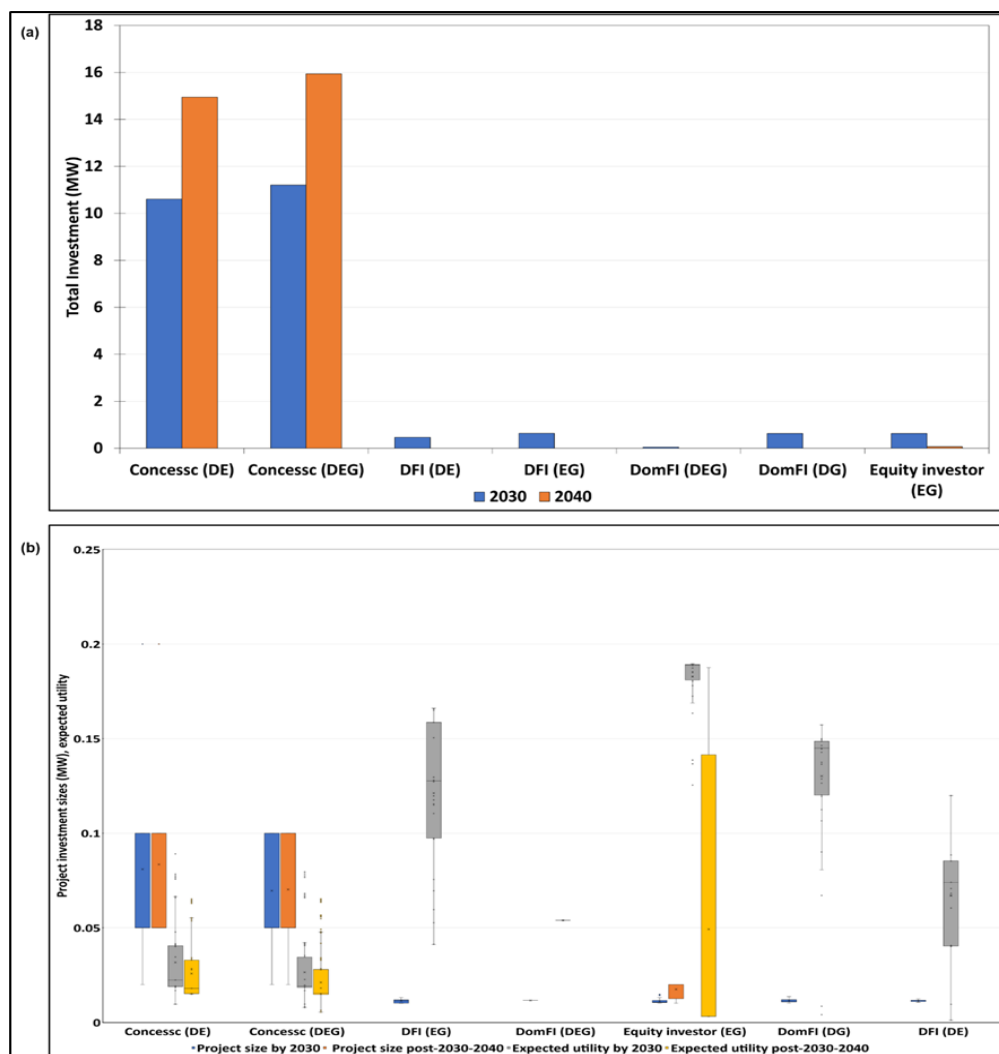


Figure 5-12 (a) Total investment and (b) project capacities and expected utility by investor types by 2030 and post-2030.

Only 10% of investment capacity contributions were made by non-concessional investor types pre-2030 (see Figure 5-8). Non-concessional investors refer to all other modelled investors excluding concessional DE and concessional DEG investor types. Post-2030, apart from the equity (EG) investor type, other non-concessional investor types did not invest, thus reducing their contributions to 4% of total investment by 2040. The decline in investment from other investor types can be explained by lower EU (see Figure 5-12b), which resulted from reduced profitability and revenues driven by inflation, local currency depreciation, higher discount rates, risk-aversion and model assumptions on price elasticity. The assumption of price elasticity, as adopted from previous studies (37) meant the cost of developing an additional project in a location by an investor increased with each successive investment. Figure 5-13 illustrates the effect of price elasticity in 2026. The results reveal a diverse mix of investors investing in the initial projects (project 0) while subsequent projects were financed with concessional investment. This is because the increased project costs, coupled with a higher discount rate among more risk-averse non-concessional investors, result in their inability to meet the investment criteria, specifically for potential projects exhibiting lower EU than concessional investors. Once concessional investors reach their annual investment capacity thresholds, locations with lower investment potential are left without further investment. This result suggests that while concessional investors provide the critical funding to catalyse investment, they may, on the other hand, impede other investor types by making investment choices in more economically attractive locations especially when incentives are offered irrespective of investor type. This finding is consistent with literature (234) which indicates concessional capital tends to crowd out other private capital.

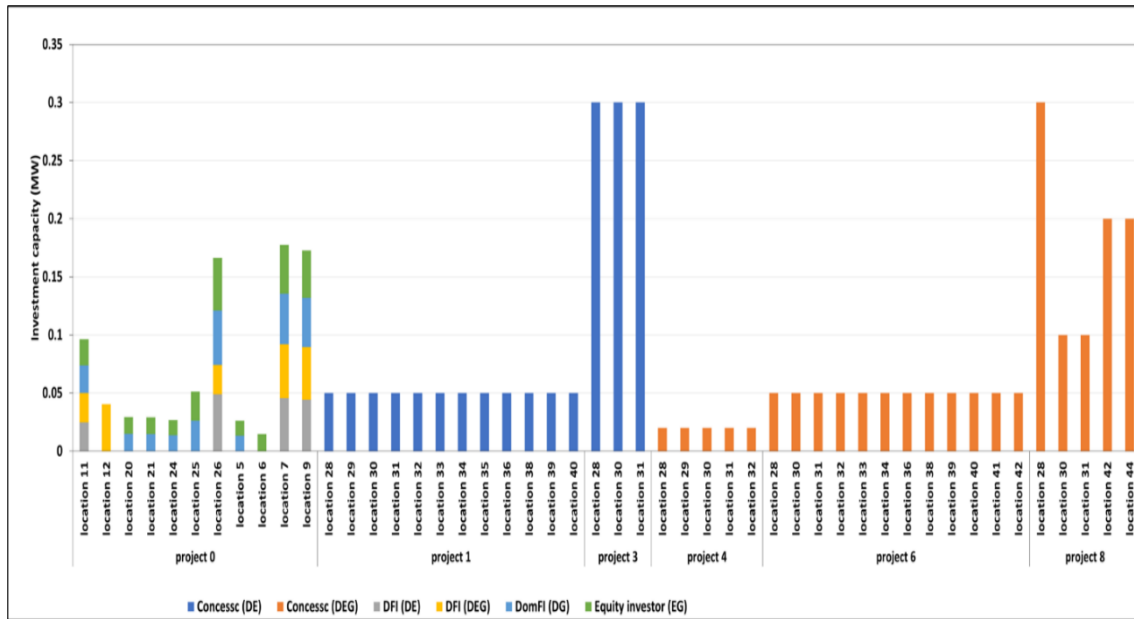


Figure 5-13 Impact of price elasticity on investment year 2026 cross-section.

5.4.2 Scenario analysis of mitigation options

This section first presents the impact of the mitigation options on investment and investor types during specific electricity access target periods in 2030 and 2040. This is followed by the spatial impact of the mitigations on electricity access. Detailed analysis is focused on three scenarios (S1, S2, and S3), while results for scenarios S4, S5, and S6 are summarised due to the comparatively lesser impact of the latter.

5.4.2.1 Temporal results

Figure 5-14 and Figure 5-15 compare the BAU case's total investment, investor mix, and electricity access results against the scenarios. Similarly, to the BAU case, the modelled scenarios do not meet the 2030 and 2040 electricity access targets overall. Nevertheless, by 2040, scenarios S1, S2, and S3 increased capacity investment by 88%, 2%, and 99% respectively from the BAU case.

A comparison of the temporal total electricity access level of the BAU case with S1 indicates that doubling the BAU case funding across all investor types improves the overall electricity access by 74% in 2030 and 2040 electricity access levels from 43% to 82%. This result is consistent with literature that supports the call for additional funding in Nigeria and other SSA countries (5,154,233,234).

Interestingly, although doubling the BAU case funding across all investors yields 48% increase in concessional investment, non-concessional investment decline to 41% by 2040. One plausible explanation for this decline is the inability of non-concessional investors to compete with the cheaper capital from concessional investors. Moreover, additional to the low cost of capital, the low-risk-averse attribute of concessional investors result in lower NPV threshold requirement to reach investment decisions. Meanwhile the higher-risk-averse non-concessional investors require projects that offer substantial NPV at a low enough tariff, close to the consumer WTP, to meet their EU. The result for S1 indicates that although actions that increase funding can enhance investment capacity, as identified in the literature (5,102), achieving targets requires a quantum of concessional funding to fulfil investment requirements. Alternatively, additional actions must be taken to unlock investment from other financing sources.

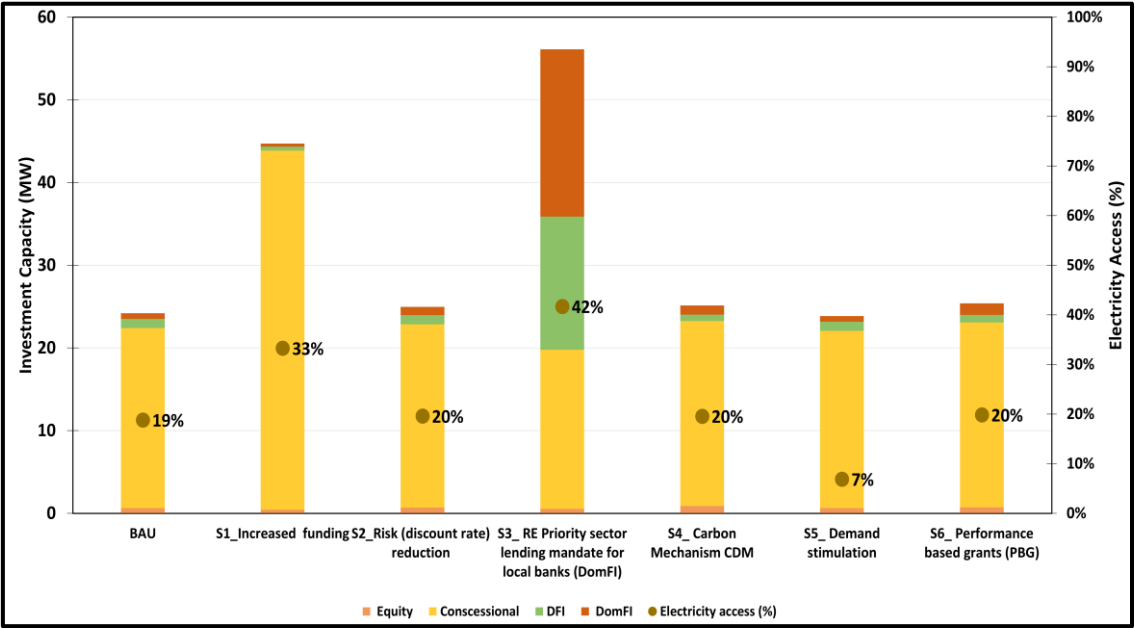


Figure 5-14 A comparison of total investment and electricity access levels in 2030 for scenarios S1, S2, S3, S4, S5, and S6

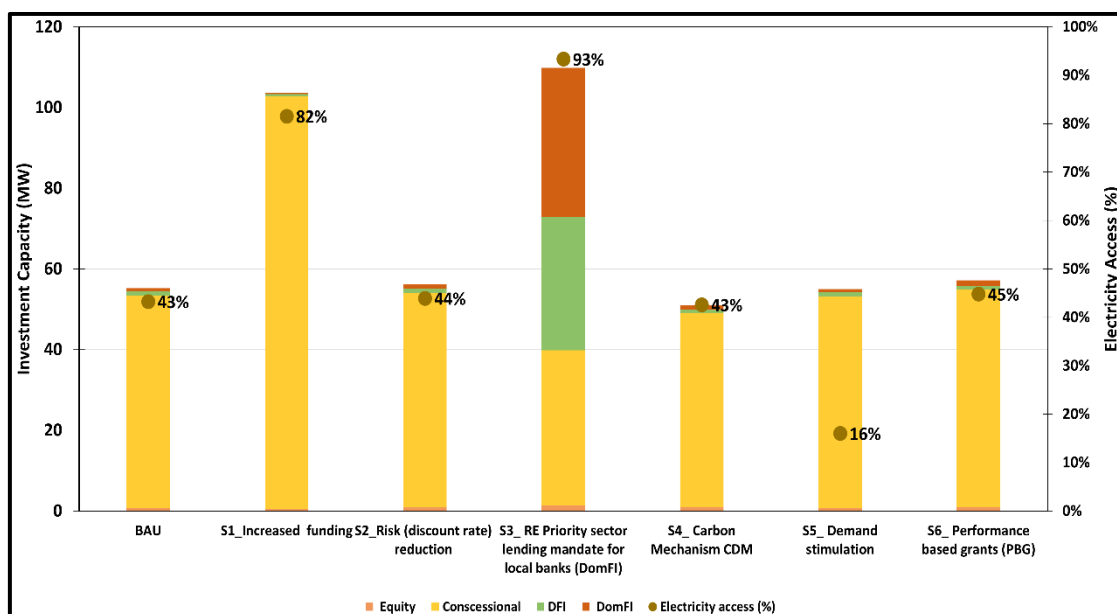


Figure 5-15 A comparison of total investment and electricity access levels in 2060 and 2040 for scenarios S1, S2, S3, S4, S5, and S6

Scenario 2 (S2) considers substantial risk reduction, resulting in an average 24% discount rate reduction. Risk reduction can result from lower risk premiums applied by investors because of reforms or mitigations of key investor risks such as revenue risk and currency related risks. The results show that reducing the discount rate improve overall investment by 3–2% and electricity access levels by 2–5% in 2030 and 2040. This aligns with findings from (14) who found mini-grid investment did not significantly increase when discount rates were reduced. The marginal increase in total investment is attributable the 16% higher non-concessional investment compared to the BAU case. The higher contribution from non-concessional investors could be explained by the reduction in the cost of capital and consequently higher profit leading to more investment. Nevertheless, as the risk aversion attributes of non-concessional investors remain the same as in the BAU case, the overall effect is marginal. This finding indicates that when mitigations only lead to a reduction in discount rates, it does not significantly investment improvement. Furthermore, policy actions that do not influence investor risk attitude may not achieve the impact level required to drive investment decisions in more risk-averse investors. This shows the significance

of collaboration and engagement between decision-makers in arriving at actions that not only impact discount rates but holistically drive investment decisions.

Scenario 3 (S3) assumed a lower risk aversion level of the DomFI investor. This change in risk aversion could be instigated by institutional changes whereby investors choose to incorporate environmental and social considerations in investment decisions or in the case of S3, imposed priority sector lending mandates, whereby local financing institutions such as DomFI are mandated by the government to finance a percentage of RE projects. S3 records 42% and 93% overall electricity access levels in 2030 and 2040 respectively, compared with 19% and 43% in the BAU case. Meanwhile, S3 increases overall investment to 132% and 99% of the BAU case in 2030 and 2040 respectively. As shown in Figure 5-16, lower risk aversion results in a more diverse investment mix whereby concessional investment contribution decrease by nearly a third and non-concessional investment contribution increases by 18-fold compared to the BAU case. The increase in the diversity of investors (more non-concessional investors) could be explained by the lower NPV threshold of the less risk aversion of DomFI investors and the associated peer effect, leading to increased attractiveness of potential investment over time. The results for S3 show that improving investors' risk aversion can significantly advance DRE investment not just from the DomFI but from other non-affected investors. As such, policymakers need to understand investor risk profiles and demonstrate that the most critical risks are addressed, thus improving risk perception.

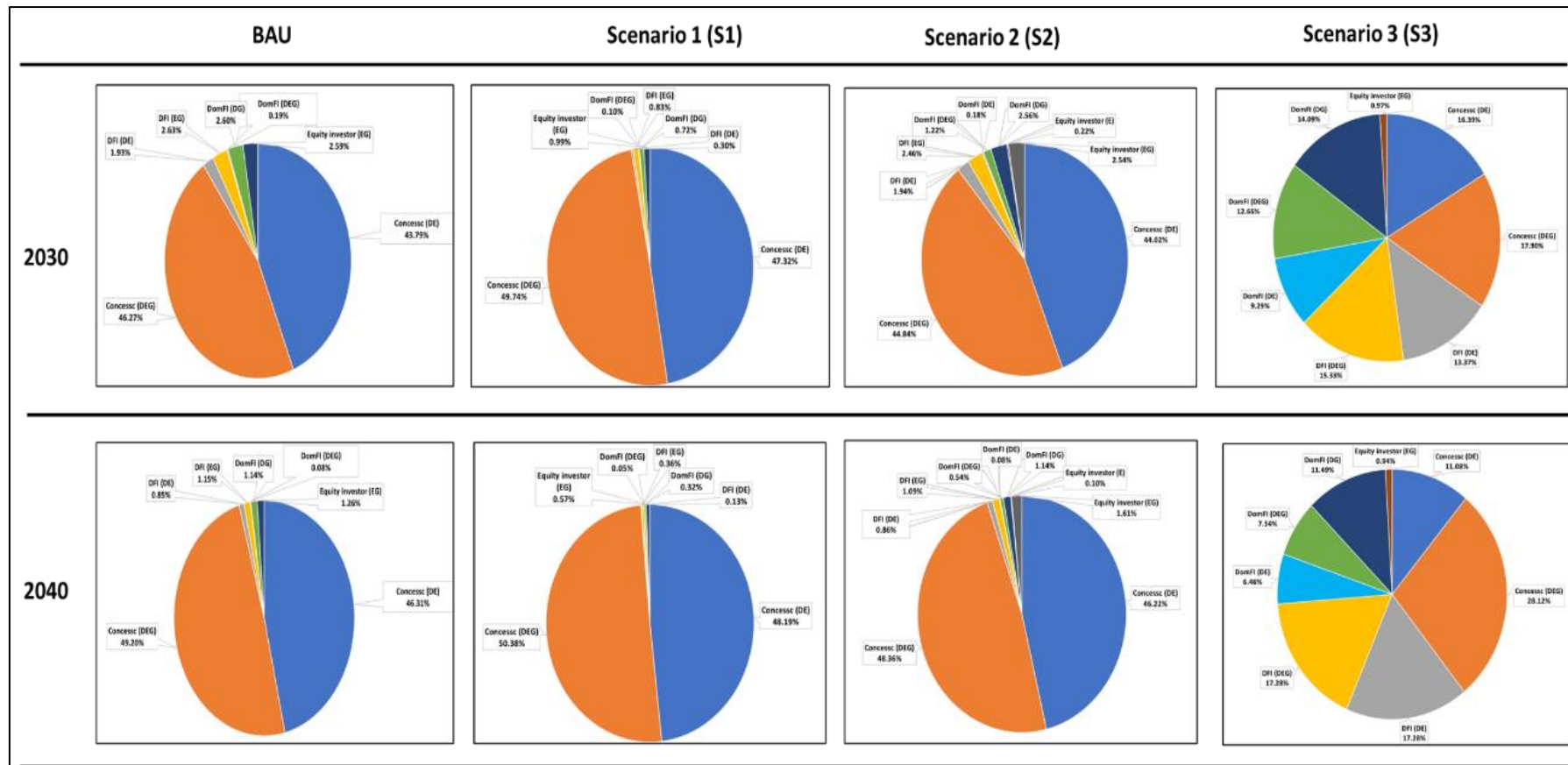


Figure 5-16 Variation in investment mix in 2030 and 2040 for scenarios S1, S2, S3

Furthermore, a comparison of the economic variables (NPV/unit investment and EU) and electricity tariff shows that the scenarios can have different implications for profitability for investors and affordability for consumers. In this study, profitability is measured as NPV per unit investment to enable a fair comparison irrespective of investment capacity. Figure 5-17b–c shows the EU results by 2030 and post-2030 results for EU, profitability, and electricity tariff ranges across investors and locations for the three scenarios and BAU. The results show that investors have the highest EU ranges of up to 150% above the BAU case average in S3, while EU reduces by 42% in S1. Meanwhile, the average EU in S2 remains the same as in the BAU case. The increase observed in S3 could be attributed to the reduction in risk aversion of DomFI investors and peer effect and improved investor diversity. In S3, investors can invest in projects that would otherwise not have met their EU in the BAU case. In S1, the reduction in EU could be attributed to the increment in concessional investment of 7% from the BAU case.

The increment in concessional investment additionally impacts the profitability range of investors in S1 by an average reduction of 3%–11% compared to the BAU case, while in S2 profitability ranges increase as expected by 7–8% on average because of the reduction in discount rates (see Figure 5-17a). For S3, however, the average profitability did not materially change (0–1% average increase on the BAU case). The results indicate that although the discount rate reduction in S2 is not sufficient to significantly increase EU, the scenario offers higher profitability for the projects which meet the investment criteria. This suggests that from the investor perspective, actions that mitigate risk and justify discount rate reduction could improve profitability and lead to investment additions. However, the overall results suggest the additions are marginal.

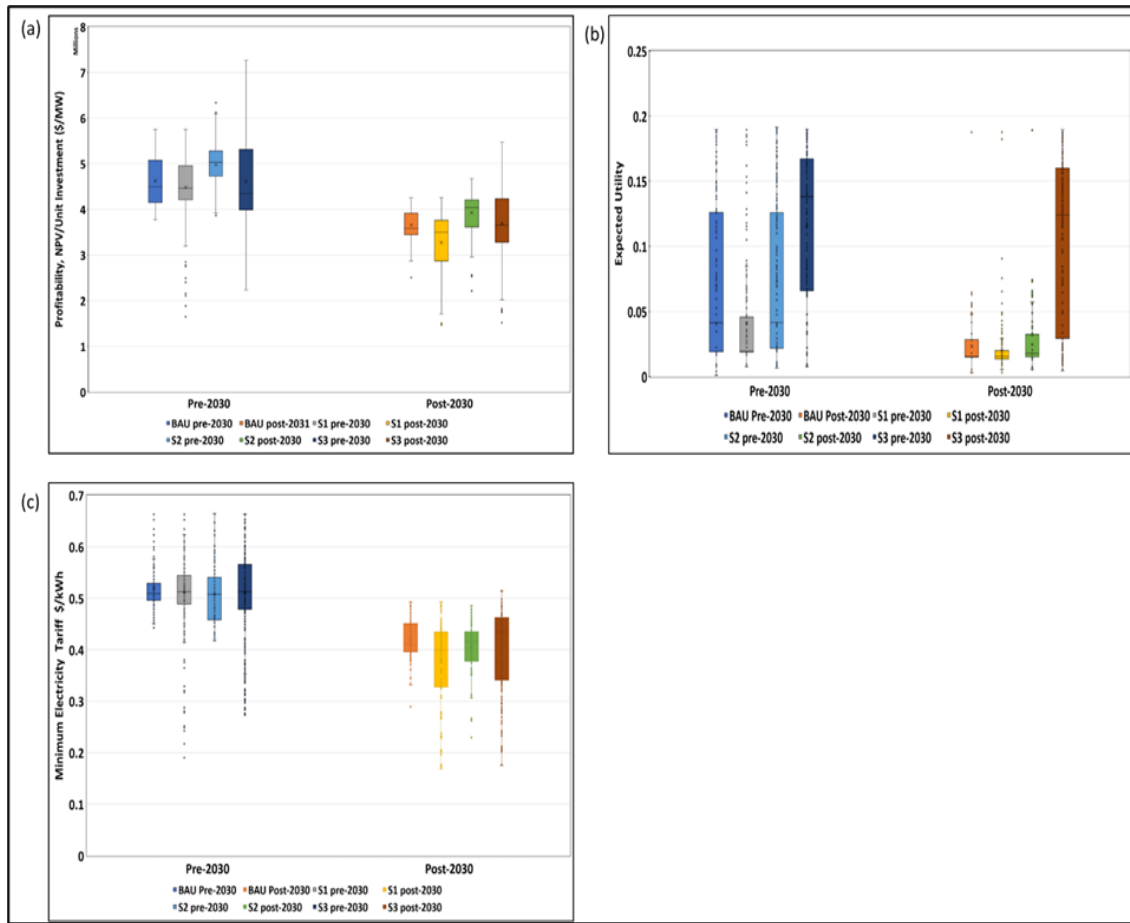


Figure 5-17 Impact of scenarios on (a) profitability, (b) utility, and (c) minimum electricity tariff

Furthermore, a comparison of the minimum electricity tariff ranges shows that tariffs decrease over time (see Figure 5-17c) because of the impact of the decline in the cost of solar components and exchange rate depreciation. Interestingly, while S2 increases profitability, it decreases average tariffs by up to 4% compared to the BAU case. However, S1 was the most impactful in reducing the average minimum electricity tariffs by up to 11% because of the impact of lower-cost concessional financing and grants. These results show that although S1 offers improved electricity access through concessional funding and affordability for consumers via lower tariffs, the scenario does not offer investors improved NPV/unit investment. This could lead to the exclusion of potential investment from other financing sources in the case of blended financing. Therefore, in selecting practical policy actions, trade-offs between the electricity tariff, the achievement

of access targets, and investor profitability need to be considered vis a vis the availability of concessional funding.

Moreover, as concessional funding remains a constraint in emerging economies (5,76), non-concessional investors should be enabled to bridge the financing gaps whilst ongoing efforts such as green financing, impact funding and development financing are being advocated. This can be achieved via actions such as mandates and incentives for investors.

Scenario 4 (S4) assumed all investors leveraged carbon markets to establish a revenue stream from projects. Carbon credit pricing varies by project type; for example, RE projects command between 2–8USD\$/tCO₂e while projects such as forestry range between 6–18USD\$/tCO₂e (235). S4 assumed investors earned 8USD\$/tCO₂e of avoided emission. The results (Figure 5-14, Figure 5-15) show that leveraging CDM marginally improves electricity access (by 1–4%) in 2030 and 2040, because the revenues, driven by pricing and project size, were insufficient to materially increase the NPV of projects. The results suggest the impact of S4 is marginal because of the small scale of DRE projects. Therefore, such project could benefit from S4 in the event of improvements in carbon credit pricing, project aggregation or when combined with other mitigation actions.

Scenario 5 (S5) represents an increase in electricity demand from tier 3 to tier 4⁵ because of higher productive uses (210). The results (Figure 5-14, Figure 5-15) show that demand increase across all locations reduces overall electricity access levels compared to the BAU from 43% to 16% in 2040. This is because the tier 4 access for all locations increased demand by nearly threefold while the location characteristics and risk profiles that drive attractiveness of investment did not change in the model. The finding differs from the literature (219), which advocates for demand stimulation to increase investment viability. This difference could be explained by the model structure which assumes demand growth is only based

⁵ The World Bank multi-tier framework (210) categorises electricity access into multiple tiers, ranging from basic lighting and phone charging (tier 1) to higher levels of access that support productive uses of electricity from tier 2 to 5.

on population growth. However, technology diffusion and economic growth are factors that can affect WTP, income and ability to pay. These factors are demand drivers which are not within the model boundary. It is thus likely that higher demand (than predicted in the model) could improve the cost per unit investment and location attractivity factors. Nevertheless, the spatial results show demand increases lead to the reallocation of investment rather than an increase in investment. Investment in 45% of locations increase, while investment in 46% of locations decrease, with no change in the remaining locations. The observed increase is likely due to the improvement in attractivity of locations driven by significant stress levels (low supply demand ratio). This result suggests that not all locations are likely to benefit from the scenario. Therefore, combining actions and targeting specific locations could improve the investment outcome.

Finally, scenario 6 (S6) depicts the current practice of issuing capital grants - performance-based grants (PBG) to DRE projects by the government. The results showed a marginal improvement in electricity access (up to 5%) to 20% and 45% by 2030 and 2040 respectively. The increase primarily stems from non-concessional investors. The result suggests that channelling PBG to non-concessional investors may further incentivise the investor group.

5.4.2.2 Spatial assessment of electricity access

Next, the impact of the scenarios on the spatial allocation of investment is analysed. Figure 5-18 shows each location's electricity access by 2030 and 2040. The results indicate S3 is the most impactful, achieving over 90% electricity access in 18% and 82% of the modelled locations by 2030 and 2040 respectively, followed by S1, which attains over 90% access in 0% and 31% of locations in the same period. Finally, S2 achieves 90% access in only 2% of locations in 2040. Whilst none of the locations achieves 100% electricity access in the scenarios, S1 and S3 achieve over 95% in 5% and 45% of modelled locations respectively in 2040. The observed improvements in S1 and S3 results suggest two interpretations. First, the result aligns with the view in the literature (56) that many locations are economically viable investment options. However, this study finds that the economic viability and subsequent investment decisions depends on the

investor's attributes and goals. Therefore, despite being economically viable, some locations may not attract investment in the scenarios. Second, the investor attributes and inherent location risks that drive investors' risk perception could impede investment. Consequently, if risk perception is improved, further investment could be unlocked with limited interventions. However, the low overall electricity access level impact of discount rate reduction in S2 suggests that cheaper capital without improved risk aversion could still limit deployment of the capital at scale towards achieving electrification targets.

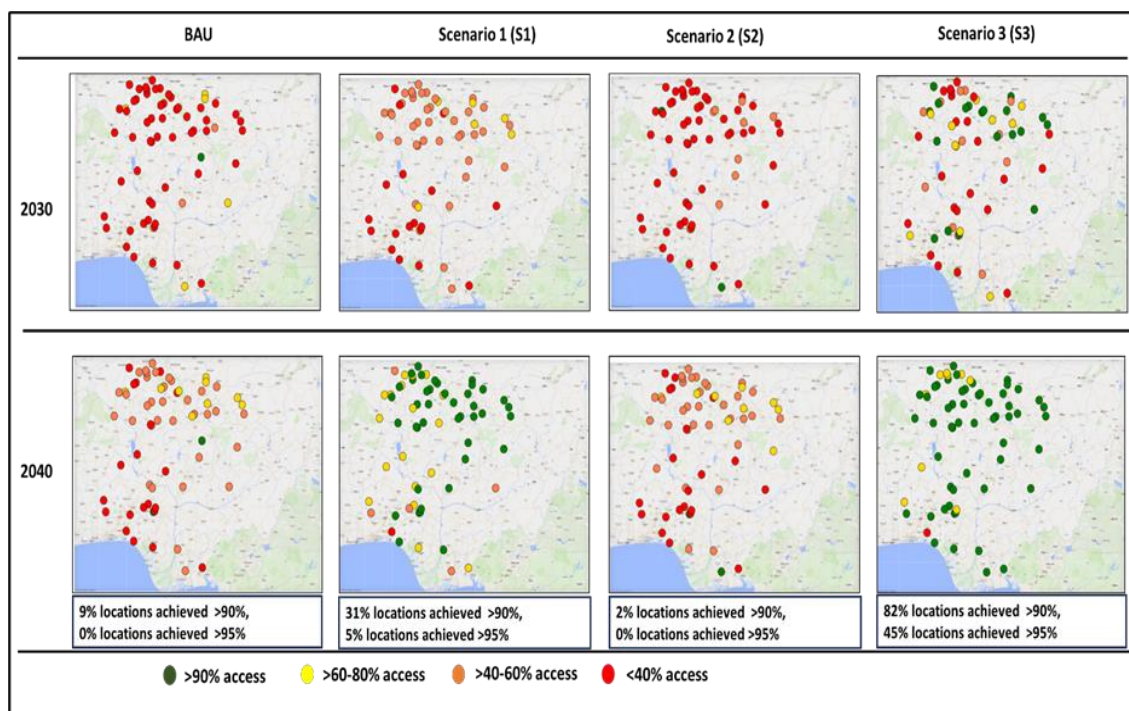


Figure 5-18 Impact of mitigations on spatial electricity access

Furthermore, an application of the model is to enable investors to identify the most viable risk-adjusted locations and investment timing, taking into consideration the location and the investor's attributes as well as attributes of other modelled investors. This feature could enable further insights into the 'investment readiness' of projects — a critical barrier to investment in RE projects as identified in the literature (76,147). It can also aid investors in narrowing down the number of locations that suit their profiles for further detailed onsite feasibility assessment. Figure 5-19 illustrates this application, showing the 2026 investment capacity additions made by the investor types in each location for S3.

Investors make decisions in the locations that offer the highest EU and met the WTP, IRR and payback requirements; as such, investment patterns vary for different investors. For example, while up to eight investor types invest in some locations, such as location 33, others, such as location 24, attract only one investor type.

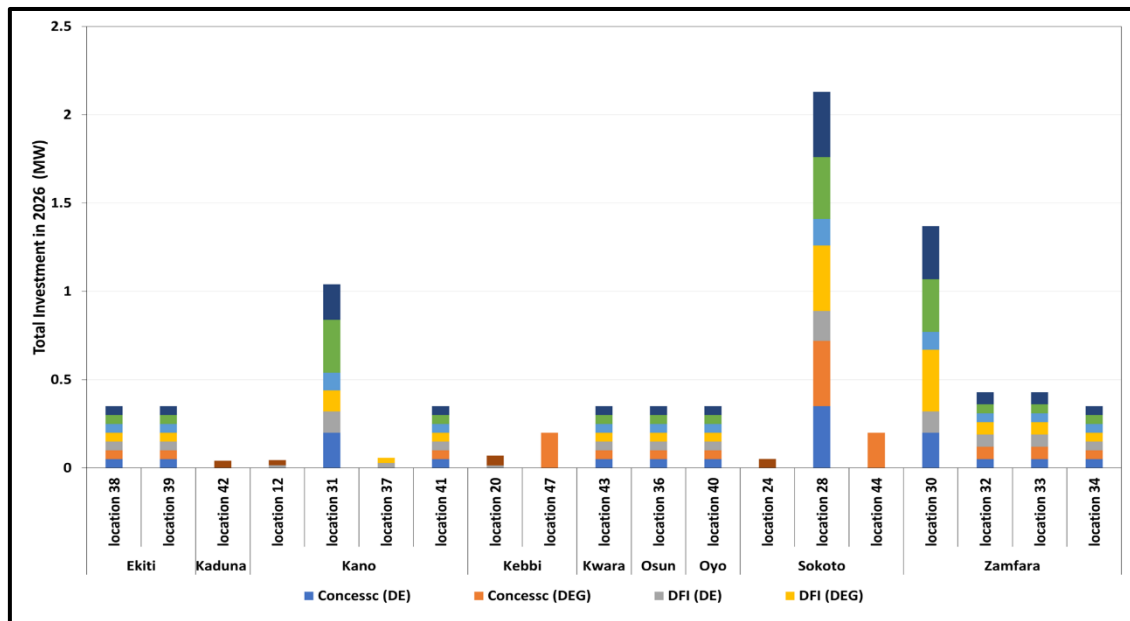


Figure 5-19 Spatial capacity additions in 2026 for scenario 3

Additionally, in Figure 5-20, the equity investors' investment profile pre-2030 in S3 show that the most profitable locations are prioritised for investment in the earlier years. The profile identifies the potential locations the investor could consider for further feasibility studies. Aside from identifying the locations that suit specific investment profiles, the model could aid developers in identifying the financing mix that best suits a location. These model capabilities thus narrow down areas of consideration for investors and enable policymakers to channel public funds to locations requiring additional interventions.

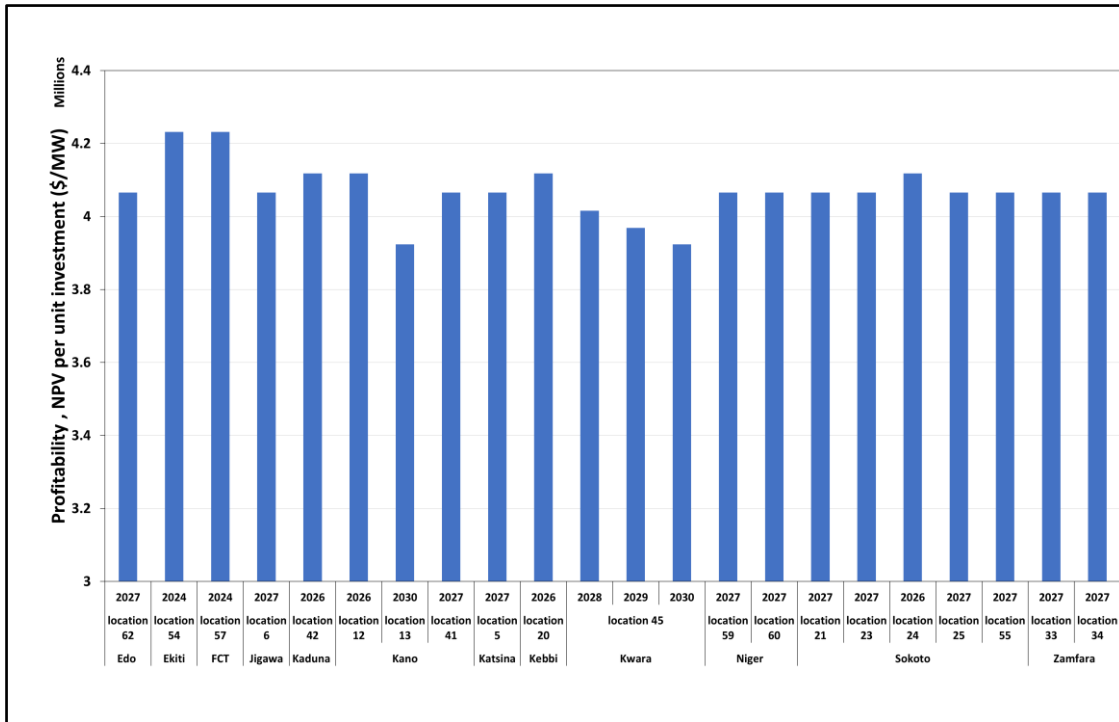


Figure 5-20 Equity investors' investment profile for 2024–2030 in scenario 3

5.4.3 Implications of findings for decision-makers

The results highlight the significance of concessional debt and grants in attaining electrification targets. In all the modelled scenarios, at least 34% of total capacity additions were funded by concessional debt and grants. The results agree with the call in the literature (76,102,147) for increased access to lower-cost financing, such as concessional capital and grants, as a risk mitigation measure. Furthermore, the results suggest policymakers should prioritise the seeking of concessional funds to boost investment. Increased concessional funding achieve two outcomes: (i) enhancement of the electricity access level and sustaining investment post-2030 and (ii) enabling affordability of electricity tariffs.

Moreover, the results suggest that the reinforcement of concessional funding will be needed to meet targets. This outcome is exemplified in the result, where overall electricity access improves by 91% when funding capacity of the BAU case is doubled (in S1) — an increase that is attributed to concessional investors. In contrast, non-concessional investors are not incentivised to invest. Given the scale of funding required (up to USD\$35 billion for solar mini-grids in Nigeria

(132)) and other competing development needs, the financing gap could remain when funding reliance is primarily on concessional investment such as impact funding, DFI concessions, and public grants. Thus, this study highlights the need to complement concessional funding with other private capital sources, such as debt from domestic financing institutions and private equity investment. Domestic funding additionally mitigates currency risks, identified as a key risk for investors (5,147). However, enabling non-concessional funding requires policies that improve liquidity (147,177) and investor risks through reduced risk aversion and discount rates via risk premium reduction.

Another impactful mitigation in improving electricity access, and investment was S3 while S2 was less impactful. Table 5-4 compares the likely effectiveness of the evaluated mitigations with the BAU case on the SDG and ETP indicators, electricity access and investment capacity. The results in S2 show that a reduction in discount rates favours investors by boosting their profits. However, there is minimal impact on the overall investment capacity additions. This aligns with the findings of (14,36), which showed that discount rate reduction had a negligible impact on the penetration of mini-grids and standalone systems. However, actions influencing risk attitude could have far-reaching implications in encouraging non-concessional investment. In S3, changing the DomFI investor's risk aversion from high to medium improves electricity access by 116% in 2040. Not only did DomFI invest, but other investors also increase investments through peer effects — whereby an investor is influenced by the decision of another. The influence of one investor's decision on other investors' actions has also been reported in (37). This result highlights the need for collaborative engagement between policymakers and investors in co-identifying mitigation actions that can influence investor risk attitudes. Such actions include the implementation of RE mandates for local banks (S3), knowledge dissemination on DRE performance, and improvements in policy implementation such as access to foreign exchange and its repatriation, off taker guarantees to protect against revenue risks and consistent implementation of custom exceptions. A further risk mitigation action that could boost investment is the aggregation of projects. In the BAU case, larger capacity projects show higher utility than smaller capacities. This is because of

the model assumption of price elasticity and lower unit development costs with increase in capacity. The impact of positive aggregation has been extensively demonstrated in the literature (28,76,147). Periodically, the government, via the REA, conducts auctions of grants for projects identified through least-cost analysis (203). Identifying and incentivising larger capacity and aggregated investment could thus prove a ‘win-win’ for policymakers and investors.

Table 5-4 A summary comparison of the potential effectiveness of mitigations on electricity accessibility and investment

Mitigation category	Mitigation action	Improvement from BAU case			
		Overall electricity access 2030	Overall electricity access 2040	Total investment by_2030	Total investment by_ 2040
Funding	Scenario 1 (S1): Increased funding	 74%	 91%	 85%	 88%
	Scenario 2 (S2): Substantial risk (discount rate) reduction	 5%	 2%	 3%	 2%
Policy	Scenario 3 (S3): Priority sector lending mandate for RE for local banks	 121%	 116%	 132%	 99%
	Scenario 4 (S4): Carbon Mechanism CDM_high	 5%	 0%	 4%	 1%
	*Scenario 5 (S5): Demand increase to Tier 4	 -63%	 -63%	 -1%	 0%
Incentive	Scenario 6 (S6): Performance based grants (PBG)	 5%	 5%	 5%	 3%

The results additionally indicate that although concessional investors provided the critical funding to catalyse investment, on the other hand they limited investment from other investor types by making investment choices in locations that would otherwise be attractive to other investors with intervention. This implication renders incentives such as PBG (S6) inessential for concessional

investors and ineffective in significantly boosting non-concessional investment. As concessional capital is a form of risk mitigation (5), concessional investor types are likely to outcompete other investor types. Investor-specific interventions could therefore level the playing field and enhance the investment value proposition for non-concessional investors. Thus, government should be selective in applying incentives that may favour concessional investors and crowd out non-concessional investor types.

Furthermore, the model can be a helpful tool for decision-makers in developing planning actions in respect of the achievement of targets in several ways. First, the model results established locations that can attract investment in a BAU case. By identifying locations requiring minimal interventions, policymakers can provide investors with a representation of 'investment-ready' projects and provide technical or financial support to locations offering lower EU to investors. This could minimise social costs and direct intervention to relevant locations. Second, policymakers can apply the model to test the likely impact of different intervention actions prior to implementation. While it is not claimed that the model can predict investment outcomes with certainty, it can indicate the potential input conditions for the actions. It can additionally provide a basis for comparison of the impact of various actions and identify trade-offs. Third, as the mini-grid regulation allows investors to charge cost-reflective electricity tariffs and as tariffs can vary by location and investor, the model can give regulators an indicative and dynamic reflection of minimum tariffs considering the location and investor attributes. Finally, as the model incorporates investment risk priorities for investors, revenue collection rates, exchange rate extrapolations, and willingness to pay, investment decisions account for high priority investment risk factors. Thus, the model can be applied to narrow down risk-adjusted locations that suit an investor's profile for further detailed onsite assessment.

5.5 Conclusions

DRE technologies such as solar mini-grids have been identified as key enablers to achieving SDG7 and ET transition goals in Nigeria. Since 2001, reforms in Nigeria's electricity sector policy landscape have led to its evolution towards the

deployment of RE. The political will to implement these reforms, along with technical and financial concessional facilities and grants from the government, DFIs, and development agencies, has contributed to the increase in the adoption of solar mini-grids. However, investment in mini-grids and other DRE technologies is not at the scale required to achieve the target of 90% and universal electricity access by 2030 and 2040, respectively. To improve electricity access in Nigeria and other SSA countries, effective actions are needed to address investor risk and increase investment decisions.

Previous DRE studies primarily employ least-cost considerations and location attributes to evaluate the economic feasibility of DRE in specific locations (57,225). However, these studies lack details regarding the types of investors, the locations, or the conditions under which investment decisions may occur. As such, there is limited quantification of the effectiveness of mitigation actions on spatial and temporal investment decisions of different investor types and how subsequent influence of these decisions on electricity access (23,41,187,194,227). These analyses could better inform policymaking and investor decision-making.

This study employs the SD-ABM model developed in Chapter 4 to evaluate the impact of six mitigation actions on the spatial investment capacity additions, electricity access levels, electricity tariff, and investor profit for a base (BAU) case comprising 65 potential solar mini-grid locations in Nigeria. The mitigation scenarios include S1: doubling base case funding, S2: risk reduction resulting in an average 24% discount rate reduction, S3: PSL mandate (reduced risk aversion), S4: leveraging carbon markets, S5: demand stimulation, and S6: wider scale implementation of PBG.

The results of the study indicate that electricity access targets are not being met in the BAU scenario, where only 9% of the modelled locations achieve 90% electricity access. This suggests that while previous studies show the locations are economically viable, only a few may attract the necessary investment when heterogeneity, risks and system interactions and feedback are considered. Furthermore, none of the modelled scenarios achieve the electricity access

targets, emphasising the importance of a combination of actions. The most impactful mitigation is S3, the implementation of priority sector lending mandates by domestic finance institution such as local banks, which achieves 90% electricity access in 82% of the modelled locations. The second most impactful is the increase in availability of capital funding, S1, which achieves 90% electricity access in 31% of the modelled locations in 2040. Although S2 only marginally improves overall electricity access compared to the BAU case, it offers the highest investor profits.

Moreover, the analysis shows that 34–98% of investment comes from concessional investors, highlighting the significant role of concessional capital and grants in achieving electrification targets. These findings are relevant for policymakers in Nigeria and other similar countries, where DRE is seen as a solution to achieve universal electricity access. To attain access targets in such locations, continued and increased concessional investment is essential. However, given the limited public funds, it is necessary to encourage non-concessional investment through actions such as priority sector lending mandates, which have been effective in countries like India and Bangladesh. Another finding from the model is the impact of project aggregation can have in boosting investment as demonstrated in the literature (28,76,147). This study recommends policy that enables aggregation through grants incentivising larger capacity and aggregated investment such as grant auctions specifically for aggregate projects. Furthermore, targeted incentives for non-concessional investors could improve the impact of concessional investment by focusing on locations that may not meet expected utilities of non-concessional investor types. Additionally, the study highlights the need to consider the potential side-effects on electricity tariffs and consequently affordability for the consumer in encouraging more non-concessional investment.

This study has some limitations. Firstly, the results of this study are specific to the investor and location attributes employed in the model. The investor profiles used in the model could vary in goals and attributes, leading to different outcomes for electrification. Nevertheless, this study utilises profiles representative of the DRE

sector in Nigeria. Additionally, the model can be updated to incorporate other investor profiles. Secondly, this study was implemented for 65 locations due to the availability of data and limitations in model processing durations. Future research could expand the focus to include additional locations. Thirdly, assumptions were made regarding some location attributes due to data limitations. For instance, the ability to pay was determined by poverty levels, while willingness to pay was defined by the cost of alternative electricity sources in the modelled locations. This data was only available at the state level. A higher resolution of this data could enable improved parametrisation of these factors. Lastly, uncertainties have not been considered in the model. For example, future exchange rates, fuel costs, technology costs, and population were extrapolated based on historical data and may present a source of uncertainty. A future version of the model could incorporate these uncertainties using methods such as Monte Carlo analysis, which could enhance the model's robustness.

While this study focused on testing the implications of policy scenarios on 65 locations in Nigeria, the methodological contribution is applicable for similar countries or other technology contexts if the parameters — technology data, risk priorities, investor, and location attributes — are available. Future research could test the implications of other mitigation actions in Nigeria and for other country contexts. Overall, this study finds that the ambitious SDG and ETP objectives can be achieved if investment is channelled into DRE and supported by appropriate mitigation actions.

6 Overall discussion

This chapter presents a reminder of the aim of the thesis followed by a general discussion of the thesis findings, linking the outcomes from all the chapters. It additionally highlights wider implications of the thesis for policymakers, investors, and researchers.

6.1 Reminder of the thesis aim

Improving electricity accessibility through DRE implementation, especially in developing countries, requires a scale-up in private investment (17). However, this endeavour is impeded by the high investor risk perception (18–20). This risk perception of DRE investors is shaped by interdependent and multidimensional risk factors which can ultimately impact returns and influence investment decisions (23). A comprehensive understanding of these multidimensional risk and system interactions from the perspectives of different investors, is crucial for identifying high-priority risks and developing effective mitigation strategies.

However, DRE risk management literature is fragmented and lacks consideration of the multidimensions of risks and system interactions leading to investment decisions (23). This gap underscores the need for a holistic and structured approach to risk management in DRE projects. Consequently, this limitation serves as a key motivation for the overall aim of the thesis — to develop, validate, and implement a holistic risk management framework that incorporates an investment decision model to evaluate the impact of risk mitigation actions on improvements in DRE investment and electricity access in a spatial context.

6.2 General discussions and implications of the work

In Chapter 2, the literature on RE risks was critically assessed to inform the development of a holistic risk management framework. This Chapter examined the methods used for identifying, evaluating, and mitigating RE investment risks in developed and developing countries, including those in SSA. It was found that the majority of the SSA risk literature is treated in a fragmented manner and utilised qualitative methods for risk identification and mitigation, while quantitative

methods were used in other developing countries such as China (23). The work in this Chapter emphasises the need for the application of quantitative methods that consider location-specific risks and complexity to identify potential risk mitigations in SSA countries. The critical assessment and synthesis of the literature resulted in the development of a 'holistic multi-dimensional investor risk management framework'. This framework constitutes an important contribution of this thesis, providing a structure not only for identifying and evaluating investor risk priorities but also quantifying the likely effectiveness of mitigation measures whilst considering complex system interactions. Existing RM frameworks (83,84) do not consider mitigation evaluation and complex system interactions. The framework is applied to the developing country context of SSA to identify suitable methods to evaluate risks and analyse the potential effectiveness of specific mitigation actions towards the improving investment and electricity access in a structured manner **(objective 1)**. This framework is also adaptable to DRE in other countries.

By implementing the proposed framework in Chapter 3, this study addresses the dearth of empirical data concerning the evaluation of risk priorities among distinct investor groups—specifically, developers, domestic finance institutions (DomFI), development finance institutions (DFI), and impact investors **(objective 2)**. Thus, enhancing previous RE literature in developed and developing countries which predominantly focused on reviewing or evaluating risks from singular (1,31,58) or maximum of two (32) investors' perspectives.

In addition to recognising investor specificity, this study acknowledges the location specificity of DRE risks and employs a case study of Nigeria to illustrate the SSA context. The multidimensional evaluation of investment risks using online survey (N=70), and AHP technique, supported by interviews (N=21) and focus groups (N=3) facilitated the identification and evaluation of 40 risk factors across six categories, thirteen of which had not been previously identified in published literature for Nigeria. For instance, revenue risk and foreign exchange volatility, which were among the highest priority risk factors, were not identified in previous Nigeria related literature.

Contrary to previous studies (25,26,143,144) that underscored the significance of technical and SE risk factors for Nigeria such as limitations in quality control and manufacturing capacity, limited training and technical skills, inadequate infrastructure, and low adoption, our findings suggest that these factors may have become less significant to investors over time. This shift could be attributed to interventions such as capital and technical grants, concessional financing, the implementation of enabling regulations such as the mini-grid regulations, and increased awareness and adoption of solar PV technology. These factors, along with enhanced local developer experience through project implementation over the years, may have contributed to the diminishing importance of technical risk factors. Moreover, the previous studies (25,26,143,144) lacked empirical data from the diverse range of investors considered in this study.

This study finds that there were distinct variations in the prioritisation of risk factors among investors groups, necessitating tailored de-risking actions depending on their profiles. Consequently, the work in this Chapter established a normalised risk prioritisation index in identifying the most prevalent and significant (referred to as high priority) risk factors among investors that require attention. Notably, six of the thirteen risk factors emerged as mutually high priority for all investor groups. Overall, the mutual high priority risk factors that require attention encompassed revenue risks (E1), insecurity (SE5), FX volatility, repatriation, and accessibility (E3, F6), access to financing, financial capacity, and experience related risk factors (F2, F3, F1, F4, F5), and inadequate policy implementation (P4). Collectively, these factors accounted for 37%—58% of the risk weightings, depending on the investor group, implying that policies addressing these risks could substantially enhance risk perception and mitigate their impact on costs and returns. Furthermore, the overall results varied with other countries such as Ghana, which found political risks to be the most important risk category (1), compared to economic and financial risks in this study. This outcome confirms the literature (1,28,139) that risks are location-specific and highlights the need for country-specific studies.

The interviews and focus groups provided context to the variations in risk priorities and their drivers. Notably, the DomFI group additionally considers collection loss and technical risk factors, such as limited training, limited developer capacity as high priority. In contrast, most developers perceive collection losses as a low priority because of established design and operational practices. Interviews revealed that the disparity stems from DomFIs' risk perception being influenced by past experiences in the grid sector privatisation, marked by low revenue collection rates and unprofitability. This finding underscores the impact of path dependence on risk perception, suggesting that potential investors might be unaware of the effectiveness of existing risk reduction practices, resulting in a disproportionately elevated perception of risks. There needs to be a shift in risk response, moving beyond improving technical capacity development (25) to improving financiers' understanding of DRE and its successes. Therefore, one of the recommendations of this thesis is the dissemination of benchmark performance data to demonstrate the DRE performance and improve risk perception. This can unlock local financing and inherently mitigate currency related risks which were considered high priority.

Further specific measures for Nigeria context that require policymakers' attention is outlined in Chapter 2 and highlighted. In addressing the inadequate policy implementation (P4), it is recommended that policymakers focus on enhancing consistency in implementing and enforcing existing policies. This can be achieved through the development of institutional capacity and inter-agency cooperation within government. Another crucial measure, aimed at fostering risk sharing to enhance access to financing, address insecurity, and alleviate developer capacity constraints involves the establishment of strategic partnerships and collaborations. These partnerships could be formed among developers, between developers and communities, between developers and distribution companies, and among investors. Mandating such collaborations through renewable purchase obligations (RPO) is suggested, wherein a percentage of electricity from generation or distribution companies must originate from RE sources. Despite the existence of RPO in the regulations (172), its current lack of enforcement diminishes its potential impact. Furthermore, to

enhance local financing from domestic finance institutions, priority sector lending mandates are recommended. Additionally, measures such as leveraging carbon markets, providing incentives such as grants and tax reductions, and stimulating demand are identified to improve revenue, mitigate FX volatility, and enhance access to financing.

The evaluation of the potential effectiveness of these mitigations and their consequent implications for accessibility is an overlooked aspect DRE risk literature (23). Consequently, this thesis considers the DRE planning and decision-making literature. Many DRE system models utilised for planning and decision-making (8,14,36) neglect the interactions and feedback between the risk perspectives of different investor types, their attributes, and location attributes. As a result, these models do not establish spatial investment decisions or quantify the effects of risk mitigation actions on electricity access.

For the first time, in Chapter 4, an integrated SD-ABM has been developed to establish spatial DRE investment decisions for different investor types while considering complex system interactions and feedback (**objective 3**). The model encompasses four primary investor profiles, each with unique attributes (such as risk aversion, financing thresholds and mix, and risk priorities), and geographical locations of population clusters. These clusters are defined by spatially explicit attributes e.g., solar irradiation potential, population size, demand, accessibility (distance to cities), conflict level, alternative fuel cost, and poverty level (which represent willingness to pay (WTP) and affordability). The model improves upon existing least-cost models (8,36) by accounting for heterogeneous investor attributes, risks, dynamic peer effects, and other spatially explicit location factors — specifically, WTP and affordability indicators crucial for revenue considerations. Another attribute representing investor heterogeneity was their diverse risk priorities established in Chapter 3. The AHP risk priority weightings were used to define risk levels and subsequently model changes in risk levels. Additionally, risk factor drivers identified in Chapter 3 and the literature such as inflation, revenue collection rates and exchange rates were incorporated into the model calculations to capture their effects on investment outcomes.

The validation results showed that the model adequately captured the historical trends in total generation capacity resulting from investment decisions over the simulated period. However, the spatial generation capacity was moderately underpredicted, which could be attributed to assumptions on investor characteristics and investment decision timings that could not be verified due to data limitations. A comparison of the base model to an alternative DRE model, which did not account for investor heterogeneity and risk factors, demonstrated the model's capability of better estimating investments. For example, in the alternative model, at the end of the model horizon, 95% of electricity demand was achieved compared to 34% in our model which aligned with the historical value of 32% of demand. The close fit of the validated model's output to historical data highlights the importance of incorporating factors such as investor heterogeneity and risks into planning and decision support models. This is essential to avoid overestimating the potential for investment, thereby preventing unrealistic expectations regarding the achievement of access targets.

Furthermore, the results in Chapter 4 showed the impact of investor risk attributes sensitivities on the temporal and spatial allocation of investment. The findings highlighted investment delays and limited spatial extent of investment at high-risk aversion compared to the low-risk aversion sensitivity case. These spatial differences were not explored in existing studies (8,12); instead, the outcomes of the studies found locations to be either viable (least-cost) or not for specific technologies. Lastly, findings on changes in investor available funding align with the literature (5,176) that increased funding can lead to more widespread investment. Nevertheless, we found that only concessional investors supported by grants were incentivised to invest. The validated model and insights from the sensitivity analysis provided a platform and basis for testing the impact of mitigation scenarios on unelectrified population clusters earmarked for solar mini-grid electrification in Nigeria.

The validated model provided a foundation for establishing spatial and temporal investment decisions by different investors in 65 unelectrified population clusters in a baseline model, spanning the periods 2030 and 2040, representing 90% and

universal electrification targets, respectively. Prior studies employ least-cost considerations and location attributes to assess the economic viability of these locations (57,225). However, the studies do not specify the types of investors, the locations, or the conditions under which investment decisions may occur. For example, the baseline model results revealed that only 9% of the modelled locations identified in previous studies as least-cost achieve 90% access by 2040. This implies that while the modelled locations may be least-cost, this alone does not necessarily attract investment to meet targets under baseline conditions. This highlights the importance of considering the electricity access problem from a more holistic perspective.

Another key insight from the baseline model suggests that aggregating projects in location clusters of proximity could enhance investor expected utility even at relatively lower revenues. This suggests potential tensions between economies of scales and universal electricity accessibility which needs to be balanced. Nevertheless, it is recommended that policies facilitating portfolio aggregation, such as increasing the capacity threshold of interconnected mini-grids (IMGs) and extending the existing RE feed-in tariff (REFiT) to IMGs, should be adopted. This approach not only has the potential to unlock access to diverse financing sources but also facilitates risk mitigation options for DRE projects, such as currency guarantees which are typically accessible to larger-scale projects.

(8,12)(5,176)The results from Chapter 3 on the identification of potential mitigation actions informed the scenarios tested in Chapter 5. In Chapter 5, six mitigation actions were applied to the baseline model to assess their potential effectiveness in influencing spatial investment decisions, ultimately impacting SDG and Nigeria's energy transition plan indicators (**objective 4**). The targets include achieving 90% and universal electricity access by 2030 and 2040, respectively. Compared with previous studies (225) which indicated the modelled locations are economically viable, the baseline (BAU) result shows that only a few locations may lead to potential investment when heterogeneity, risks, system interactions, and feedback are considered.

Among the six evaluated mitigation actions, two were found to be the most impactful in enhancing electricity access, warranting focused attention from policymakers. The first significant mitigation involves increased funding access for DRE, aligning with recommendations in the literature (5). However, the literature lacks a clear definition of the funding source or the spatial impact of this mitigation. Building on identified literature (5,102), this study reveals that increasing funding can enhance investment decisions by up to 60% compared to the baseline in 2040. Notably, the primary contributors to this investment are concessional-type investors supported by grants. Specifically, policymakers are advised to prioritise seeking concessional and low-risk averse investors to enhance electricity access levels. Recognising the constraint of concessional funding in emerging economies (5,76), this study suggests that non-concessional investors, such as those from private equity, domestic, and international finance sectors, should be enabled to fill financing gaps through supportive policies and incentives, such as grants. However, a nuanced approach is essential in applying incentives across all investor types, as results indicate that certain incentives and policies may favour concessional investors and crowd out others. This phenomenon could be attributed to the inability of non-concessional investors to compete with the more affordable capital from concessional sources. Furthermore, considerations should be given to the broader implications of this recommendation for affordability (36) and the sustainability of DRE operations (148). For instance, the results indicate that while selectively incentivising non-concessional investors improves their competitiveness against concessional investor types, the electricity tariff may be higher than when both concessional and non-concessional investors are incentivised.

The second impactful mitigation measure involves reducing the risk aversion of non-concessional investors, particularly domestic finance institutions, through the application of priority sector lending mandates (PSL), capacity building, and knowledge dissemination that showcase benchmarks and performance of DRE projects. The model demonstrates that this mitigation measure is the most spatially impactful, achieving 90% electricity access in 82% of the modelled locations in 2040. Furthermore, through peer effects, a wider range of investor

types is attracted compared to the mitigation measure of increasing funding availability. This approach can effectively leverage domestic capital and diminish the impact of currency-related risks. While recommending the implementation of PSL, which has proven effective in other countries, including India and Bangladesh, the study acknowledges that the policy could lead to market distortion and necessitates controls, such as eligibility criteria. Nevertheless, the impact of such a mandate if not monitored may not be realised. Thus, requiring institutional capacity for policy monitoring and evaluation.

6.2.1 Reflections on the Participatory Approach

This thesis adopted a participatory approach by engaging diverse stakeholders through online surveys, and subsequent interviews and focus groups. This approach enabled the corroboration and refinement of initial findings on risk priorities, providing further insights on risk drivers, and discussing mitigations thus shaping the direction of the research on scenario evaluations. This iterative process highlighted the value of participatory approaches in research, as supported by studies, such as McGookin et al. (50). Through the stakeholder engagements, this study reconciled risk perceptions of diverse stakeholder groups, fostering improved understanding of various perspectives. For instance, the approach revealed that while developers perceived collection losses as a low priority risk factor, the domestic financial institution group ranked it high and required evidence supporting its low priority. This participatory process can enable a transition from subjective risk perceptions to evidence-based and enhanced understanding of risk perspectives among stakeholders.

During the model validation stage, the model's structure and assumptions were shared with stakeholders, demonstrating transparency, and allowing for feedback. For example, the impact of mitigations identified in this study, such as performance-based grants, was tested within the developed model to explore the impact on investment and electricity access. Testing mitigation actions in this context demonstrated the model's practical application and stimulated discussions, reinforcing the significance of the participatory approach. For instance, policymakers appreciated the perspective of recognising interactions

that influence investment which is largely unaccounted for in the commonly applied least cost approach; while an investor wanted to see how the model benchmarked with existing data and its applicability to other regions. Additionally, regulators were interested in extending the model to provide insights on the impact of scenarios on reducing emissions and achieving climate change policy targets.

Although the implementation of the participatory approach to mitigation action scenario analysis was conducted on a limited scale due to its application at an earlier stage of model implementation (model validation stage), our approach underscores the potential for stimulating shared ownership of research outcomes and developing actionable policy recommendations. For policymakers, this research showcases a pathway towards adopting participatory modelling for evidence-based decision-making, whereby policy recommendations are grounded in the understanding of diverse stakeholder perspectives and incorporating system complexities.

6.3 Wider implications of findings for policy and practice

The findings in this study provides a valuable reference to policymakers, investors, and researchers. This research offers a beneficial reference for policymakers, investors, and researchers. Researchers can use the proposed risk management framework as a comprehensive guide for identifying and mitigating risks. However, the applicability of the framework may be limited by the availability and accuracy of location data. Therefore, it is crucial for future implementations to be customised and validated with input from location specific stakeholders to ensure relevance.

This research informs policymakers about the perceived risks from various investors groups and identifies the most significant risks requiring attention. It provides insights into areas where policy improvements can mitigate risks and enhance investment, allowing policymakers to tailor actions to attract the required capital. For example, this research underscores the necessity for capacity building and knowledge dissemination of benchmark DRE performance data for domestic finance institutions. This recommendation focuses on improving the risk

perception of domestic finance institutions, while prior literature (25) emphasised the need to build technical capacity of developers. This research additionally urges collaboration among developers, investors/financiers, and communities. These strategic partnerships can unlock opportunities for small-scale DRE projects.

While the empirical data derived from investor risk perceptions provide valuable insights for identifying risk mitigation actions, the use of purposive and snowball sampling for interviews, surveys, and focus groups introduces some limitations. This sampling method, while beneficial for targeting specific groups of interest, may not fully represent the diversity within the broader investor community, potentially biasing the findings. To mitigate this limitation, future policy recommendations should ensure broader consultation with a wider array of investors beyond the initial purposive sample. Continuous engagement and validation of these insights with a more extensive and varied investor base would enhance the generalisability and applicability of the findings. Additionally, expanding the sample size or implementing a stratified sampling method in future research could also help in capturing a more representative view of investor risk perceptions across the DRE sector.

The SD-ABM model can aid decision-making by offering insights into the spatial implications of various mitigation actions on investment decisions and electricity accessibility. It can offer insights into spatially differentiated policies needed to boost investment while aligning with investor criteria and consumer willingness to pay. By determining locations requiring minimal interventions for different investor types, the model can help direct public interventions to relevant areas, minimising costs. Furthermore, developers could benefit from optimising project decisions during the project identification stage based on their profiles. This outcome can significantly impact the decision on where to invest and the size of the investment from among several potential locations, ultimately reducing project development costs.

These model capabilities are particularly relevant following the implementation of the 2023 Electricity Act, which grants States in Nigeria the autonomy to make

laws, issue licences, and establish power markets for electricity generation, transmission, distribution, and supply within their respective areas of jurisdiction (236). The Act encourages decentralisation of electricity and empowers States to develop strategies to meet their respective electricity demands. The developed model offers States a robust framework to assess intervention needs, investor compatibility, and strategy implications for stimulating investment and achieving electrification objectives.

More broadly, the developed model can be adapted to other regions within Nigeria, other SSA countries, and DRE projects in other developing and developed countries. Achieving this adaptability involves establishing risk priorities for different investors in the location of interest and evaluating them. The risks identified in chapters two and three serve as a starting point. Additionally, the model needs to be adapted to each region by updating input parameters, including geographical coordinates and location attributes such as population, solar radiation, poverty level, conflict level, accessibility, demand, etc. The parameters identified in this study are relevant to SSA. Therefore, in adapting the model for other regions, these location attributes should reflect factors relevant to influencing DRE investment in that specific region. Investor attributes specific to the location also need to be parameterised. Furthermore, the model should undergo validation with historical data to establish confidence in the model output.

In adopting the model, users should consider that the deterministic nature of the model may lead to overly precise predictions as it may not fully capture the uncertainties inherent in real-world scenarios such as uncertainties in macro-economic factors and market dynamics. Additionally, the model's effectiveness is contingent upon the resolution of location data and assumptions on investor attributes. The model limitation in input location data resolution could potentially simplify spatial differentiation, leading to less nuanced outcomes for policy and investment decision support. The model's assumptions about investor attributes, while based on empirical data and literature, may not fully capture the variability of actual investor behaviours and preferences. To improve the model's generalisability and robustness, future iterations could incorporate stochasticity

to better represent uncertainties. Additionally, employing higher resolution location data and engaging with a broader range of investors can provide more nuanced insights into investor decisions. These improvements will make the SD-ABM model a more robust tool for policymakers and investors in the DRE sector.

7 Conclusion

This concluding chapter provides the thesis' empirical, methodological and policy contributions to knowledge. Furthermore, the key limitations of this research are identified with the recommendations for future research.

7.1 Contributions to knowledge

The developed framework, its implementation, and model in this thesis provide empirical, methodological, and policy contributions which are addressed in this section and summarised in Table 7-1. This thesis addresses the scant literature on DRE investment risks and the lack of quantitative evaluation of the impact of risk mitigation measures on spatial investment and the achievement of electricity access targets. The thesis further addresses the fragility of policy analysis in energy models (237) by incorporating the behaviour choices resulting in distinctive responses of investors.

7.1.1 Academic contributions

7.1.1.1 Development of a holistic risk management framework

Chapter one (Objective one) contributes to literature by providing a critical synthesis of RE risk management literature to develop a holistic RM framework for DRE projects covering the entire spectrum risk management (23). The distinguishing feature of this framework from existing literature (83,84) lies in its unification of four key considerations that are often treated in a fragmented manner in the literature. These include considering the multi-dimensional perspective of risks (24), the interdependencies of risks and complex interactions (119,120,138), the dynamic nature of risks (72,85,89,112), and holistic approach to risk identification, analysis, evaluation, and mitigation of priority risks in accordance with ISO 31000 (49). This framework can serve as a template for selecting appropriate risk management methods (from risk identification to mitigation) for developing and developed countries. In addition to this methodological contribution, this study contributes to the scant DRE and SSA risk literature by implementing the proposed framework to identify suitable methods for SSA. Furthermore, this chapter builds on previous risk review literatures

(83,84) which review methods from a risk identification or evaluation perspective only. By reviewing methods holistically including risk mitigation, this study serves as a valuable reference to researchers in selecting appropriate methods for risk management studies.

7.1.1.2 Empirical insights on diverse DRE risk perceptions

Objective two, addressed in Chapter two, aimed to evaluate the risk perceptions of investors and stakeholders in Nigeria, and identifying their mitigations. Through a participatory approach, this study contributes by enriching the understanding of investor risk perceptions in Nigeria's DRE sector. Firstly, it reveals empirical data on 13 risk factors previously unreported in the literature as specific to Nigeria (25,26). These risk factors ranked among the high priority risks for investors. Secondly, it enriches the literature by providing a nuanced understanding of the shift in the risk landscape. For example, unlike previous studies (25,26) which found social and technical factors among the prominent risks, this study found economic and finance risks as the high priority risks.

Additionally, by assessing and evaluating risks from a multidimensional and multi-stakeholder perspective, this study presented empirical data on the differences in risk priorities among different investor types (and other stakeholders) alongside the risk drivers and interdependencies. In contrast, the previous risk studies (1,25,58,139) predominantly reviewed risks from single investor perspective. These outputs can be valuable for policy makers, researchers, and investors offering insights into priority risks and potential risk mitigation actions as perceived by the investors.

Table 7-1 Contributions of the thesis objectives

Objective	Chapter	Gaps identified	Contributions
1	2	<p>1.Scant DRE risk management literature, especially in SSA (23).</p> <p>2.Fragmented approach to RE and DRE risk management (23,25,27,143).</p>	<p>Academic Contributions</p> <p>1.Provided a critical review and synthesis of RE investment risks and management methods in both developed and developing countries.</p> <p>2.Developed a ‘holistic multi-dimensional investor risk management framework’.</p> <p>3.The framework is applied to SSA using a participatory approach.</p>
2	3	<p>1. Limited of data on diverse investor perspectives of DRE risks (23,25,27,143).</p> <p>2. Limited quantitative risk evaluation methods deployed for SSA countries (23).</p> <p>3. Fragmented approach to risk management for SSA countries (23,29,89).</p>	<p>Academic Contributions</p> <p>1. Established empirical data contribution from a survey (N=70) of DRE investment risk</p> <ul style="list-style-type: none"> 13 risk factors not previously identified in the risk literature as relevant to Nigeria were established. <p>2. Provided empirical evaluation of risk factor priorities, drivers, and their variations among four investor groups and other stakeholders’ groups.</p> <p>Academic and policy contribution</p> <p>1. Identified risk mitigation measures for the high priority investor risks.</p>

3, 4	4, 5	<ol style="list-style-type: none"> 1. Limitation in existing investment planning and decision models in the quantification of spatial and temporal DRE investment decisions (23). 2. Limitations include: <ul style="list-style-type: none"> • Existing DRE planning and investment decision models for incorporate least-cost considerations (8,12,36); but do not account for heterogeneity, complex interactions and feedback presented by DRE, which can impact the evolution of investment decisions. • Current approaches (35,37–39) for analysing investment decisions in complex systems predominantly represent grid-connected liberalised market structures and present limitations for their application to DRE. 	<p>Academic contribution</p> <ol style="list-style-type: none"> 1. Developed a new integrated SD-ABM to establish spatial DRE investment decisions of different investor types whilst considering complex system interactions and feedback. 2. The key distinguishing features include: <ul style="list-style-type: none"> • capability to explore the spatial and temporal investment by different investor types across various geographical locations. • incorporation of key characteristics of DRE projects such as location attributes, consumer willingness to pay, investor risk attributes, and system interactions and feedback. <p>Policy and practice contribution</p> <ol style="list-style-type: none"> 1. Introduced the SD-ABM model as a decision-making and feasibility tool to support investment decisions particularly in the context of the 2023 Electricity Act. 2. Aligns the model's capabilities with the decentralisation objectives of the 2023 Electricity Act, aiding in state-level policy formulation for DRE investments.
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4	5	Limited quantification of the effectiveness of risk mitigation actions on spatial and temporal investment decisions of different investor types and how these decisions impact electricity access (23,41,187,194,227).	<p>Academic contribution</p> <ol style="list-style-type: none"> 1. Methodologically, implemented the SD-ABM model, and evaluated future spatially explicit investment patterns for 65 modelled locations under a baseline case and for six mitigation actions. 2. Established an evaluation of the potential effectiveness of the mitigation actions on spatial investment patterns and electricity access targets provided basis for policy recommendations. <p>Policy contribution</p> <ol style="list-style-type: none"> 1. Clarified prioritisation of concessional type investors while underscoring need to encourage scale-up of non-concessional type investors. 2. Recommended nuanced investor specific incentive structures while advocating for implanting policy safeguards and incentives to maintain electricity affordability. 3. Recommends the adoption of Priority Sector Lending mandates to stimulate investment from risk-averse non-concessional investors and mitigate risk.
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7.1.1.3 The development and application of a new SD-ABM model

Objective three addressed the insufficient application of quantitative methods for identifying the potential effectiveness of risk mitigation actions on investment decisions and electricity access spatially. This was achieved by developing and validating a decision-support model for DRE which enhances existing methods, by using a spatially explicit SD-ABM approach. The primary contribution is the model's capability to explore the spatial and temporal investment patterns of different investor types across various modelled geographical locations. Furthermore, the model is the first to incorporate key characteristics of DRE projects involving complex interactions and feedback between heterogeneous investors and locations. This unique approach contrasts with other DRE decision and planning models, which primarily focus on location attributes and cost (8,9,14). When complexity was considered in the literature (35,52,238), mainly in centralised grid-connected systems, spatial heterogeneity was not considered. The model can be beneficial to DRE investors, financiers, developers, and researchers and is most applicable at the development or pre-investment stage of project planning.

Finally, Objective four aimed to first, implement the validated model to establish investment outcomes in unelectrified population clusters identified as potential locations for mini-grids and second, analyse the impact of risk mitigation measures on the spatial investment decisions of investor types and electricity access targets. Although existing DRE decision and planning studies use least cost considerations to identify the economic viability and technology mix in locations (41,187,194,227), they do consider the spatial investment decisions of different investors regarding where and under what conditions the investment decisions may occur, ultimately leading to changes in electricity access. The main contributions are the methodology and the insights generated on the extent to which mitigation actions affect investment decisions and electricity access for different locations. By making these implications spatially explicit, the model can be utilised to inform broader discussions on which risk mitigation measures could potentially facilitate the achievement of electricity access targets.

7.1.2 Policy and practitioner contributions

The contributions of this thesis towards policy are relevant to addressing the ambitious targets set by the Nigeria Energy Transition Plan (ETP), which identifies a pressing need for \$35 billion in DRE investments to achieve its 2040 electricity access goals. The investment challenge highlights the critical need for a substantial scale-up in private sector investment. However, the precise sources of investment and the mechanisms to effectively mobilise them remain largely unexplored.

7.1.2.1 Funding source and incentive structures

Traditionally, public funding and concessional investments from development finance and impact investors have dominated DRE investment. This research emphasises the necessity of prioritising concessional investment to leverage its advantages while also diversifying investment sources to adequately scale-up DRE deployment, acknowledging that concessional funds alone will not suffice. The distinction between concessional (characterised by below-market terms to spur development objectives) and non-concessional (market-rate equity and debt such as from risk averse equity investors and domestic finance institutions) investments is crucial for attracting a broader investment base.

This study calls for the creation of nuanced incentive structures tailored to attract non-concessional investments, as the current one-size-fits-all approach has limitations in adequately motivating diverse investor types. Specific, investor-targeted incentives, such as differentiated grants, are proposed to mitigate the risk of non-concessional investments being 'crowded out'. The potential impact of selective incentivisation on the affordability and long-term sustainability of DRE operations requires careful consideration. This thesis recommends exploring mechanisms to balance the competitiveness of non-concessional investors with the need to keep electricity tariffs affordable. This might involve implementing policy safeguards that prevent excessive tariff increases or designing incentives that ensure equitable electricity tariffs across all consumer segments.

7.1.2.2 Advocating for priority sector lending (PSL)

PSL mandates are recommended as a strategy to encourage investment from risk-averse non-concessional domestic finance institutions, drawing on successful applications in other countries like India. Such mandates can mitigate the impact of exchange rate volatility, the most significant DRE risk factor, and significantly expand the investment pool for DRE in Nigeria. To prevent potential market distortions, this thesis advises establishing clear eligibility criteria and building institutional capacities for policy monitoring and evaluation.

7.1.2.3 Leveraging the SD-ABM model for policy development in support of the 2023 Electricity Act

The SD-ABM model serves as a vital tool for policy development, decision-making and assessing feasibility of potential locations. By identifying potential investment locations that align with diverse investor profiles, the model can aid policymakers in detecting regions attractive to non-concessional investors and those necessitating targeted support. The model's capabilities align with the decentralisation objectives of the 2023 Electricity Act, opening new opportunities for state-level policy development. By facilitating an understanding of where and how to effectively stimulate investment, the model can support States in devising tailor-made policies that utilise the Act's provisions to maximise DRE investment and deployment.

7.2 Limitations

The limitations to this research have been identified in the respective chapters and summarised in this section. These provide opportunities for future research which are discussed in section 7.3.

In Chapter 2, online surveys, interviews and focus groups were conducted to establish investor risk priorities. The prioritisation of risks could be influenced by the number of experts involved and their subjective judgement (23,100). The use of purposive sampling, while beneficial for targeting specific groups, may not fully represent the diversity within the broader investor population, potentially biasing the findings. For instance, despite the online survey's response rate of 59%, there

was a disproportionately low representation of some groups, such as the impact investor group. This imbalance might have an influence on the prioritisation of risks, potentially overshadowing perspectives that could differ significantly among the underrepresented groups. Although necessary consistency checks were carried out to ascertain data reliability, a larger sample size, could enhance the generalisability of the study.

Although the framework in Chapter 1 recommends the use of interviews with Delphi method to provide a consensus of findings for risk assessment, Chapter 2 subsequently applied an online survey, AHP and semi-structured interviews and focus groups. This was due to the limited availabilities of participants for multiple rounds of interviews as required in the Delphi method. Nevertheless, the methods employed have been widely used in previous literature. Moreover, the AHP results had consistency ratios below 10% and were validated with the different groups during interviews.

Chapters 2 and 3 recognised risks as dynamic (72). However, the time and event dependencies of some risk priorities were not considered because of data availability. Instead, while the model simulations occurred over time, the risk priorities of investors represented the responses obtained during the survey period. Therefore, the model did not dynamically reflect changes in investor risk priorities. This means that a policy change scenario which could result in a reduced risk priority and consequently lower risk premium, for example, is not reflected in the model, as risk priority remains constant. However, the risk changes in risk priority levels are reflected through sensitivity tests or scenarios. The model can be enhanced by studying the evolution of policy and its resulting impact on risk priority levels and risk premiums. This could better improve the evaluation of future policy effectiveness.

The findings in Chapters 4 and 5 are specific to the investor and location attributes employed in the model. This is highlighted as a limitation, as different assumptions about investor attributes and goals could lead to varied investment and electrification outcomes. Although this study utilised investor profiles representative of the DRE sector in Nigeria based on executed projects, certain

attributes, such as risk aversion, were assumed. The model sensitivity analysis in Chapter 4 showed that investment and electricity access were highly sensitive to risk aversion. Therefore, further exploration and quantification of investor attributes could improve the model outcomes. Additionally, incorporation of stochasticity and uncertainties inherent in real-world scenarios can improve the robustness of the model.

Furthermore, assumptions regarding location attributes were necessitated by data limitations. For example, poverty levels served as a proxy for the ability to pay, and consumer willingness to pay was determined by the cost of alternative electricity sources in the modelled locations, mirroring approaches found in prior literature. Nevertheless, the available data for poverty levels and the cost of alternative electricity was only accessible at the state level rather than for each specific location. A higher resolution of this data would enhance the parameterisation of these factors.

7.3 Recommendations for future research

Listed below are key areas for future research to enhance the model and its application.

Expand application of the model to other technologies, investor profiles, and geographic regions.

- The SD-ABM model was implemented for 65 locations identified as potential locations for solar mini-grid electrification (225). Additional locations mentioned in the literature were not modelled because of limitations in location data and model processing time. If these two limitations can be overcome, future research could expand the number of geographical locations.
- Additionally, future research could enhance the model's capability as a location model. The model developed in this study is applicable to other technologies and the broader SSA region, if the necessary parameters, such as technology data, risks, investors, and location attributes, are available.

- Alternatively, the SD-ABM model could be integrated with other location models such as the open-source spatial electrification tool (OnSSET) (180), which incorporates GIS approach, to establish a robust decision and planning tool.
- This thesis focused on testing the implications of selected mitigation scenarios on 65 locations in Nigeria. The methodological application is extendable to other similar countries and scenarios. Therefore, future research could test the implications of other policy actions in Nigeria, especially for net-zero goals alongside electricity access, and for other country contexts.

Explicit consumer representation in the model

- In modelling investment decisions, poverty levels and alternative cost of fuel were used as proxies to consumer affordability and WTP. The model has the potential to incorporate different consumer categories as agents characterised by different demand levels, affordability, and willingness to pay. This enhancement could improve the accuracy of revenue projections and the spatial model outcomes. Additionally, such a model could be adapted to explore consumer adoption and energy-use behaviours.

Incorporate uncertainty modelling.

- The model could be improved by incorporating stochasticity and uncertainties in exogenous parameters, including future exchange rates, fuel costs, technology costs, and uncertainties related to population growth and demand, which were not considered in the current version of the model. Subsequent iterations of the model could analyse the impact of these uncertainties on the outcomes using methods such as Monte Carlo analysis to enhance its robustness.

In conclusion, the attainment of the ambitious SDG7 target is feasible, contingent upon the strategic selection of effective mitigation measures that specifically target investors, fostering increased investment. This study emphasises the high impact and significance of investors offering concessional capital and grants to propel advancements in universal electricity access. Notably, these investors

tend to be international investors who prioritise addressing economic and financial risks, necessitating targeted mitigation efforts. Concurrently, governmental decision-makers should actively pursue local investors and financiers. To facilitate this, there is a need to enhance the institutional capacity of domestic finance institutions, particularly in addressing technical risk perception and economic risks. The framework and model developed in this study serves as a valuable tool for assessing the potential impact of proposed policies before their adoption, thereby contributing to the progression of electricity accessibility.

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Appendix

Appendix A Ethical approval letter

Data Protection

We take your data privacy very seriously and will only use your information to provide the products and services you have requested from us. We will not sell, license or trade your information without your consent. For more information about how your data will be processed, please see our [privacy policy](#). Where required, we may share your information across the University and with our commercial subsidiaries.

Part 1: Summary Details

Lead Researcher (Applicant)

Title	First Name	Surname
<input type="text" value="Mrs"/>	<input type="text" value="Zara Y Abba"/>	<input type="text" value="Abba"/>
School	<input type="text" value="School of Water, Energy and Environment"/>	
Course code	<input type="text" value="DPENYFRC"/>	
Email	<input type="text" value="Y.Abba@cranfield.ac.uk"/>	

Lead Researcher status

☒ Student ☐ Staff

Please confirm mode of study

- ☒ Full-time
☐ Part-time

Please confirm method of study

- ☐ Taught
☒ Research

Please confirm which project type your application is supporting

- ☒ Thesis
☐ Group Project
☐ Other

Part 6: Declarations and Signatures

Researcher Declaration

- The completed form is accurate to the best of my knowledge and belief.
- I undertake to abide by Cranfield University's [Ethics Policy](#) in undertaking this project.
- I understand that ethical approval for projects, and that the seeking and obtaining of all other necessary approvals and permissions prior to starting the project is my responsibility.
- I understand that I must not begin the research until I have received approval from the Cranfield University Research Ethics System (CURES).
- I understand that any significant changes that I would like to make to this project after receiving approval from CURES, will require a new application to be submitted.

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Researcher Signature

Signed: This form was signed by Mrs Zara Y Abba Abba (Y.Abba@cranfield.ac.uk) on 02/06/2020 5:04 PM

Supervisor Declaration

- I confirm that I have read and fully support this application and will be acting as the supervisor of the lead researcher (student) for this project.
- I have checked that the application has been completed correctly and is of good quality.
- In my opinion, the proposal is viable.
- I understand that the lead researcher I am supervising must not begin the research until they have received approval from the Cranfield University Research Ethics System (CURES).

Lead Supervisor Signature

Signed: This form was signed by Professor Nazmiye Ozkan (n.ozkan@cranfield.ac.uk) on 02/06/2020 5:47 PM

Students must obtain a signature from their supervisor.

Once your supervisor has signed the form, your application will be automatically submitted.

Appendix B Supplementary information on survey, interviews, and risk evaluation

B.1.1 Online survey letter

Dear Sir/Madam,

Thank you for your time today. I am a doctoral researcher inviting you to contribute to important ongoing research into a holistic risk management approach to driving investment decisions in decentralised renewable energy systems in Nigeria.

Data collected from this survey will be used to develop a framework for assessing multi-dimensional risks and their interactions within the decentralised renewable energy systems in Nigeria. The research further aims to draw insights from the framework to identify impactful actions that can influence favourable investment conditions in Nigeria and by extension adapted to other developing countries. This survey is targeted at actors (e.g., investors, developers, public sector institutions/policy makers, financial institutions) in the renewable energy systems (solar mini grids in particular) sector in Nigeria and internationally.

Please note the responses you provide are completely anonymous and confidential.

The research outcome will be in an aggregate format with no reference to any individual and data collected will be subsequently discarded.

The survey consists of 3 parts:

I: Background information about the respondent,

II: Renewable energy investments and projects in Nigeria,

III: Investment risks in decentralised renewable energy systems. The survey is estimated to take about 15-20 minutes to complete. Aggregate results will be shared with you if you fully complete this survey.

To proceed, please read and fill the following consent form. If you would like to receive more information and for any queries about this project, you may contact me, Zara Abba, via email (y.abba@cranfield.ac.uk)

Thank you for your time and I look forward to your insightful contributions.

B.1.2 Participant consent for online survey

Part 1: Consent to participate and note the ability to withdraw.

1. I confirm that I have been informed about this research project and I agree to take part.
2. I understand that all personal information I provide will be treated with confidence and my name will not be used in any report, publication or presentation.
3. The researcher(s) will record data against my participant number instead of recording my name. The file linking my name to my participant number will be accessible only to the main researchers and will be securely destroyed after 30th November 2021.
4. I understand that I can withdraw from this project at any stage by informing a member of the research team, for whom contact details have been provided. I also understand that I can withdraw my data for a period of up to 3 months from today, as after this time it will not be possible to identify my individual data from the aggregated results as explained in point 3.

Part 2: Security of data storage. I understand that the data I provide will be used by Cranfield University for the purpose of research. The data will be stored on the University's network that can only be accessed by authorised users, in line with UK Data Protection Act 2018.

Part 3: Datasets being created and what will happen to each. 1. Recorded questionnaire results will be saved as text files. These files (and any backups) will also be securely deleted as soon as they are no longer required.

2. Analytical software will be used to aggregate the results of the research and every reasonable step will be taken to anonymise the data.

I confirm all statements below: 1. I understand that the aggregated data will be published in support of the research findings. 2. I understand that the final analysis will be published in support of the research findings. 3. I confirm that I have read and understand the information provided on this form and give my consent to taking part in this research.

B.1.3 Online survey questions

Name:

Email:

Organisation:

PART A: General information

1. Which of the following best describes your organisation?
 - a. Developer
 - b. Financial institutions such as development finance institution, commercial bank etc
 - c. Investor – Equity provider
 - d. Investor – Debt provider
 - e. Consulting and other professional services
 - f. Public agency e.g., Regulator, Ministry, legislative
 - g. Other – please state.

2. What is your age range?
 - a. 18 – 25 years
 - b. 26 – 35 years
 - c. 36 – 50 years
 - d. 51 – 60 years
 - e. > 60 years

3. What is your gender?
 - a. Male
 - b. Female
 - c. Prefer not to say.

4. What is the length of your industry experience?
 - a. 0 – 5 years
 - b. 5 – 10 years
 - c. 10 – 15
 - d. 15 - 20
 - e. > 20 years

5. How would you describe your position in your organisation?
 - a. Entry level
 - b. Junior level
 - c. Middle management
 - d. Senior management
 - e. Executive /board member Other (please specify

6. Which of the following best describes your organisation?
- Developer
 - Domestic financial institution e.g. commercial banks, microfinance banks etc
 - International financial institution e.g. commercial banks, microfinance banks etc
 - Private equity firm
 - Development finance institution / Multilateral development bank
 - Impact Investor
 - Consulting and other professional services
 - Public sector institution e.g., Regulator, Ministry, legislature. Please indicate.
 - Other – please specify.

PART B

Private investor risks

Several risks that need to be considered in renewable energy system investments have been identified in literature. These risks can be specific to location and application. In this section, you will be asked to rate the applicability of risk factors grouped into 7 categories in terms of their importance to investments in DRE in Nigeria

- Please identify the applicable system to which you will be ranking risk factors in the next set of investment risk questions.
- Please rate each of the following risk factors in terms of the extent to which they impact on DRE investments in Nigeria (*Please rate from 1- not important to 5-extremely important*)⁶

A	Risk categories	Importance					N/A
		1	2	3	4	5	
a	Technical risk (These are risks that impact on the design and therefore efficiency, cost, longevity, profitability of the project)						

⁶ Note: (1-not important, 2- low importance, 3- moderate importance, 4-high importance, 5-extremely important)

b	Policy/regulatory & political risk These are uncertainties in revenue, cost or development of the project due to changes in legislation, policies or regulations, political events						
c	Financing risk These may arise from barriers in the financial environment e.g., low access to low-cost capital, inability to source local currency funding etc that affect the revenue, cost and sustainability projects						
d	Economic risk (These may arise from changes in economic environment e.g., currency fluctuation, ability to pay etc thereby affecting the sustainability of the project)						
e	Market risk (These may arise from uncertainties brought by variation or limitations in markets such as market access barriers, competition etc.)						
f	Social, Environmental risk (These may arise due to changes in social conditions and potential impact on the environment)						

3. Please rate each of the following risk factors in terms of the extent to which they impact on DRE investments in Nigeria (*Please rate from 1- not important to 5-extremely important*)

A	Technical risk factors	Importance					
		1	2	3	4	5	NA
a	Limitation in training, research and development capacity.						
b	Low availability of technical skills during construction, operations and maintenance phases.						

c	Limitation in developer's capability to effectively execute projects.						
d	Limitation in the quality control of hardware and manufacturing capacity.						
e	Uncertain load profile due to variability in demand, uncertainties in population distribution patterns etc.						
f	Inadequate infrastructure and collection systems e.g., roads, mobile payment technologies.						
g	Site characteristics such as gradient, resource variability						
h	Other, please specify						

B	Social and Environmental risk factors	Importance					
		1	2	3	4	5	NA
a	Lack of social acceptance or resistance to change.						
b	Poor consumer awareness on renewable energy benefits						
c	Lack of integration of renewable energy systems to support development of host communities						
d	Difficulty in acquiring land/ competition with land uses						
e	Insecurity						
f	Other- Please specify						

C	Market risk factors	Importance					
		1	2	3	4	5	NA
a	Sensitivity of competitiveness of renewable energy to prices of traditional fossil sources.						
b	Low competitiveness of renewable energy due to subsidies on alternatives e.g., grid electricity						
c	Market access barriers - lack of competitive hardware and labour market						
d	Poor market and consumer data availability						

e	Market access barriers - regulations e.g., taxes, tariffs						
f	Uncertain market growth potential						
g	Other- Please specify						

D	Financing risk factors	Importance					
		1	2	3	4	5	NA
a	High initial investment cost						
b	Inadequate access to low-cost capital						
c	Mismatch between short loan terms and long project lifecycle						
d	Limited local financial sector experience in renewable energy						
e	Limited financial capacity and experience of developers/ local investors in renewable energy						
f	Difficulty in accessing foreign exchange and repatriation of funds to foreign investors						
g	Other- Please specify.						

D	Economic risk factors	Importance					
		1	2	3	4	5	NA
a	Revenue uncertainty due to low affordability, demand variability, lack of willingness to pay etc						
E	Collection losses due to line tampering, theft, non-payments.						
c	Foreign exchange volatility leading to cost-revenue mismatch.						
d	Inability to achieve single off-taker or cluster effect for off-takers to diversify and achieve scale						
e	Inability to charge cost-reflective tariff						
f	Other- Please specify.						

E	Political risk factors	Importance
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		1	2	3	4	5	NA
a	Effect of political changes or political instability						
b	Inadequate political will to diversify into renewable energy.						
c	Political events that adversely impact the value of investments (e.g., war, civil disturbance, currency inconvertibility, breach of contract, non-honouring of obligations)						
d	Other- Please specify						

F	Policy/regulatory risk factors	Importance					
		1	2	3	4	5	NA
a	Insufficient or undefined policy/legal frameworks to support investments e.g. tax incentives, efficient processing of permits, licences & approvals, strong regulator, competing incentives.						
b	Unclear regulations with inadequate guidelines)						
c	Retroactive policy changes						
d	Poor/ lack of policy implementation						
e	Duplicative policy development through institutions with overlapping responsibilities						
f	Inconsistent policy application						
g	Uncertainty in implementation of regulations for interconnection of mini grids into main grid						
h	Uncertainty in grid extension plans						
i	Other- Please specify						

PART C: Background information on DRE projects you have been involved in (applicable to DRE in Nigeria)

- What is the typical project funding structure? Please provide % split.
 - Equity ____
 - Debt : ____
 - Grant : ____
- What currency is your organisation typically able to invest in? Please tick all that apply.
 - NGN

- b. USD
- c. EUR
- d. Other

3. Could you please provide any additional information on your response **above related to ability and preference to invest in local currency.**

4. What kind of off grid projects have you been involved in? Please tick all that apply.

	Up to 200kw	>200kw-1MW	>1MW	Rural	Commercial/residential - Urban	Industrial
Mini grids – hybrid solar-diesel						
Mini grids – solar with/without battery						
Interconnected mini grid						
Other, please specify						

The following questions are for debt instrument providing investors.

- 7. What is the minimum ticket size or funding amount for debts you provide?
- 8. What is the maximum debt or gearing (in terms of %) that can be acceptable to you as an investor?
- 9. What is the average loan tenor for funding extended to projects?
- 10. Please provide the following information regarding loan pricing for funding projects in USD/EUR/NGN as applicable
- 11. Please provide the following information regarding loan pricing for funding projects in USD/EUR/NGN as applicable

The following questions are for equity investors.

12.What is the typical minimum ticket size or funding amount for equity you provide?

13.Please indicate your typical minimum or preferred ownership %.

- a.** Minority (up to 25%)
- b.** Significant minority (25%-49%)
- c.** Joint venture (50%)
- d.** Majority (>51%)
- e.** Not applicable

14.What is the typical minimum expected internal rate of return (% IRR) for equity investments?

The following questions are for investors providing grants or technical advisory.

15.Please indicate the nature of the grant or technical advisory facility.

- a.** Repayable
- b.** Not repayable
- c.** Please state further details if any

16.Please specify the maximum grant amount available

The following questions are for project developers.

17.Please state the minimum requirements for project development investment

18.Please indicate return expectation for project development funding as a multiple of initial investment

Thank you for your time today and contributions to this study which aims to identify impactful actions that can influence favourable renewable energy investment conditions in Nigeria and by extension adapted to other developing countries.

If you would like to receive more information and for any queries about this project, you may contact Zara Abba, via email (y.abba@cranfield.ac.uk).

Please respond to the following question before finishing the survey.

Would you be open to participate in a follow-up interview on this topic?

Yes, contact me via email provided in earlier part of this survey

Yes, contact me via this email , **No**

B.1.4 Risk categories and risk factors

Table 1 Risk factor definitions and a comparison of risk factors in this study with previous studies. Adapted from (8)

	Risk Factor	Definition	Risk identified for Nigeria in literature	Risk identified in this study	Reference
Economic risks					
E1	Revenue risk	Results from default by off-taker, unwillingness to pay, low affordability, seasonal income etc		x	(22,28,29,32, 74,89)
E2	Collection losses	This could be a result of technical, financial, and behavioural factors that lead to non-revenue-generating consumption.		x	(22)
E3	Foreign exchange (FX) volatility	FX volatility results in a mismatch between revenues denominated in local currency and hard currency-denominated obligations		x	(28,29,76,89, 97,98,136)
E4	Inability to achieve single off-taker or cluster effect	Limited creditworthy off-takers impacting project viability and revenues		x	(22)
E5	Non-cost reflective tariff	Unattractive regulated tariff	•	•	(22,25,62,85)
Finance risk					
F1	High cost	High initial cost, unaffordable tariff	•	•	(25,74,94–96,98)

F2	Inadequate access to low-cost capital	limited access to affordable finance due to factors like liquidity constraints, experience, high-interest rate	•	•	(22,26,32,74,76,96,102,138)
F3	Short loan terms	A mismatch between short loan tenors and project lifetime.			
F4	Limited local financial sector experience	Limited experience in the financial sector	•	•	(74,76,94,95)
F5	Limited financial capacity and experience of developers/ local investors	Limited financial capacity and execution capabilities of developers. Domestic investors' lack of familiarity with RE	•	•	(74,76,94,95)
F6	Difficulty accessing/repatriating Forex	1. Inability to convert local currency into hard currency due to Government action or inaction 2. restrictions to repatriate funds add uncertainty to investors		x	(96,97)
Policy and Political risks					
P1	Insufficient policy/legal support framework	Insufficient supporting policy frameworks and incentives. Complex Institutional structures with overlapping responsibilities	•	•	(25–27,85,94,95,138,239)
P2	Unclear regulations/guidelines	Impact of unclear guidelines	•	•	(26)
P3	policy changes	Legislative changes/ retroactive change in policy	•	•	(26,29,78,90,138)

P4	lack of policy implementation	Policy and regulatory uncertainty due to non-implementation of existing policy	•	•	(22,26,74,77)
P5	Duplicative policy development	Impact of duplicative policies and institutions		x	
P6	Inconsistent policy application	Policy and regulatory uncertainty due to inconsistent policy application	•	•	(22,26,74,77, 90,96)
P7	uncertainties in IMG regulations implementation	Uncertainties in mini-grid regulations for IMG		x	(77)
P8	Grid extension uncertainty	Uncertainty in grid extension plans and technical regulations for integration of mini-grids into the main grid	•	•	(22,27,28,74, 96)
P9	political changes/instability.	Effect of political changes, e.g., reshuffling of institutions, changes in Government	•	•	(26,27,29,74)
P10	Inadequate political will	Political decision-making and target-setting impacted by political will	•	•	(95,96)
P11	Adverse political events	Political events that adversely impact the value of investment (e.g., war, breach of contract)	•	•	(76,95,97)
Technical risks					
T1	Limited training and R&D	limited training and R&D in RE	•	•	(26)
T2	Technical skills limitation	Limited technical skills and capacity in operations and maintenance	•	•	(22,25,26,28, 62,76,95,239)

T3	Limitation in Developer's capability	limitations in developers' experience in executing projects		x	(28,62)
T4	Limitation in QC & manufacturing capacity	Limitations in the quality control and availability of hardware	•	•	(25,28,95)
T5	Uncertain load profile	Poor understanding of customer needs or usage patterns leading to variability in demand		x	(62,96)
T6	Inadequate infrastructure	lack of supporting infrastructure, and facilities and inadequate access to project locations		x	(96)
T7	Uncertainties in site characteristics	Uncertainties in estimating power potential and its variability	•	•	(25,29,32,76, 94,96,136)
Market risk					
M1	Sensitivity of renewable energy (RE) projects to fossil fuel prices	Sensitivity of competitiveness of RE to changes in prices of conventional energy sources	•	•	(25,89,90,96, 98,136,239)
M2	Low competitiveness of RE due to subsidies on alternatives	Impact of subsidies on alternatives on RE competitiveness	•	•	(29,138,239)
M3	lack of competitive hardware and labour market	Limitations in the availability of competitive labour and equipment locally		x	
M4	Poor data availability	Limited market and consumer data availability	•	•	(27,74,102)
M5	Barriers due to regulations	Regulatory barriers to market access and competitiveness	•	•	(26,138)

M6	Uncertain market growth potential	Uncertainty in market growth potential due to uncertain demand, market size and potential		x	(138)
Social and environment risks					
SE 1	Lack of social acceptance	Public resistance to adopting RE technology	•	•	(26,28,29,94)
SE 2	Poor consumer awareness	Poor awareness of solar benefits	•	•	(26,94–96)
SE 3	Lack of integration of RE systems	Poor integration of RE into the energy mix	•	•	(26)
SE 4	Difficulty in acquiring land/	Difficulty in acquiring land, competition with land uses	•	•	(25,29,89,95)
SE 5	Insecurity	Instability caused by security and social events, e.g., riots. Insecurity of infrastructure	•	•	(25,29,95,97)

B.2 Calculation of AHP risk priorities (weightings)

The AHP risk priorities were computed following previous studies (1,31,139,141) using equation 1, while the consistency of weight estimates was determined using equation 2.

$$Aw = \lambda_{max} \times w \quad (B-1)$$

where A is the comparison matrix, w is the Eigenvector of size $n \times 1$ or priority vector, and λ_{max} is the maximum Eigenvalue.

The degree of consistency of the estimation (consistency ratio, CR) was determined using Equation 2.

$$CR = CI/RI \quad (B-2)$$

Where $CR \leq 10\%$ indicates an acceptable level of consistency in judgements.

$CI = (\lambda_{max} - n)/(n-1)$, and the random index (RI) is used as the consistency index when the matrix entries are random (139). The standard values of RI are shown in Table 2.

Table 2 Standard values of random index

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0	0.52	0.89	1.25	1.35	1.4	1.45	1.49

B.3 Interviews and focus groups.

B.3.1 Interview and focus group consent.

Title of the project:	A holistic risk management approach to driving investment decisions in Nigeria's DRE systems.
Name of the researcher:	
Researcher's contact details:	
Participant number:	
Date:	

Part 1: request consent to participate and note the ability to withdraw.

I confirm that I have been informed about this research project and I agree to take part.

I understand that all personal information I provide will be treated with confidence and my name will not be used in any report, publication, or presentation.

I have been provided with a participant number as shown above. The researcher(s) will record data against my participant number instead of recording my name. The file linking my name to my participant number will be accessible only to the main researchers and will be securely destroyed 3 months from the interview date.

I understand that I can withdraw from this project at any stage by informing a member of the research team, for whom contact details have been provided. I also understand that I can withdraw my data for a period of up to 1 month from today, as after this time it will not be possible to identify my individual data from the aggregated results as explained in point 3.

Part 2: confirm the security of data storage.

I understand that the data I provide will be used by Cranfield University for the purpose of research. The data will be stored on the University's network that can only be accessed by authorised users, in line with UK Data Protection Act 2018.

Part 3: list datasets being created and what will happen to each.

Interviews and/ focus group sessions will be recorded and securely stored on the Cranfield University network as audio files. These audio files will be securely deleted as soon as they are no longer required.

The recordings will be transcribed and saved as text files. These files (and any backups) will also be securely deleted as soon as they are no longer required.

Anonymised transcripts will be created, by removing or replacing identifiers such as name, age, and location. These anonymised transcripts may be quoted from or published in full, in support of findings (e.g. in journal articles, conference papers).

I am happy for my anonymised transcript to be published: Yes / No (delete as appropriate)

Analytical software will be used to aggregate the results of the research and every reasonable step will be taken to anonymise the data.

I understand that the aggregated data will be published in support of the research findings.

☐

I understand that the discussions will be audio-recorded and transcribed for analysis.

☐

The analysis will be only used for this research project and for no other purpose.

I will respect the confidentiality of the others taking part in the workshops by not discussing comments made outside of the room (applicable for group discussion only)

☐

I am happy for the researcher to acknowledge my contribution in an acknowledgement.

☐

section of related publications.

I confirm that I have read and understood the information provided on this form and give my consent to take part in this research.

Participant's signature:		Date:	
Participant's name:			
Researcher's signature:		Date:	

One copy of this form must be given to the participant and one copy held by the researcher.

B.3.2 Interview and focus group session questions.

Interview information sheet

The following information sheet was provided to each participant. It includes a brief overview of the research and the questions, applicable to both Interviews and focus group sessions.

Introduction

Private investments are critical enablers to achieving energy access for over 770 million people worldwide. Despite decreasing capital costs, investments in renewable energy (RE) projects in developing countries are low due to unattractive risk-return profiles. Through understanding key risk drivers and their interactions, actionable insights can be drawn to mitigate investment risks, making energy more accessible.

This research aims to develop a model for investment planning and decision-making that incorporates multi-dimensional risks and their interactions. This can be used to identify impactful actions that can influence favourable investment conditions in decentralised renewable energy (DRE) in Nigeria.

During the research, we identified and evaluated DRE investment risks in Nigeria from survey responses. A conceptual holistic model for investment decision and planning was subsequently developed. The framework considers heterogeneity in investment attractiveness for different investors. Mitigations such as policy actions can be applied to understand the effects on investment decisions and energy access.

It is planned to conduct a focus group discussion where feasible or a semi-structured interview to discuss survey findings on DRE investment risk, present initial model findings and elicit suggestions for mitigations.

Purpose of the session

The purpose of the session is to:

1. Present results of the survey on DRE investment risks as envisioned by various stakeholder groups in Nigeria.
2. Elicit feedback on risk causal factors and interactions
3. Present (and obtain feedback on) the developed model that aims to analyse the impact of interactions of the risks and location attractiveness on DRE investments.
4. Gather feedback to identify interventions to mitigate the identified risks

Participant Information

The sessions are targeted at actors (e.g., investors, developers, policymakers, financial institutions) in Nigeria's DRE sector.

Methodology

Participants will be required to fill out a consent form and briefed regarding the anonymity and confidentiality of data collected, including how transcripts will be used. Each session will be moderated by the interviewer, audio-recorded and transcribed.

Semi-structured interview and focus group questions.

Where a focus group is not feasible, semi-structured interviews will be held. Questions are listed below:

Part 1 A

1. Can you tell me about your background and your role?
2. We analysed the results from a survey on DRE investment risks by stakeholder groups. Focusing on chart 1, do you agree that these are the most critical in terms of their impact on investments/ investment decisions in Nigeria and ability to meet RE targets? If not, what other factors are important and why?
 - a. What are the actual causal factors for these risk factors?

- b. What do you think are the interactions between the factors? For example, could one cause affect a different risk?

PART 1 B (relevant to investors)

3. What are your criteria for providing funding?

What factors determine if an investment is viable? Please can you rate them in terms of importance?

5. Can you rate the risk averseness level of your organisation on a scale of 1-4? (1-not risk averse, 2 very low-risk averseness, 3 moderately risk averse, 4-highly risk averse)

6. What is the: typical mix of financing, minimum and maximum investment threshold, typical cost of finance and loan tenor.

Part 2:

1. How could the risks discussed in section 1 be mitigated?
2. How effective could the mitigations be. - use a scale of 1(very low effectiveness) – 7 (extremely effective)
3. What is the ease of implementation?
4. How could current policy interventions be realistically further enhanced to achieve access goals?

Part 3:

Interviewer will provide an overview of the model, assumptions and share the result for a mitigation scenario.

1. Are there any assumptions that could be reviewed?
2. What is your expectation of investment outcome under the mitigation in no. 1?
3. How could this model be improved for planning and decision-making support?

B.4 AHP results

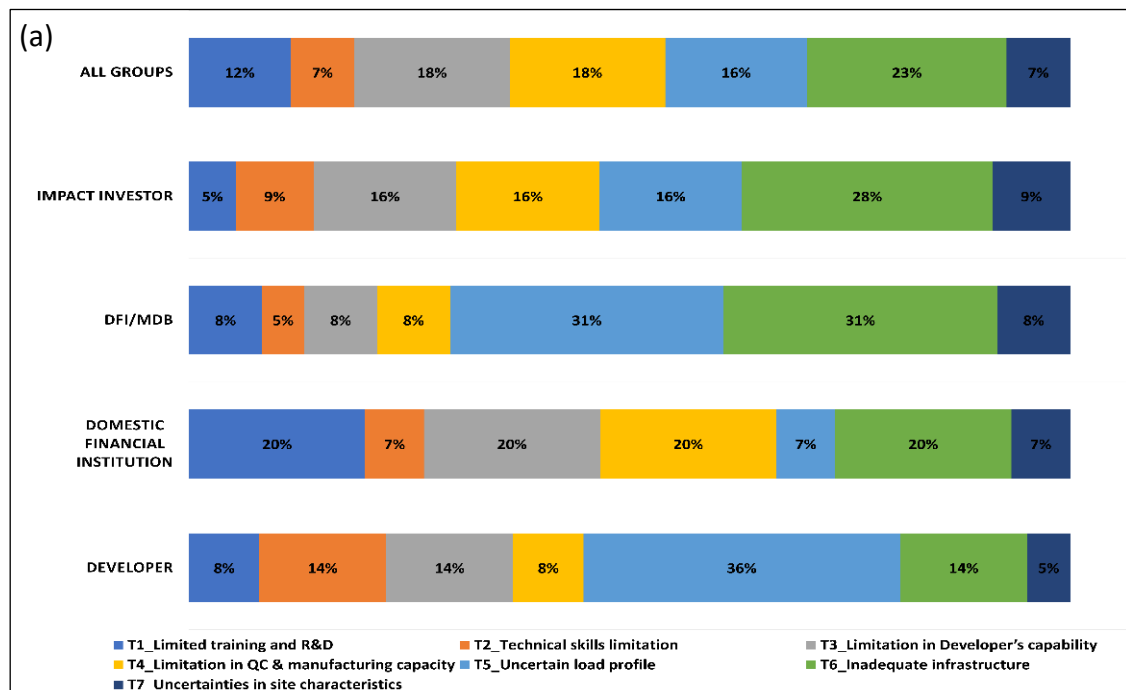
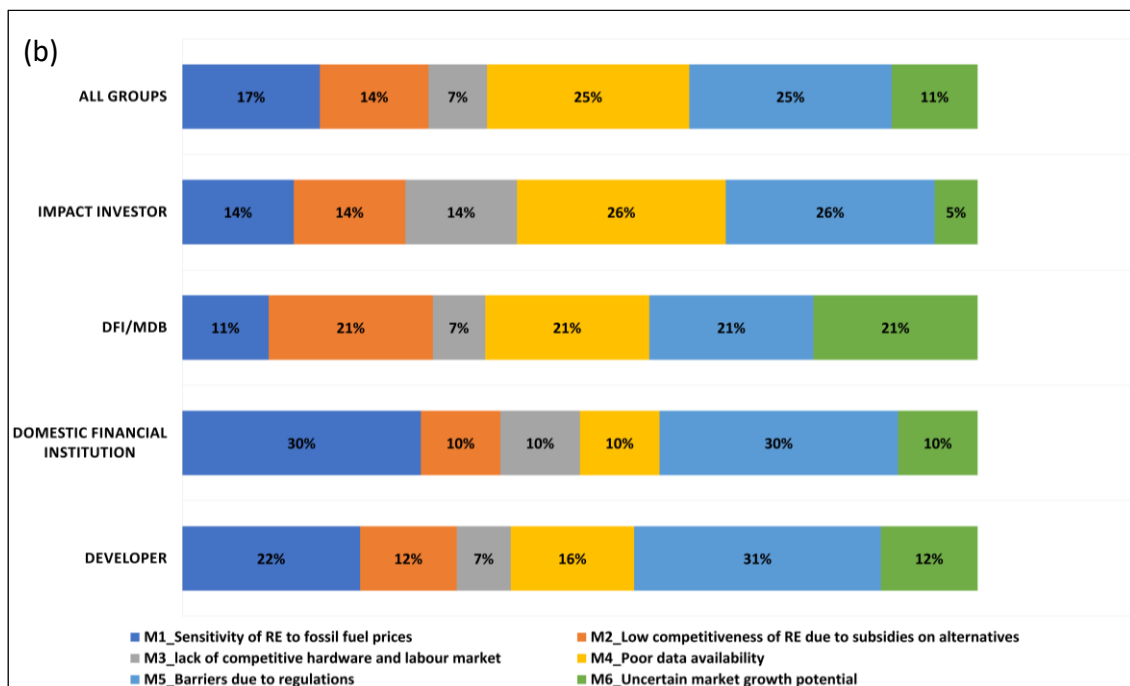
Table 3 Risk factor priority overall ranking (AHP results) by respondent group and indications priority changes identified in interviews.

ALL groups (Collective view)	Developer	DomFI	DFI	Impact Investor	Consulting and other professional services.	PI	Other	Development Agency
E3_Foreign exchange volatility (9.6%)	F1 (9%)	F1 (6.6%)	E1 (13.9%)	E3 (16.1%)	F1 (11.1%)	E1 (6%)	E3 (9%)	E1 (7.6%)
F2_Inadequate access to low-cost capital (8.2%)	↓*E2 (7.3%)	F2 (6.6%)	E3 (13.9%)	M4 (6.1%)	T4 (9.7%)	E3 (6%)	P3 (5.8%)	E3 (7.6%)
E1_Revenue Risk (4.8%)	E3 (7.3%)	F3 (6.6%)	E2 ↓ (7.8%)	M5 (6.1%)	E3 (8.5%)	F2 (6%)	P8 (5.8%)	E5 (7.6%)
E2_Collection losses (4.8%)	↓P12 (5.9%)	F6 ↓ (6.6%)	F2 (5.5%)	E1 (5.8%)	T1 (6.2%)	M1 (4.8%)	M1 (5.8%)	F2 (6.9%)
E4_Inability to achieve single off-taker or cluster effect (4.8%)	F2 (5.5%)	T1 (6.2%)	F3 (5.5%)	E2 ↓ (5.8%)	F2 (3.9%)	M2 (4.8%)	F4 (5.2%)	F3 (6.9%)
E5_Non-cost reflective tariff (4.8%)	↓P10 (4%)	T3 (6.2%)	F6 (5.5%)	E4 (5.8%)	F4 (3.9%)	M4 (4.8%)	F5 (5.2%)	F4 (6.9%)
F1_High cost (4.1%)	E1 (3.6%)	T4 (6.2%)	*E4 ↑ (4.4%)	M1 (3.3%)	F5 (3.9%)	T1 (4%)	P10 (3.5%)	P10 (6.7%)
F3_short loan terms (4.1%)	E4 (3.6%)	T6 (6.2%)	E5 (4.4%)	M2 (3.3%)	F6 (3.9%)	T4 (4%)	P1 (3.5%)	SE5 (3.1%)
F4_Limited local financial sector experience (4.1%)	E5 (3.6%)	E5 (5%)	P6 (2.7%)	M3 (3.3%)	E5 (3.9%)	T5 (4%)	P5 (3.5%)	E2 (2.5%)
F5_Limited financial capacity and experience of developers/ local investors (4.1%)	T5 (3.3%)	M1 (3.4%)	SE5 ↑ (2.5%)	E5 (3.2%)	T3 (3.7%)	T6 (4%)	M3 (3.3%)	E4 (2.5%)
F6_Difficulty accessing/repatriating Forex (4.1%)	SE5 (3.1%)	M5 (3.4%)	↑E5 ↓ (2.5%)	F1 (2.5%)	T6 (3.7%)	↓E2 (3%)	M5 (3.3%)	P11 (2.4%)
SE5_Insecurity (2.8%)	F3 (3%)	F4 (2.2%)	T6 (2.5%)	F2 (2.5%)	M4 (3.3%)	E4 (3%)	F3 (3.1%)	P12 (2.4%)
M4_Poor data availability (2.5%)	F4 (3%)	F5 (2.2%)	F1 (2.1%)	F4 (2.5%)	E4 (2.4%)	E5 (3%)	E1 (2.5%)	P1 (2.4%)
M5_Barriers due to regulations (2.5%)	F6 (3%)	P8 (2.1%)	↑M2 (1.6%)	F5 ↑ (2.5%)	SE5 (2.1%)	F1 (3%)	E2 (2.5%)	P2 (2.4%)
P10_political changes/instability. (2.2%)	M5 (2.8%)	T2 (2.1%)	M4 (1.6%)	F6 (2.5%)	T2 (2.1%)	F3 (3%)	E4 (2.5%)	P3 (2.4%)
P1_Insufficient policy/legal support framework (2.2%)	P7 (2.5%)	T5 (2.1%)	M5 (1.6%)	T6 (2.4%)	T5 (2.1%)	F4 (3%)	T2 (2.3%)	P5 (2.4%)
P7_uncertainties in IMG regulations implementation (2.2%)	P1 (2.4%)	T7 (2.1%)	M6 (1.6%)	P6 (2.2%)	F3 (2.1%)	F5 (3%)	T3 (2.3%)	P7 (2.4%)
P8_Grid extension uncertainty (2.2%)	P4 (2.4%)	P7 (2%)	↑P10 (1.5%)	P7 (2.1%)	M2 (1.9%)	F6 (3%)	T6 (2.3%)	P8 (2.4%)
T6_Inadequate infrastructure (2.2%)	P8 (2.4%)	E2 (1.9%)	P12 (1.5%)	P8 (2.1%)	M6 (1.9%)	M5 (2.5%)	SE1 (2.2%)	F1 (2.3%)

T3_Limitation in Developer's capability (1.7%)	M1 (2%)	E3 (1.9%)	P4 (1.5%)	SE5 (1.6%)	E2 (1.5%)	M6 (2.5%)	P11 (2%)	F5 (2.3%)
T4_Limitation in QC & manufacturing capacity (1.7%)	F5 (1.7%)	E4 (1.9%)	P7 (1.5%)	T3 (1.4%)	T7 (1.3%)	T7 (2.2%)	P6 (2%)	F6 (2.3%)
M1_Sensitivity of RE to fossil fuel prices (1.7%)	M4 (1.4%)	P1 (1.7%)	P8 (1.5%)	T4 (1.4%)	P10 (1.3%)	SE5 (2%)	P7 (2%)	T4 (1.5%)
T5_Uncertain load profile (1.6%)	P2 (1.3%)	SE2 (1.6%)	F4 (1.3%)	T5 (1.4%)	P1 (1.3%)	M3 (1.5%)	F1 (1.9%)	T6 (1.5%)
P12_Adverse political events (1.6%)	T2 (1.3%)	SE5 (1.6%)	F5 (1.3%)	M6 (1.3%)	P4 (1.3%)	T2 (1.3%)	M2 (1.7%)	M1 (1%)
P4_limitation in policy implementation (1.6%)	T3 (1.3%)	M2 (1.1%)	SE4 (1.2%)	F3 (1.3%)	P7 (1.3%)	T3 (1.3%)	M4 (1.7%)	M2 (1%)
M2_Low competitiveness of RE due to subsidies on alternatives (1.3%)	T6 (1.3%)	M3 (1.1%)	M1 (0.9%)	P1 (1.2%)	P8 (1.3%)	P2 (1.2%)	M6 (1.7%)	M3 (1%)
T1_Limited training and R&D (1.1%)	P11 (1.3%)	M4 (1.1%)	P11 (0.8%)	P2 (1.2%)	M1 (1%)	SE2 (1.2%)	SE5 (1.3%)	M4 (1%)
M6_Uncertain market growth potential (1.1%)	P5 (1.3%)	M6 (1.1%)	P5 (0.8%)	P3 (1.2%)	M3 (1%)	P10 (1.2%)	SE4 (1.2%)	M5 (1%)
P11_Inadequate political will (1%)	P3 (1.3%)	P4 (0.8%)	P3 (0.8%)	P4 (1.2%)	M5 (1%)	P11 (1.2%)	P12 (1.2%)	P4 (0.9%)
P3_policy changes (1%)	SE3 (1.2%)	E1 (0.7%) ↑	T1 (0.7%)	P5 (1.1%)	E1 (1%)	P12 (1.2%)	P2 (1.2%)	P6 (0.9%)
P5_Duplicative policy development (1%)	M2 (1.1%)	P2 (0.7%)	T3 (0.7%)	SE2 (0.9%)	SE3 (0.9%)	P1 (1.2%)	F2 (1.1%)	SE1 (0.6%)
P6_Inconsistent policy application (1%)	M6 (1.1%)	P3 (0.7%)	T4 (0.7%)	T2 (0.7%)	P12 (0.7%)	↑P4 (1.2%)	F6 (1.1%)	SE2 (0.6%)
SE2_Poor consumer awareness (0.8%)	P6 (0.8%)	P5 (0.7%)	T7 (0.7%)	T7 (0.7%)	P3 (0.7%)	P6 (1.1%)	E5 (1%)	SE3 (0.6%)
SE3_Lack of integration of RE systems (0.8%)	SE2 (0.7%)	P10 (0.7%)	M3 (0.5%)	P10 (0.7%)	P5 (0.7%)	P7 (1.1%)	T4 (0.9%)	SE4 (0.6%)
SE4_Difficulty in acquiring land/ (0.8%)	T1 (0.7%)	P11 (0.7%)	P1 (0.5%)	SE1 (0.5%)	P6 (0.7%)	P5 (0.9%)	T5 (0.9%)	T1 (0.5%)
P2_Unclear regulation/guidelines (0.8%)	T4 (0.7%)	P6 (0.7%)	SE3 (0.5%)	SE3 (0.5%)	SE2 (0.5%)	SE3 (0.7%)	P4 (0.8%)	T2 (0.5%)
M3_lack of competitive hardware and labour market (0.7%)	M3 (0.6%)	P12 (0.7%)	SE2 (0.4%)	SE4 (0.5%)	SE4 (0.5%)	SE4 (0.7%)	SE2 (0.8%)	T3 (0.5%)
T2_Technical skills limitation (0.7%)	T7 (0.4%)	SE3 (0.6%)	T2 (0.4%)	P12 (0.5%)	P11 (0.4%)	P8 (0.6%)	T1 (0.6%)	T5 (0.5%)
T7_Uncertainties in site characteristics (0.7%)	SE1 (0.3%)	SE4 (0.6%)	P2 (0.3%)	T1 (0.4%)	P2 (0.4%)	SE1 (0.4%)	SE3 (0.5%)	T7 (0.5%)
SE1_Lack of social acceptance (0.5%)	SE4 (0.3%)	SE1 (0.3%)	SE1 (0.3%)	P11 (0.3%)	SE1 (0.3%)	P3 (0.4%)	T7 (0.4%)	M6 (0.3%)

↓ Indicates risk factor importance was downgraded. ↑ Indicates risk factor importance was high graded in the interviews.

B.4.1 Technical, market, and policy and political risk categories priorities



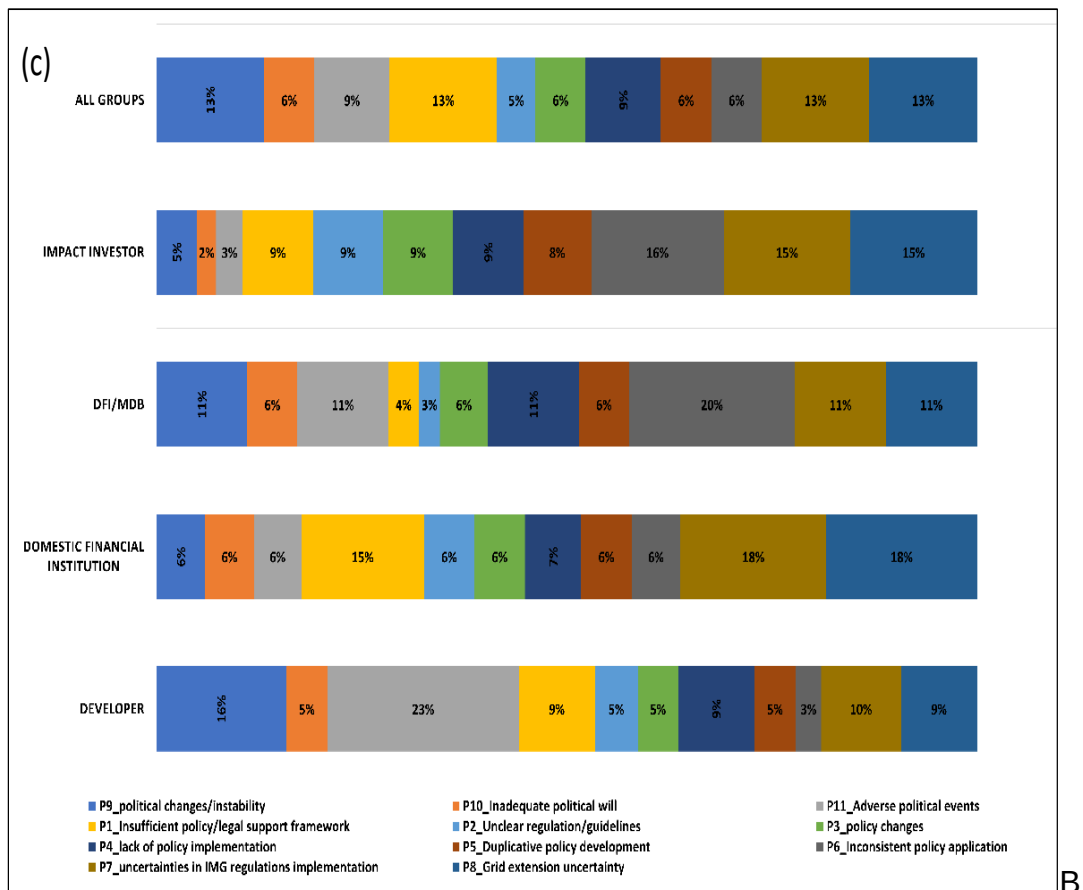


Figure B-1 Collective and individual groups risk priorities in the (a) technical, (b) market, and (c) PP risk categories.

B.5 Selected supporting interview quotes.

Reference	Quote
1	<i>'[...] the energy sector for the past at least 4 years, it's being a bit stable. It's progressed and not regressed.'</i> (D3001)
2	<i>'It will help a long way if customs agree to the government [policy]. The customs duty on batteries is 20%. Then you have VAT of 7.5% and other port charges of up to 7%. Based on those policies, when you have a grant of, say, 50-60%, you could have 30% of that grant erode.'</i> (D5001).
3	<i>'[As] a local investor, even though [some of] my CAPEX is USD based, it's a one-time risk for me. I only have that FX volatility at one point in the project when I'm executing. I'm trying to buy [exchange] dollars to import equipment, but my project is a Naira [denominated] project so it's less important to me.'</i> (DFI2001).
4	<i>'[FX volatility] is important for people who import.'</i> (DFI3001).
5	<i>'Revenue risk definitely would be number one.'</i> (DFI2001)
6	<i>'Revenue risk is basically a transaction key, if you cannot get to pay [or] get your money back, then it's</i>

	<p><i>difficult to make the investment or to provide the loan.</i></p> <p><i>So, I think that one is in the right place.’ (DFI1001).</i></p>
7	<p><i>‘The most important thing especially if your priority is being able to get your money back [is] revenue.’</i></p> <p><i>(DomFi2001).</i></p>
8	<p><i>‘You see a community that has been provided a mini-grid, and then you go there at night, and you find that instead of going inside to turn on their fan...they are outside [manually] fanning themselves.’ (P1001)</i></p>
9	<p><i>‘Purchasing power in rural areas is generally low and minimum wage is about 1000 naira per day.’</i></p> <p><i>(DomFi2001).</i></p>
10	<p><i>‘Some of these projects are deployed as constituency projects with attached viability gap funding. So now that creates the problem because for me as a villager, I will say this is a government project, so it should be free electricity. In some cases, the politician would have already campaigned for free power’. (PF3001-7)</i></p>
11	<p><i>‘[Collection losses], will probably be in the right place. If you're a regular Disco, [utility]. But if you're in a mini-grid, by design, I'm surprised that 3 [collection losses] would be that important because this factor, you can control a little bit by a very intimate knowledge of the customer and the ability to track and police how much energy they use.’ (DFI1001)</i></p>
12	<p><i>‘[...] lose more on the technical side before it gets to the customer.... from other parasitic loads within the</i></p>

	<i>network, even the metres and community service equipment like street lighting’ (D3001).</i>
13	<i>‘Even your own staff [mini-grid] conniving with people and selling [electricity credits] and not accounting for it.’ (D2001),</i>
14	<i>‘It’s easy for them to catch it [E2] because [developers] monitor [usage].’ (PF3001-7).</i>
15	<i>‘Most of the metering we’re getting now give us a back end where we can tell when people are stealing electricity so we can catch it and quickly go and check it.’ (D1001).</i>
16	<i>‘So as soon as we see that our revenue is not as it should be, we start asking questions, the team goes to the field and starts checking house by house. And luckily, because our connections are still not too many like the grid, before you know it, they’ve already fixed that.’ (D1001).</i>
17	<i>‘Payment solution providers [...] have built products that are tailored to the DRE sector, which have significantly reduced this risk.’ (D3001).</i>
18	<i>‘Yes, so, this, I agree with inability to achieve single cluster effect.’ (DFI3001).</i>
19	<i>‘During demand analysis and community engagement, you can identify potentials within the community that would trigger such kind of cluster effect.’ (D4001).</i>

20	<i>'Last mile locations pay more for fuels such as petrol and diesel to power generators... This benefit is not apparent to customers; we have to demonstrate the cost reduction opportunities to customers.'</i> (D3001).
21	<i>'No, this is not really a risk for us because [...mini-grids] have meter tariff that is cost reflective tariff unlike grid tariffs.'</i> (D4001).
22	<i>'[...] inadequate access to low-cost capital, that is the first one, but I think, maybe to come with that is not only low-cost capital, but also high tenure'</i> (P1001).
23	<i>'[F5] is also very, very big for me. I would have that in fact as number one.'</i> (D1001)
24	<i>We really don't [have access to low-cost capital]. It is not anywhere in Nigeria.'</i> (D3001).
25	<i>'It is difficult to source capital from foreign market as a Nigerian company.'</i> (D3001).
26	<i>'Why should we use short-term loans to do long-term project?'</i> (D1001).
27	<i>'[You] want a combination of low cost and high tenure; up to five, seven years.... I've had discussions with the developers and ... What I've see them saying is what the banks are ready to give is about two or three years.'</i> (P1001).

28	<i>'There is low interest in RE projects. One of the reasons is past experience of power sector privatisation with low liquidity and inability to recover cost. Most banks have not distinguished between RE sector and the power sector. An RE project is first seen as a power transaction and appraised accordingly. There is need to repackage the RE sector.'</i> (DomFI2001).
29	<i>'no benchmark, so people depend on us, our experience.'</i> (DomFI1001).
30	<i>'It's important because sometimes this foreign parties are also the ones that are able to provide you with the long-term financing. And sometimes to provide this long-term financing at concessional rates, relatively cheap rates of capital. So, because of that, I would say that it's important, and it's probably in the right place in terms of rank order.'</i> (DFI1001).
31	<i>'I placed an LC for \$250,000. I have only gotten about \$32,000 after 10 months. In fact, in the 4th month, the original equipment manufacturer threatened to cancel the invoice because the price had changed, and I had to take a finance loan to fund that. That means another loan on top of a transaction to credit the supplier to avoid cancellation.'</i> (D2001)
32	<i>'[In]security and political tension add to investor appetite. We have been on a fundraise for over 9-10 months now at a point you see that it's falling apart because of [in]security... yesterday they said to me,</i>

	<i>we heard in Niger state they killed people they kidnaped people, is it not the same place you're taking us to invest?' (D2001)</i>
33	<i>'No incentive can equate to human life.' (D4001).</i>
34	<i>'You can always hedge [FX volatility]; you can decide not to take a certain kind of loan.' (D1001).</i>
35	<i>'Our customer base is commercial clients where we sign PPAs to guarantee our revenues' (D6001).</i>
36	<i>'But the problem with them [co-lending] is that they don't do anything less than USD10 million and they don't do full investment, it means that I have to look for another USD10 million somewhere else [...] Because you don't have the capacity, [the constraint is] mostly equipment supply.' (D1001).</i>
37	<i>'The [interest] rates are high; the requirements are high' (D2001)</i>
38	<i>'They [developers] are unable to provide tangible collateral, and those items [mini-grid assets] do not have a secondary market for them.' (DomDFI1001).</i>
39	<i>'There is limited supply of the funds, investors in this sector.' (P1001).</i>
40	<i>'As developers, [we] do what we call social engineering, you can engineer constant revenue. Not just throw mini-grid out there and allow the people run it. No, you should be interested in business</i>

	<i>development, you should be interested in engaging this community, help them....[it] is key to sustainability of each project' (D2001).</i>
41	<i>'Help desk; they've [incorporated] that at NERC [regulatory agency]'. (D3001).</i>
42	<i>'Most of them [developers] just don't want to deal with DisCos because even though they [Discos] are not going to power those areas, by the time they realise that developers are going to make an investment, they can be a bit difficult. So, Discos' apathy affects developers and in turn, investment into the mini-grid sector'. (PF3001-3)</i>
43	<i>'We have to bring DisCos into this arena, because that is the way the average cost of this business will drop. If you socialize the costs as part of the distribution costs, ...you won't see any high costs' (PF3001-3).</i>

Appendix C Supplementary information on model equations and methods

C.1 Nomenclature of equation parameters

i	Investor
l	Location
pn	Project n
s	Project scenario
$\omega_{1,i}$	Relative importance of cost.to emission avoidance
$\omega_{2,i}$	Relative importance of emission avoidance to cost.
Y	Technology
α_i	Arrow-Pratt coefficient
θ_s	Probability of scenario s
τ_c	Corporate tax
$A_{1,i,Y}$	Attractiveness of a technology to an investor
$A_{2,l}$	Attractiveness of a location to an investor
$CAPEX_{generationcapacity}$	Project capital expenditure
$Cidep$	Depreciation cost
$Cloan$	Loan service
$C_{i,l}^{OPEX}$	Operating expenditure of a project
$Ctax$	Cost of tax
$D_l(t)$	Demand
Dh	Household demand
$EU_{i,l}^{invest}$	Expected utility of an investment in a location for an investor
F_i^{debt}	Debt fraction of the financing
F_i^{equity}	Equity fraction of the financing
F_i^{grant}	Grant fraction of the financing
$FutureDemand^{total}$	Total demand in all locations
$Gen_l^{current}$	Current supply

$Gen_{total,i,Y}^{potentialcapacity}$	Potential generation capacity of an investor in a technology
$Gen_{i,l}^{potentialcapacity}$	Potential generation capacity of an investor in a location
$Gen_{i,l}^{investedOnstream}$	New generation capacity
$Gen_l^{retired}$	Retired generation capacity
$InvestorThreshold_i^{minGenerac}$	Investor's maximum threshold
n	Number of people in a household, number of years
$n_{emissionavoidance}$	Avoided CO ₂ emission
P_l	Population in location
$P_{i,l}^n$	Potential project size of an investor in a location
r_g	Population growth rate
Re_i	Economic risk priority weighting
Rf_i	Financing risk priority weighting
$R_{i,INV}$	Total investment risk
Rm_i	Market risk priority weighting
Rp_i	Policy and political risk priority weighting
Rse_i	Social and Environment risk priority weighting
RT_i	Technical risk priority weighting
R_i^{debt}	Cost of debt
R_i^{equity}	Cost of equity
$r_{inflation}$	Inflation rate
T_{site}	Location factors informing attractiveness of a location
$U_{i,l,s,pn}^{invest}$	Utility for each potential project scenario
$wn_{,i}$	Risk factor priority weighting for investor
$wn_{,i_m}$	Effectiveness of mitigation, m on risk factor

C.2 Methodology for location data attributes extraction

C.2.1 Number of towns and cities within a 25km radius of each location

The section below describes the brief methodology for the identification of the number of towns and cities within a 25km radius of each location.

Data inputs:

Location data supplied in Excel (containing Ward name)

GRID3 – Nigeria Ward Boundaries (from ArcGIS online)

City and Town locations extracted from Open Street Map

Software:

- ArcGIS Pro 2.9

Method:

In the process of geospatial analysis for the project, several steps were initiated to enhance the accuracy and relevance of the location data. The methodology undertaken is outlined below:

Ward Centroid Point Creation: The centroid point for each ward polygon within the dataset was initially established.

Joining Ward Centroid Points to Location Data: The next step involved linking the ward centroid points to the location data stored in an Excel spreadsheet. This linkage was based on the common factor of the ward names.

Identification of Unmatched Location Data Records: During this stage, numerous instances of unmatched location data records were encountered. To address this, a manual review was conducted. Each un-matched record underwent scrutiny, with comparisons made against the ward dataset. Decisions were made to correctly associate the location data with the appropriate ward.

Conversion to Nigerian Coordinate System: To facilitate accurate distance measurements in meters, the data was converted to the Nigerian coordinate

system to allow distance to be recorded in meters. This projection used is shown below and was uniformly applied across all locations.

Projected Coordinate System	Nigeria Mid Belt
Projection	Transverse Mercator
WKID	26392
Authority	EPSG
Linear Unit	Meters (1.0)
False Easting	670553.98
False Northing	0.0
Central Meridian	8.5
Scale Factor	0.99975
Latitude Of Origin	4.0

Geographic Coordinate System	Minna
WKID	4263
Authority	EPSG
Angular Unit	Degree (0.0174532925199433)
Prime Meridian	Greenwich (0.0)
Datum	D Minna
Spheroid	Clarke 1880 RGS
Semimajor Axis	6378249.145
Semiminor Axis	6356514.869549775
Inverse Flattening	293.465

Proximity Analysis Between Ward Centroids and Town/City Locations: A proximity analysis for all locations, comparing the ward centroids associated with the location data to town and city locations. The tool used for this analysis was ‘Generate Near Table’.

Calculation of Nearest Towns/Cities within a 25km Radius: Following the proximity analysis, we calculated the nearest towns and cities to each ward location, considering a 25km radius. These are depicted in C-1.

Exporting Near Table to Excel: The results of the proximity analysis were exported to an Excel spreadsheet for further reference and analysis.

Calculation of Coordinates for Location Data: Coordinates for the location data were computed by adding x, y, latitude, and longitude fields to the relevant dataset. Calculations were carried out using the ‘Calculate Geometry’ option in the attribute table. The x, y coordinates were determined for the projected layers (Nigeria Mid Belt), while latitude and longitude fields were calculated for the original centroid ward layer (WGS_1984). The x, y field represents measurements in meters, while the latitude and longitude field values are expressed in Decimal Degrees.

These steps were undertaken systematically to ensure the accuracy and consistency of the location data, making it suitable for subsequent analyses and interpretations in the project.

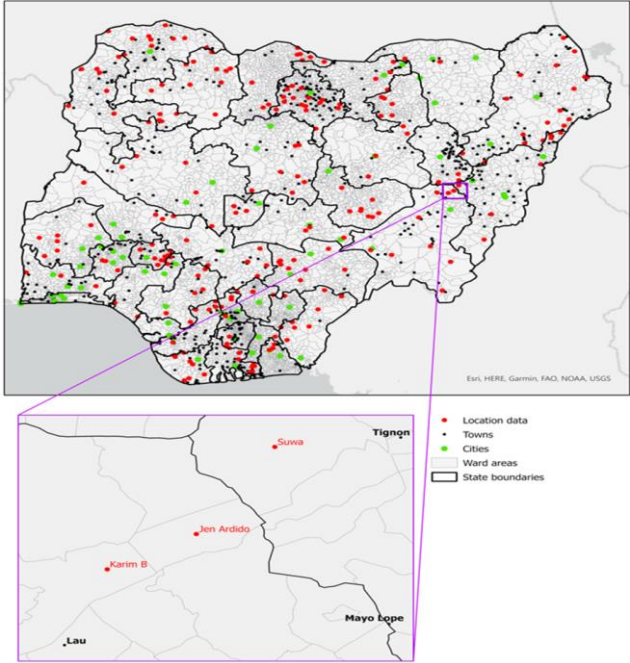


Figure C-1 Towns and cities within 25km

C.2.2 Location input data

Table C-1 below presents the locations in the model and input parameters comprising geographical coordinates and spatial location attributes. The following respective attributes were normalised between 0-1, with 1 being the most attractive, for number of town and cities within 25km, poverty, and solar irradiation potential (GHI). The model uses historical alternative fuel cost and conflict data from 2013 to 2018.

Table C-1 Attributes of location agents in the model.

Data source (57,169,213,214,217)

State	LGA	GISPoint_ Ward	Ward_ Latitude	Ward_ Longitude	Alternative fuel Cost USD per kW_ 2013	Normalised (0-1)			
						Number of towns within 25km	Numbe r of towns within 25km	Poverty level	GHI
Abia	Arochukwu	Ania Ohoafia	5.6432	7.83399	0.234345	0	0	0.966025	0.175206612
Adamawa	La murde	Suwa	9.56	11.7	0.196816	0.071429	0	0.443489	0.872727273
Adamawa	Jada	Jada II	8.77	12.15	0.196816	0.142857	0	0.443489	0.874380165
Adamawa	Maiha	Mayo Nguli	10.0628	13.1866	0.196816	0.142857	0.125	0.443489	0.92892562

Adamawa	Madagali	Duhu/Shuwa	10.7642	13.4396	0.196816	0.428571	0	0.443489	0.92892562
Akwa Ibom	Ikot Ekpe ne	Ukpom/Ikon o south	5.21028	7.79389	0.21986	0.071429	0.125	0.878142	0.061157025
Akwa Ibom	Ini	Ikpe 11	5.4	7.78	0.21986	0.071429	0.125	0.878142	0.061157025
Kaduna	Kauru	Dokan Karji	10.52527	7.4011	0.23244	0.214286	0	0.48707	0.720661157
Edo	Ikpoba-Okha	Obayantor	6.2848	5.67072	0.240844	0.071429	0.125	0.8703	0.305785124
Cross River	Biase	Umon Island	5.61801	8.10188	0.268319	0	0	0.817112	0
Sokoto	Gudu	Kurdula	13.57604	4.36905	0.216	0	0	0.05357	1
Niger	Katcha	Bisanti	8.76121	6.31292	0.2046	0	0	0.363416	0.53553719
Rivers	Etche	Egbeke	5.1116	7.13679	0.252384	0	0.125	0.929348	0.00661157
Plateau	Shendam	Angwan Rina and Demshin	8.68946	9.44602	0.2082	0	0	0.579575	0.695867769
FCT (Abuja)	Kwali	Kigbe	9.06422	7.48131	0.2028	0.142857	0	0.819115	0.480991736
Niger	Magama	Tungan Jika	11.17317	5.27663	0.2046	0.071429	0	0.363416	0.53553719

Ogun	Ijebu-East	Gbamu Gbamu	6.74068	4.16139	0.236997	0.07142 9	0	0.94231 3	0.10578512 4
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Table C-2 Risk factor Attributes of location agents in the model-2.

Data source (57,212)

State	LGA	GISPointWard	wardLatitude	wardLongitude	Normalised conflict factor (0-1)					
					2013	2014	2015	2016	2017	2018
Abia	Arochuku	Ania Ohoafia	5.6432	7.83399	0.999162	1	1	0.988859	0.919203	0.96547
Adama wa	Lamurde	Suwa	9.56	11.7	0.949288	0.752431	0.912267	0.922781	0.902899	0.847796
Adama wa	Jada	Jada II	8.77	12.15	0.949288	0.752431	0.912267	0.922781	0.902899	0.847796
Adama wa	Maiha	Mayo Nguli	10.0628	13.1866	0.949288	0.752431	0.912267	0.922781	0.902899	0.847796
Adama wa	Madagali	Duhu/Shuwa	10.7642	13.4396	0.949288	0.752431	0.912267	0.922781	0.902899	0.847796
Akwa Ibom	Ikot Ekpe ne	Ukpom/Ikono south	5.21028	7.79389	0.993294	0.999646	0.998555	0.99539	0.951087	0.9791
Akwa Ibom	Ini	Ikpe 11	5.4	7.78	0.993294	0.999646	0.998555	0.99539	0.951087	0.9791

Kaduna	Kauru	Dokan Karji	10.52527	7.4011	0.9371 33	0.9045 09	0.9433 94	0.9231 66	0.9547 1	0.8646 07
Edo	Ikpoba- Okha	Obayantor	6.2848	5.67072	0.9903 6	0.9962 86	0.9978 99	0.9976 95	0.9934 78	0.9890 96
Cross River	Biase	Umon Island	5.61801	8.10188	0.9807 21	0.9989 39	0.9985 55	0.9765 66	0.9297 1	0.9668 33
Sokoto	Gudu	Kurdula	13.57604	4.36905	0.9958 09	0.9994 69	1	0.9996 16	1	0.9836 44
Niger	Katcha	Bisanti	8.76121	6.31292	0.9941 32	1	0.9946 15	0.9842 49	0.9775 36	0.9954 57
Rivers	Etche	Egbeke	5.1116	7.13679	0.9953 9	0.9946 95	0.9897 56	0.9427 58	0.9746 38	0.9745 57
Plateau	Shenda m	Angwan Rina and Demshin	8.68946	9.44602	0.8432 52	0.9030 95	0.9613 87	0.9953 9	0.9413 04	0.7582 92
FCT (Abuja)	Kwali	Kigbe	9.06422	7.48131	0.9903 6	0.9755 97	0.9948 78	0.9850 17	0.9931 16	0.9750 11
Niger	Magama	Tungan Jika	11.17317	5.27663	0.9941 32	1	0.9946 15	0.9842 49	0.9775 36	0.9954 57
Ogun	Ijebu- East	Gbamu Gbamu	6.74068	4.16139	0.9941 32	0.9982 32	0.9990 81	0.9623 51	0.9945 65	0.9945 48

C.3 Model Overview, design concepts and details (ODD) protocol

The model description follows the overview, design concepts, and details (ODD) protocol (240). This protocol was developed to improve model acceptability by decision-makers, transparency, and replicability, which have been highlighted as limitations of ABMs (240) .

C.3.1 Purpose

The purpose of the hybrid system dynamics – agent-based model (SD-ABM) is to simulate the dynamic and spatial development of DRE investment decisions of diverse investor types. The model adopts an agent-based approach to recognise the interactions between location factors, risks, and investors' attributes that influence investment decisions.

The SD-ABM model is a spatial model which has the following attributes: (i) explicit location-specific attributes, individual investor agents' decisions and their interactions at a micro level for each modelled location, (ii) feedback mechanisms that aggregate individual investor decisions into a unified system perspective; facilitating a spatial perspective of DRE development over time and (iii) incorporation of investment risk considerations.

These features can enable assessment of conditions and actions that promote DRE investment aligned with electricity access targets. Additionally, potential investors can identify locations that are likely to suit their investment profiles. The specific questions addressed by the model are (i) what is the impact of risk levels on investment decisions? (ii) which investor types are likely to invest and in which locations? (iii) Under what conditions and policies are investors likely to invest? (iv) how can investment be improved towards attaining electricity access goals? The model is implemented and validating it for a case study of Nigeria.

C.3.2 Entities and state variables

The model includes two entities: investor and location agents. The agents and variables are described below. The agents' state variables are stored in databases to enable easy updates or applications to other regions or countries.

Investor agents

These are heterogeneous decision-making agents with complex adaptive system characteristics of learning and bounded rationality. Investors compete to meet demand in a location based on technology and location attractiveness factors, and rules that meet their decision criteria.

In this study, investor heterogeneity is depicted by a stylised representation of blends of funding sources referred to as investor types (agents). These include Type 1 (concessional), Type 2 (Equity), Type 3 (DFI debt) and Type 4 (DomFI debt) investors based on dominant funding sources. The investor types are further decomposed into nine sub-types as defined by their attributes in Table C-3. The model can be adapted to portray other investor profiles by updating the input database containing investor parameters.

Table C-3 Investor attributes

	Investor types ³		Financing	Investor goal		Investment threshold		Risk attribute	Expected payback time (years)	Initial WAAC* (%)
	Type	Sub-type		Economic (LCOE)	Environmental (CO ₂ emission reduction)	Minimum (kW)	Maximum (MW)	Risk aversion (arrow Pratt coefficient)		
1.	Type I (Mainly Equity)	Equity (E)	100% E	0.9	0.1	10	1	High (1e ⁻⁵)	-	15.9
		Equity (EG)	95% E, 5% G	0.8	0.2	10	1	High (1e ⁻⁵)	-	15.9
2.	Type II (Primarily DomFI Debt)	DomFI (DEG)	65% D, 30% E, 5% G	0.8	0.2	10	1	High (1e ⁻⁵)	5	11
		DomFI (DE)	70% D, 30% E	0.8	0.2	10	1	High (1e ⁻⁵)	5	10.9
		DomFI (DG)	80% D, 20% G	0.8	0.2	10	1	High (1e ⁻⁵)	5	9.3
3.	Type III (Primarily Concessional debt)	Conc (DEG)	50% D _c , 30% E, 20% G	0.4	0.6	10	1	Low (1e ⁻⁷)	10	8.8
		Conc (DE)	11% D _c , 39% E, 50% G	0.5	0.5	10	1	Low (1e ⁻⁷)	10	10
4.	Type IV (Primarily DFI debt)	DFI (DEG)	60% D, 30% E, 10% G	0.4	0.6	10kW	1	Moderate (1e ⁻⁶)	10	9
		DFI (DE)	70% D, 30% E	0.5	0.5	10kW	1	Moderate (1e ⁻⁶)	10	9.1
	Reference		Actual project (208)	Actual project (208)	Actual project (208)	(133)	(133)	(37)	Actual project (208)	Actual project, (208), interviews

*WACC is calculated from cost of DFIdebt 8.2%, cost of impact debt, 8.6%, Cost of DomFIdebt, 12.5%, Cost of Equity 15.9%

C.3.3 Risk module

The key output from the risk module is the risk premium calculation for various sources of financing, which serves as an input to the investment module for determining the WACC. Following Waissbein et al. (41), the risk premium recognises that higher financing costs in developing countries are reflective of actual or perceived investment risk priority levels. The initial risk level, $R_{i,INV}(t(0))$, is defined by the AHP risk priority weighting results obtained from the evaluation of a survey of DRE investors' (N=70) in Nigeria (see Chapter 3 for details). Six risk categories are considered: political and policy (R_p), technical (R_T), economic (R_E), financial (R_F), market (R_M), and social and environment risks (R_{SE}), each with five to eleven risk factors. Each risk category has up to eleven risk factors with weighting, w_{x_i} , where x_i represents any of the six risk categories for an investor. Overtime, risk priority levels may change when a mitigation is applied depending on the importance of the risk factor to the investor, i and its effectiveness, $m(t)$. This change is expected to reflect on the risk premium, $riskPremium_i$, cost of debt R_i^{debt} , cost of equity, R_i^{equity} , and consequently, WACC. The equations for the risk module are shown below.

Investment risk level: (C-1)

$$R_{i,INV}(t) = R_{p_i}(t) + R_{T_i}(t) + R_{E_i}(t) + R_{F_i}(t) + R_{SE_i}(t) + R_{M_i}(t)$$

Where,

$$R_{x_i}(t) = w_{x_{1,i}}(t) * (1 - w_{x_{1,i}}, m(t)) + w_{x_{2,i}}(t) * (1 - w_{x_{2,i}}, m(t)) \dots w_{x_{n,i}}(t) * (1 - w_{x_{n,i}}, m(t))$$

E.g., for technical risk (and similarly R_{p_i} , R_{E_i} , R_{F_i} , R_{SE_i} , and R_{M_i})

$$R_{T_i}(t) = w_{T_{1,i}}(t) * (1 - w_{T_{1,i}}, m(t)) + w_{T_{2,i}}(t) * (1 - w_{T_{2,i}}, m(t)) \dots w_{T_{n,i}}(t) * (1 - w_{T_{n,i}}, m(t)) \quad (C-2)$$

Cost of debt

$$R_i^{debt} = baseCost_i^{debt} + riskPremium_i^{debt}(t) \quad (C-3)$$

Cost of equity (C-4)

$$R_i^{equity} = baseCost_i^{equity} + riskPremium_i^{equity}(t)$$

Risk premium for debt

$$riskPremium_i^{debt}(t) = riskPremium_i^{debt}(t(0)) * R_{i,INV}(t)/R_{i,INV}(t(0)) \quad (C-5)$$

Risk premium for equity

$$riskPremium_i^{equity}(t) = riskPremium_i^{equity}(t(0)) * R_{i,INV}(t)/R_{i,INV}(t(0)) \quad (C-6)$$

C.3.4 Investment module

The Investment module calculates economic variables for potential projects and determines which projects are selected in the investment decision sub-module. Firstly, the WACC, $WACC_i$ for each investor type is calculated based on input from the risk module as investor agents may have different financing structures and risk priorities. Secondly, the outcome of the investment decision sub-module, and WACC are used to calculate the economic variables such as TNPV required to determine the economic viability of the potential projects and make investment decisions. The model additionally assumes a 5% annual decline in the cost of solar equipment due to technological development and scale of adoption (218). It further considers revenue risks by incorporating the revenue collection rate and currency risk by incorporating the impact of historical exchange rate depreciation and inflation in the cashflow calculations.

The equations are listed below:

Variable	Equation
----------	----------

<p>Weighted average cost of capital, $WACC_i$</p>	$\frac{R_i^{debt}(t) \cdot F_i^{debt} \cdot (1 - \tau_c) + R_i^{equity}(t) \cdot F_i^{equity}}{1 - F_i^{grant}}$ <p>where F_i^{debt} is the debt fraction of the financing for investor i.</p> <p>F_i^{equity} is the equity fraction of the financing for investor i.</p> <p>τ_c is corporate tax</p> <p>F_i^{grant} is the fraction of the grant share of the total investment for investor i.</p> <p>Each investor type i has a different financing structure.</p> <p>It is assumed that grants are not repayable</p> <p>(C-7)</p>
<p>Allowable tariff for a project</p>	<p>For SSA region, countries have used multi-tiered approach to tariff setting according to size of Minigrid. This parameter is specifically calculated for Nigeria.</p> <p><100kW Minigrid uses willing buyer/willing seller model. 60% of consumers must agree to the tariff set. For consumers to agree, tariff should be competitive with alternative source of electricity, fossil fuel. -</p> <p>100kW – 1MW Minigrid - regulated individualised cost-based tariff.</p> <p>The later incentivises the investor and customers by ensuring cost recovery in event of grid extension and cost reflective and fair rates respectively.</p> <p>The regulator specifies that the rate of return of the investor should not exceed debt interest rate+6%. Allowable tariff is calculated on this basis.</p>
<p>Total NPV of investor i, location, l, $TNPV_l^{i,l,p}$</p>	$\sum_t^{projectLife} \frac{Cost - Benefit}{(1 + WACC_{i,l,p})^t}$ <p>(C-8)</p> <p>Where:</p> <p>Cost =</p>

	$CAPEX_{\text{generationcapacity}} + C_{i,l}^{OPEX}(t(1 \text{ to end of life}))$ $+ C_{\text{loan}}(t(1 \text{ to end of loan tenor}))$ $+ C_{\text{dep}}(t(1 \text{ to end of life}))$ $+ C_{\text{tax}}(t1 \text{ to end of life})$ <p>(C-9)</p> <p>Expected Revenue = Allowable project tariff * ProjectAnnualGeneration (C-10)</p> <p>Allowable project tariff = Cost * $(1 + \frac{\text{Profit}}{1-\text{tax}})$ (C-11)</p> <p>Where profit is cost of capital + 6%</p> <p>ProjectAnnualGeneration = AnnualGenerationduration*1000*solarCapacityFactor* $Gen_{i,l}^{\text{potentialcapacity}}$ (C-12)</p> <p>Where AnnualGenerationduration is 8030hours based on 22 hours/day availability</p> <p>solarCapacityFactor is 0.25</p> <p>Benefit = Expected Revenue</p> $C_{i,l}^{OPEX} = OPEX * (1 + r_{\text{inflation}})^{t-1}$ <p>(C-13)</p> <p>OPEX comprise fixed and variable cost:</p> <p>Maintenance, fuel (if applicable), battery changeout</p> <p>Fixed: overheads- salary, insurance, smart meter royalty/collection fees,</p> <p>For simplicity, we assume an OPEX of 2% CAPEX (241)</p> <p>Ctax</p> <p>Tax is paid annually at 30%</p>
--	--

	$\tau_c * (revenue(t) - C_{dep}(t)) - C_{loan}(t) - C_{i,l}^{OPEX}(t)$ <p>(C-14)</p> <p>C_{loan}, Loan service per annum for respective tenor period</p> <p>P (initial principal or loan amount) = debtFraction*CAPEX</p> <p>r (interest rate per period) = (costOfDebt/12) e.g. 5% per annum would be 5%/12months</p> <p>n (total no of payment periods) = loan tenure (years)*12</p> <p>Monthly repayment = $P (r (1 + r)^n) / ((1 + r) (n - 1))$</p> <p>(C-15)</p> <p>Annual repayment = Monthly repayment * 12</p> <p>C_{idep}, Annual depreciation = $(60\% * CAPEX_{generationcapacity}) / asset\ life$</p> <p>For simplicity it is assumed depreciation is applied to 60% of $CAPEX_{generationcapacity}$.</p> <p>The model accounts for exchange rate differences by converting project revenues to USD at the prevailing rate or forecast exchange rate based on historical data</p>
CAPEX _{generationcapacity}	<p>CAPEX is dependent on capacity of the project.</p> <p>CAPEX_{generationcapacity (t0)} for three project size ranges is provided below for the reference year, 2018: (242)</p> <p><10kW, 7,335USD/kW</p> <p><50kW, 5,400USD/kW</p> <p>>100kW, 4,500USD/kW</p> <ul style="list-style-type: none"> Each year, the cost of solar equipment is expected to decrease due to technological development and scale of adoption. We assume a solar equipment cost reduction of 5% per annum.(243)

	$CAPEX_{\text{generationcapacity}}(t)$ $= CAPEX_{\text{generationcapacity}}(t_0) * (\omega_{\text{solarhardwareImported}}(t_0) * \left((1 - 5\%)^t + \omega_{\text{LocallysourcedComponents}}(t_0) + \omega_{\text{otherhardwareImported}}(t_0) \right))$ <p>(C-16)</p>
LCOE (244)	$\frac{CAPEX + \frac{M * [1 - (1 + r)^{-n}]}{r}}{\frac{E * [1 - (1 + r)^{-n}]}{r}}$ <p>(C-17)</p> <p>Where,</p> <p>M is fixed O&M cost per annum, $C_{i,l}^{\text{OPEX}}$</p> <p>r is the WACC</p> <p>E is the annual energy generation, MWh= Project capacity MW* number of hrs/year (245)</p>

C.3.5 Investment decision sub-module

The key output from this sub-module is a decision by an investor agent, i , regarding their potential total capacity investment in a technology, Y , $Gen_{total,i,Y}^{\text{potentialcapacity}}$, followed by a decision on the potential total investment capacity in a location, l , $Gen_{i,l}^{\text{potentialcapacity}}$. Finally, investment decisions on projects are made based on investor-specific criteria that follow.

In each time step, the sub-module first calculates the $Gen_{total,i,Y}^{\text{potentialcapacity}}$ based on the total demand and the investor's relative attractiveness to the technology, Y , $Relative\ Attractiveness_{i,Y}$ which informs how much an investor could be willing to invest in a technology relative to other technologies (35). Technology attractiveness is dependent on the investor's preference for economic benefit against environmental benefit, measured as LCOE and CO₂ emission avoidance respectively. The model can calculate $Gen_{total,i,Y}^{\text{potentialcapacity}}$ of five decentralised technology types (onshore wind, combined cycle gas turbine, small hydro, petrol

generator and solar PV mini-grid) for each investor agent. However, as the technologies available to the population in the case study are solar PV and the alternative of petrol generators, the next section detailing investment decisions considers these two technologies.

Second, the model determines the total investment by investor, I in location, l , $Gen_{i,l}^{potentialcapacity}$ in each technology, by distributing the calculated $Gen_{total,i,Y}^{potentialcapacity}$ across the locations according to the relative attractiveness of each location to an investor, $Relative\ Attractiveness_l$. The location attractiveness is determined from the location's attributes identified in Table .

$$Gen_{total,i,Y}^{potentialcapacity} = FutureDemand^{total}(t) * Relative\ Attractiveness_{i,Y} - Gen_i^{current}(t) \quad (C-21)$$

$$Relative\ Attractiveness_{i,Y} = \frac{A_{1,i,Y}}{\sum A_{1,i,alltechnologies}} \quad (C-18)$$

Attractiveness of investor, i to technology,

$$A_{1,i,Y} = e^{-(\omega_{1,i} * LCOE_{i,l} + \omega_{2,i} * n_{emissionavoidance_i})} \quad (C-19)$$

where:

The avoided emission (this means petrol generators are not used),

$$n_{emissionavoidance} =$$

$$penetration\ rate * Demand * 1.3 * KgCO2equivalent/kWh \quad (246)$$

(C-20)

$\omega_{1,i}$ and $\omega_{2,i}$ are investor dependent parameters and represent the relative importance of emission avoidance to cost.

Penetration rate is 40% for solar (246)

Penetration rate is the share of technology in the energy mix targeted.

$$Gen_{i,l}^{potentialcapacity} = Gen_{total,i,Y}^{potentialcapacity} * Relative\ Attractiveness_l \quad (C-23)$$

Where,

$$Relative\ Attractiveness_l = \frac{A_{2,l}}{\sum A_{2,l}}$$

Attractiveness of investor, i to location, l,

$$A_{2,l} = (1 + 2 * Stress_l) * T_{site_l} \quad (C-22)$$

T_{site} is a function of (familiarity of an investor to a location (market share), location accessibility, solar irradiation potential, historical conflict propensity and poverty level)

$$marketShare_{i,l} = \frac{\text{investment in location,l by investor,i}}{\text{sum of investments by all investors in this location,l}}$$

location accessibility, solar irradiation potential, historical conflict propensity and poverty level are relative normalised values between 0-1 obtained from literature and presented in Table C-1.

C.3.6 Investment decision process

After the model determines the investor's potential total capacities to invest in a technology and location, it makes investment decisions. The investment decision process encompasses three main phases (as illustrated in the flow chart in Figure 4-6): determination of (i) potential investment (project) size, (ii) viable projects, and (iii) the selection of projects for investments.

Potential project size, $P_n^{i,l}$

First, the model determines the size(s) of potential project(s), $P_{i,l}^n$, an investor may consider in each location based on investment capacity thresholds. Thresholds are investor-dependent and assumed to be constant. For an investment to be considered, the potential investment capacity of an investor in a location must exceed the investor's minimum generation threshold i.e.

$Gen_{i,l}^{potentialcapacity}(t) > InvestorThreshold_i^{minGeneration}$. If the $Gen_{i,l}^{potentialcapacity}(t)$ is above an investor's maximum threshold, another project, $P_{i,l}^n$ with an incremental size of up to $InvestorThreshold_i^{maxGeneration}$ is considered by the investor in the same time-step. It is assumed that each incremental project by an investor in a location has a different capital cost structure and thus, new economic variables. This reflects the relatively inelastic supply of labour and hardware in a location whilst ensuring that none of the locations is unrealistically dominated by one investor type (37).

Viable projects

Second, investors determine the viable projects, $viableProjects_i$ amongst their potential projects' portfolio, $P_{i,l}^n$. One key risk factor impacting DRE investment in Nigeria is revenue risk stemming from collection losses. As this can affect economic variables such as NPV, this study incorporates the impact of collection losses through project scenarios applied to predict the expected NPV outcomes for each potential project scenario $TNPV_{i,l}^{pn,s}$. A project scenario, s, is thus defined to reflect historical revenue collection rate ranges (219). Subsequently, the utility for each potential project scenario, $U_{i,l,s,pn}^{invest}$ is determined using a standard utility function which incorporates an Arrow-Pratt coefficient, α_i indicating the risk attribute of investors. Next, the EU of each $P_{i,l}^n$ is calculated (4-11). A viable project must meet the constraints of positive EU, positive cashflow, WTP and investor-specific preferences of payback time and IRR (see flow chart Figure 4-6).

$$TNPV_{i,l}^{pn,s} = \sum_t^{projectLife} \frac{(Cost_{i,l}^{pn,s} - Benefit_{i,l}^{pn,s})}{(1 + WACC_{i,l})^t} \quad (C-24)$$

Where $Cost_{i,l}^{pn,s}$ and $Benefit_{i,l}^{pn,s}$ are respectively, the total cost and benefit for a potential project scenario of an investor i in location l.

$$U_{i,l,s,pn}^{invest}(t) = 1 - e^{(-\alpha_i(t) * TNPV_{i,l,pn,s}(t))} \quad (C-25)$$

$$EU_{i,l}^{invest}(t) = \sum_s \theta_s * U_{s,i,l,p}^{invest}(t) \quad (C-26)$$

Investment decision

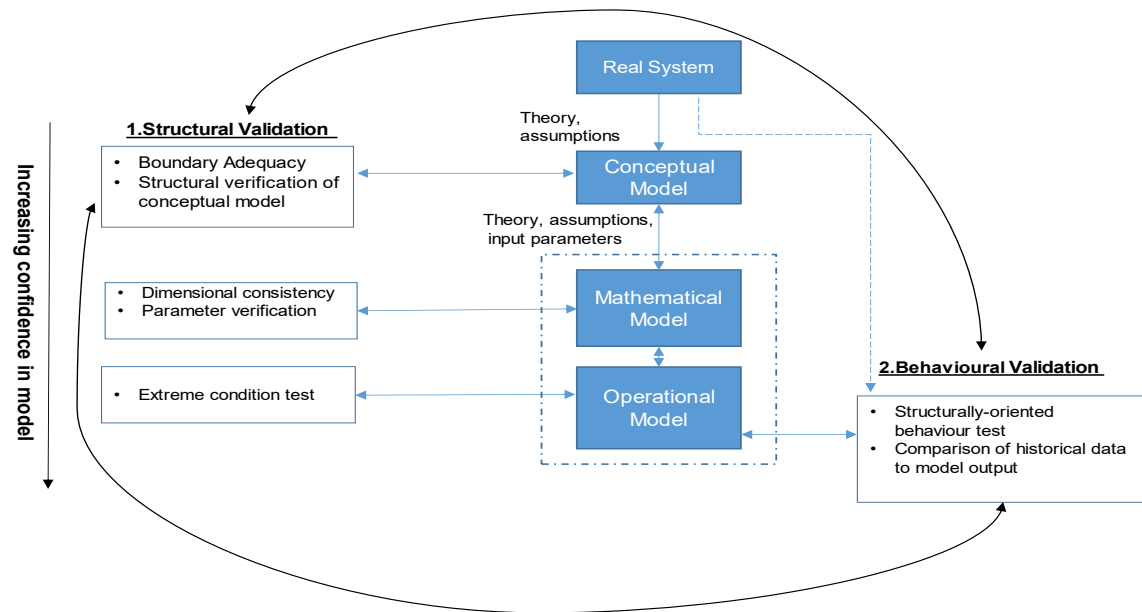
Third, all *viableProjects_i* are sorted and the projects with the highest EU up to *P_{max,i}* (where *P_{max,i}* is the investment threshold of an investor) are considered for an investment decision. Viable projects considered for investment decisions in a location by all investors are combined and sorted. If the sum of investment is less than the supply gap in a location, then, all the projects are promoted to the investment queue (*Gen_{i,l}^{invested}*) in each location agent. Otherwise, projects with the smallest size and then the least EUs are removed from the list until the projects meet the supply gap requirement. Finally, following the time delays in decision-making to the construction and operation phases (Figure 4-5), the generation module is updated with all the projects meeting the selection criteria.

C.4 Model validation

A model serves as an abstract representation of a real system. Validation is a critical process employed to enhance the credibility of the model and instil confidence in its outputs, consequently increasing the level of acceptance of recommendations by decision-makers (247). Sterman (247) argued that no model could be thoroughly validated. Nonetheless, confidence can be established through a series of tests and the evaluation of model errors (247). Two main steps to establishing the validity of a model which should be applied in sequence have been identified in (248,249). The first step involves confirming the use of an appropriate structure to represent the real system, with testing of assumptions, boundaries, parameters, and equations. Once structural validity is confirmed, the second step focuses on establishing the behavioural validity of the model, ensuring its ability to predict acceptable behaviour through a range of tests (248,249).

These tests involve comparing simulation results with empirical data, be it historical data or expectations regarding system behaviour (250). Sterman (247)

proposed a variety of tests, adapted in literature by other authors (248,249,251,252). Qudrat-Ullah et al. (248) argued that the same validation process could be applied to ABM. In this work, the validation process outlined by Barlas et al (249) and illustrated in Figure C-2 is adopted in this study. The validation process was carried out iteratively at intervals of the model development process and outlined in the sections below.



Adapted from Barlas 1989, Qudratullah 2010

Figure C-2 SD-ABM model validation process

C.4.1 Structural Validation

As illustrated in Figure C-2, the evaluation of structural validity commences during the conceptual model development phase. Initially, it ensures the adequacy of the chosen system boundary and conceptual model structure. Once confirmed, subsequent tests are conducted throughout the model development process. These tests include verifying the dimensional consistency of equations and the sources of parameters used in the model. Additionally, the structural integrity of the model is assessed under extreme conditions to ensure its robustness. Based on the outcomes of these tests, adjustments to the model structure are made to enhance its representation of the expected outcomes. The findings from the conducted structural tests are presented below.

C.4.2 Boundary adequacy

This test aims to establish that the model contains the relevant concepts and structural relationships that address the purpose of the model. It checks that concepts pertinent to addressing the problem are endogenous to the model (247,248,250). It checks for significant changes when boundary assumptions are relaxed or expanded (250). The SD-ABM model was developed based on a literature review, expert consultation and information gathered from surveys and interviews conducted on DRE investment in Nigeria. Endogenous variables are those whose behaviours are generated within the model, while the exogenous variables used in the model are split into two categories. These include (i) parameters sourced from literature such as population data, location and investor attributes, which are considered constants and specific to the case study and (ii) risk factor priorities obtained from survey data. Table C-3 below shows the endogenous and exogenous variables used in the model. Consistent with the purpose of the model, risk levels, location attractiveness, electricity demand and generation, project costs, tariffs, and investment decisions are endogenously generated in the model.

Table C-4 Endogenous and exogenous variables in the model

Endogenous variables	Exogeneous variables
Risk levels	Risk priority weighting
Total demand	Demand per household
Total generation	Mitigation scenarios
Future alternative cost of fuel	Initial population rates, growth rates
Economic variables such as cost, IRR, NPV, electricity tariff, revenues	Construction and investment decision durations
Investment capacity	Investment capacity threshold for investor
Future variables such as exchange rates	Historical fuel cost
	Location and investor attributes
	Price elasticity

C.4.3 Structural verification

This test whether the structure of the model adequately represents the real system [1]. This involved checking the system structure i.e. if the formal concepts, relationships and theory about the system behaviour are representative of the real system. Two approaches were employed in developing the model structure. Initially, available knowledge about the system and existing literature on DRE and investment risks informed the model construction. Subsequently, existing structures and concepts were adapted from the literature to describe causal relationships, constraints, and agent rules. Notable adaptations include (i) employing system simplification and the attractiveness of investments, as applied by Allen et al. (35) to define investments based on location attractiveness, (ii) incorporating insights from literature on heterogeneity in investment attractiveness due to regional differences, as demonstrated by Falchetta et al. (14,35), and (iii) integrating literature on investment decisions under risk by Bashar et al. and Chen et al. (37,38,183,184) to define agent decision rules. The utilisation of structures from existing literature enhances confidence in the theoretical validity of the model structure. The conceptual model is represented in Chapter 4.

As part of the structural validation process, it was necessary to obtain feedback from experts. Expert feedback was sought at two stages: (i) during the model development phase from academics, and (ii) with stakeholders. The model structure was thus shared with academic experts to elicit constructive criticism and facilitate model improvement. This was done in three iterations, each prompting an update to the model and progressively enhancing further confidence in the structure. Subsequently, at the final validation stage, by involving a diverse group of expert stakeholders. This group comprised domestic finance investors, impact investors, development finance institution investors, developers, policymakers, and regulators. The stakeholders participated in interviews and focus group sessions, as detailed in part 3 of Appendix B.3.2.

During the sessions, the model and its underlying assumptions were discussed, enabling stakeholders to provide feedback.

C.4.4 Dimensional consistency

This test establishes whether the equations used in the model are numerically consistent with knowledge about the real system and dimensionally consistent by checking whether the units of variables and parameters on the right- and left-hand sides of each equation are the same. The Anylogic software built-in function was used for this assessment. Where there were inconsistencies, the equations and units were reviewed to identify the source of inconsistency. below displays the Anylogic function for dimensional consistency, confirming that parameters and variables are dimensionally consistent.

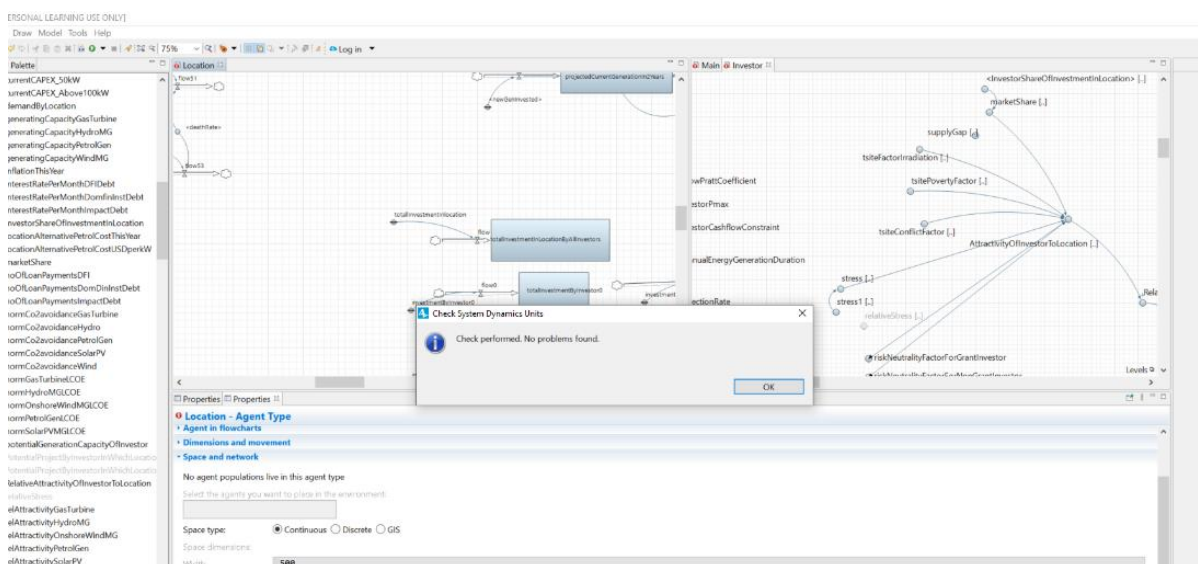


Figure C-3 Dimensional consistency checks for the model.

C.4.5 Parameter verification

A parameter is a quantity characterising a system and is typically held constant in the model but may vary in different scenarios (250). The parameter verification test aims to evaluate the validity of the parameters used in the model against existing knowledge about the real system and numerical parameters used in the literature. The table below presents some key parameters and their respective sources:

Table C-5 Key input parameters and their respective sources

Model Parameter	Source
Risk factor weightings	Survey data (Chapter 3)
Demand per household	(210)
Number in household	(210)
Initial population	(217)
Growth and death rates	(130)
Solar irradiation	(216)
Potential mini-grid sites	(57)
Actual mini-grid sites	(219)
City and town distances	(214)
Poverty level	(213)
Conflict level	(212)
Arrow Pratt Coefficient	(14,35) (37)
Solar mini-grid costs	(14,35)
Capital cost multiplier	(14,35)
Cost of Fuel	(169)
Capacity factor	(246)
Corporate tax rate	(165).
Initial discount rates	Survey, interviews
OPEX factor	(14,35)

C.4.6 Extreme condition test

In this test, selected model parameters are assigned extreme values and compared to the expected behaviour of the real system under similar conditions. The following extreme tests are conducted:

The exogenous parameter, construction timeline, is extended from 1 year to 10 years. In the case of a construction delay, Figure C-4 illustrates how the start-up of generation will be postponed by up to 10 years. Conversely, if there are minimal or no construction delays, generation occurs earlier as anticipated.

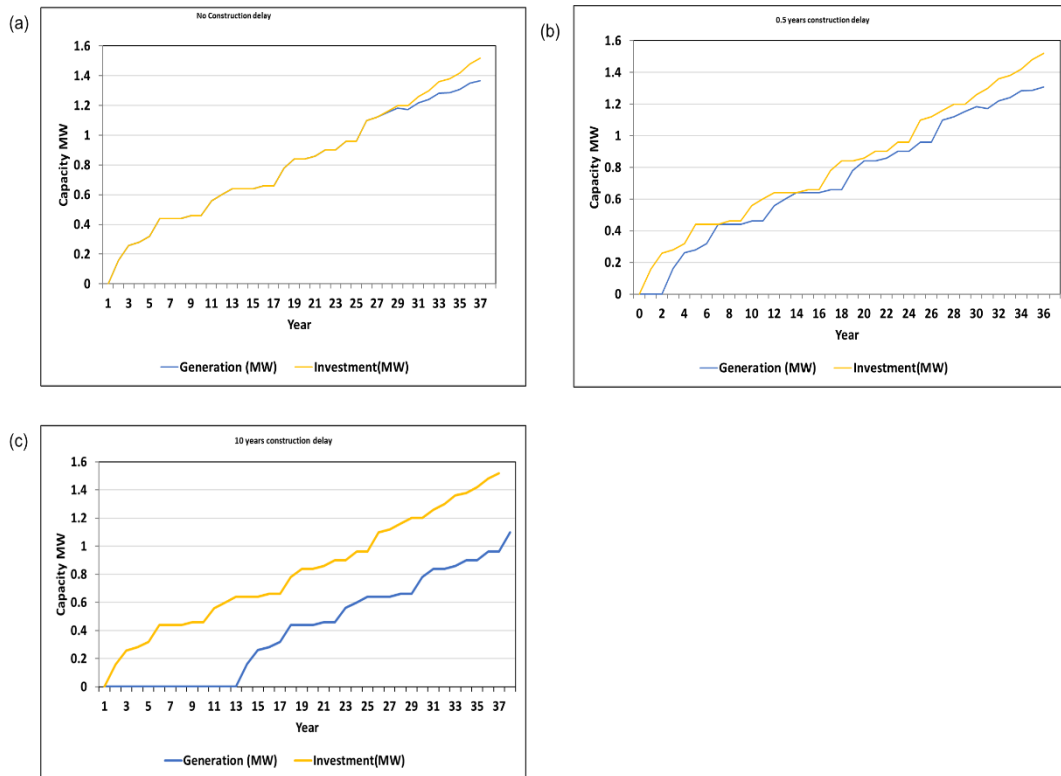
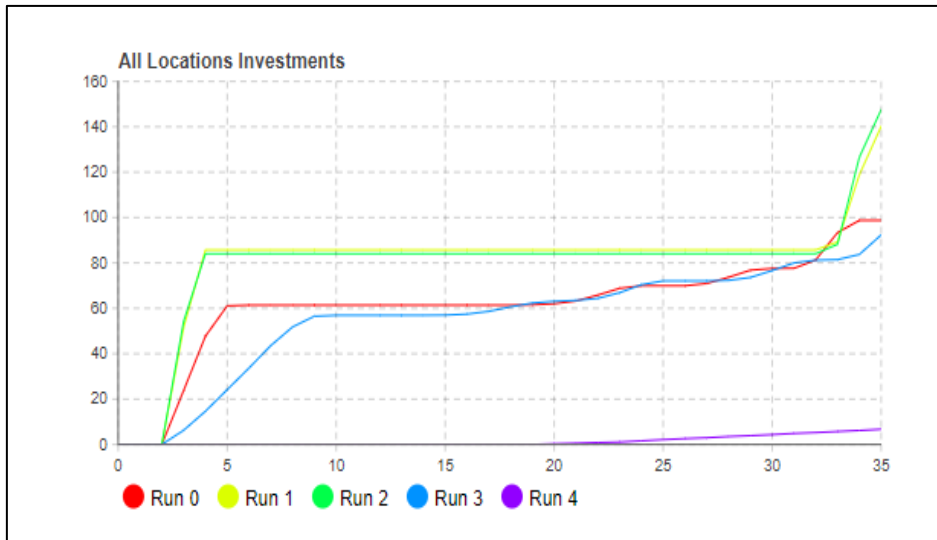


Figure C-4 Extreme condition test for (a) no construction delays, (b) 6 months, and (c) 10 years delay

Another extreme condition test focused on assessing investment trends under varying degrees of investors' risk aversion. To examine the implications of investor risk aversion on investments, a similar approach employed by Raunholz et al. (253) was adopted. Initially, uniform risk preference levels were applied across all investor types to establish the ranges for the risk aversion coefficient, given the absence of data for parametrisation. The values used by Bashar et al. (37) were considered as the baseline. Subsequently, the model underwent testing, assigning Arrow Pratt coefficients of 10^{-5} and 10^{-7} , representing high and low-risk aversion across all investor groups. In a real system, investment decisions and generation improvements are expected to align with lower risk aversion. This expectation is mirrored in the model output, as depicted in Figure C-5.



Run 0: Investors have various risk aversion levels.

Runs 1,2: All investors have a low-risk aversion.

Run 3: All investors have high-risk aversion.

Run 4: All investors have very high-risk aversion.

Figure C-5 Extreme condition test for the impact of investor risk averseness on investment and generation

Thirdly, the parameter for an investor's capacity threshold is assigned extreme values to assess whether the model exhibits logical behaviour when the investment capacity of investors is subjected to extremes. This parameter is exogenous and assumed. Figure C-6 depict investment and generation trends for various investor capacities at the end of simulation year 3. As anticipated, investments increase with higher resource availability. However, this change in the capacity of the investors does not alter the pattern of investments (i.e., 'which investor types are investing'). As shown in Figure C-6, an increase in generation capacity is solely driven by impact investors who provide concessional funding.

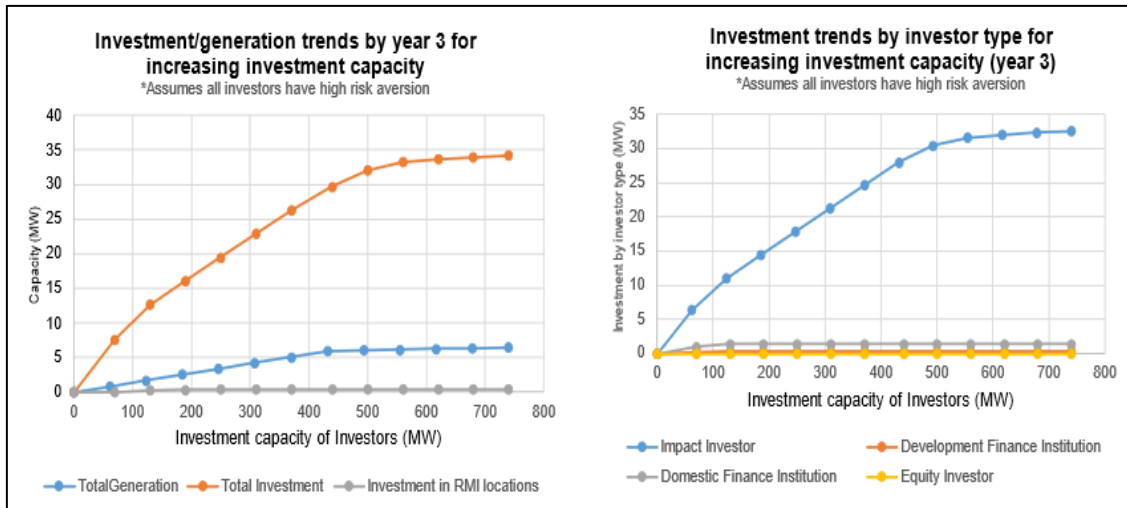


Figure C-6 Extreme condition test for investment capacity of investors

C.4.7 Structurally oriented behaviour test

Barlas (249) categorised the behaviour validation test into two parts. The first is the behaviour pattern prediction test, which determines if the model's behaviour pattern aligns closely with that of the real system (249). This test is discussed in Chapter 4. The second is the structurally oriented behaviour test, examining the sensitivity of the model's behaviour to parameter or structural changes. This aims to identify highly sensitive parameters and check the consistency of observations with the expected behaviour of similar changes in the real system (248–250). The model could exhibit outcomes (250) of (i) insensitivity to parameter changes, (ii) numerical sensitivity to changes (alterations in numerical values of variables without changes in behaviour patterns), and (iii) behavioural sensitivity to parameter changes.

Exogenous model parameters were individually tested by applying a 50% increase and decrease in the base value. For instance, increased demand (tier 5) (Figure C-7) results in higher investment due to improved attractiveness. Conversely, a lower base demand (tier 2) meant that some locations were no longer financially viable or relatively less attractive. However, the model showed a significant increase in investment is warranted by a substantial change in demand (by up to tenfold from the model baseline)

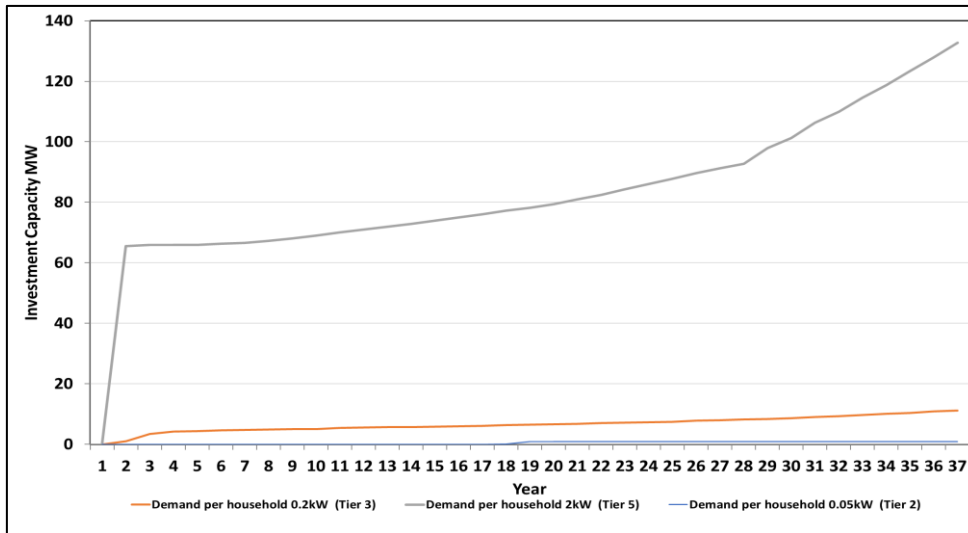


Figure C-7 Sensitivity of demand on investment

The table below summarises the parameters based on their degrees of sensitivities to investment. The sensitivity analysis for risk levels, representing discount rate, Arrow Pratt coefficient representing risk aversion and capacity threshold are presented in Chapter 4.

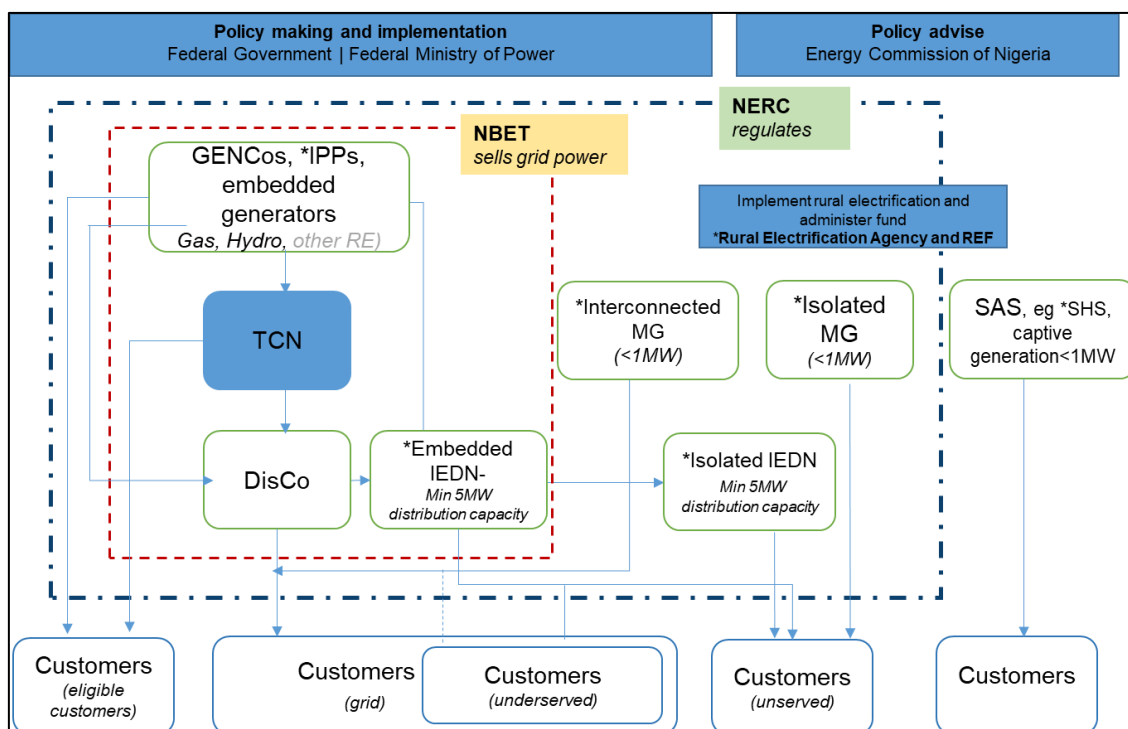
Table C-6 Sensitivity of the model behaviour to parameter changes

Model Parameter	Numerical/behavioural sensitivity
Demand	++
Risk levels (discount rate)	+
Construction time	++
Arrow Pratt Coefficient	+++
Solar mini-grid costs	++
Capital cost multiplier	++
Cost of Fuel	+
Capacity factor	++
Corporate tax rate	+
Expected profit	+
Investment capacity threshold	+++
Collection rate	++
Loan tenor	+

Appendix D Supplementary information for Chapter 5

D.1 Administrative structure of the Nigeria power sector

Figure D-1 illustrates the administrative structure of the power sector, with policy making and implementation conducted by the federal government through the Ministry of Power while the energy commission provides policy advice. Furthermore, the power sector is independently regulated by the Nigerian electricity regulation commission (NERC), while the national bulk electricity Trader (NBET) is responsible for grid market settlement. NERC is responsible for regulating grid generation, transmission and distribution, independent electricity distribution, off-grid generation capacity >1MW such as IPPs, isolated and interconnected mini-grids, captive generation, and embedded generation (133,254). NERC also has issued regulatory guidelines for off-grid generation less than 1MW, such as projects deployed in rural electrification. The Rural Electrification Agency (REA) promotes rural electrification, leveraging RE technologies, through technical and financial assistance via the Rural Electrification Fund (REF). The REA achieves its objectives through grid extension, mini-grid development, and the rollout of standalone systems in unserved and underserved communities.



Colour code: blue: Government agency, white with green outline: private or public-private partnership, white with blue outline: customers

NERC: Nigerian electricity regulation commission (regulator), NBET: Nigeria Bulk Electricity trader (grid market settlement), TCN: Transmission Company, REF: Rural Electrification Fund, IEDN: independent electricity distribution, GenCo: Generation Company, IPP: Independent power producer, DisCo: Distribution company, MG: Mini-grid, SAS: Stand-alone system, SHS: Solar home system, * Financial assistance provided by REF., **Generation >1MW requires NERC license.

Figure D-1 Nigeria's power system structure, adapted from (230).

D.2 Methodology

D.2.1 Location attributes

Table D-1 below presents the locations in the model and input parameters comprising geographical coordinates and spatial location attributes. The following respective attributes were normalised between 0-1, with 1 being the most attractive, for number of town and cities within 25km, poverty, and solar irradiation potential (GHI). The model uses historical alternative fuel cost and estimates future costs based on inflation and exchange rates. The conflict data is maintained at the 2022 value throughout the model horizon.

Table D-1 Locations attributes in the model

(source (57,225))

State	LGA	GISPoint_ Ward	Ward – Latitu de	Ward – Longit ude	Populatio n	Alternative Petrol Generator Cost USDperkW _2022	Normalised (0-1)				
							Num ber of town s withi n 25k m	Num ber of town s withi n 25k m	Pov erty level	GHI	Confli ct factor _2022
Cross River	Biase	Umon Island	5.319 41	8.082 286	5,000	0.1995	0.00 00	0.00 00	0.73 42	0.26 84	0.975 387
Edo	Ikpoba- Okha	Obayantor	6.168 487	5.561 434	13,449	0.1998	0.07 14	0.12 50	0.70 42	0.22 63	0.969 409
Ekiti	Ijero	Ekamarun Ward \ B\	7.828 521	5.094 616	4,066	0.1967	0.28 57	0.00 00	0.64 59	0.36 32	1
Ekiti	Ekiti East	Ilasa I	7.808 342	5.697 51	11,642	0.1967	0.28 57	0.00 00	0.74 10	0.45 79	1
Ekiti	Oye	Isan/ Ilafon/ Ilemeso	7.964 932	5.333 89	12,949	0.1967	0.21 43	0.00 00	0.75 47	0.47 89	1
Ekiti	Ekiti East	Isinbode	7.682 167	5.653 544	6,162	0.1967	0.28 57	0.00 00	0.73 83	0.39 47	1

Ekiti	Gboyin	Ode I	7.652 147	5.595 006	369	0.1967	0.35 71	0.00 00	0.73 63	0.38 42	1
FCT	Kwali	Kigbe	8.681 2	7.094 5	11,565	0.2010	0.60 43	0.00 00	0.81 43	0.50 53	0.968 706
Imo	Etche	Egbeke (Upgraded)	5.19	7.216	1,200	0.1962	0.00 00	0.12 50	0.69 98	0.18 95	0.980 661
Jigawa	Kafin Hausa	Balangu	12.06 786	10.11 016	35,833	0.2050	0.00 00	0.00 00	0.91 95	0.94 21	0.995 429
Jigawa	Garki	Garki	12.80 882	8.815 119	33,697	0.2050	0.07 14	0.00 00	0.64 73	0.96 32	0.995 429
Jigawa	Auyo	Dakaiyawa	12.35 551	9.870 046	19,247	0.2050	0.07 14	0.12 50	0.90 56	0.94 74	0.995 429
Kaduna	Ja ba	Fada	11.22 058	5.497 488	17,762	0.2069	0.21 43	0.00 00	0.83 50	0.76 32	0.908 579
Kaduna	Zango- Kataf	Kachia Urban	9.899 878	7.921 085	49,308	0.2069	0.07 14	0.00 00	0.80 28	0.73 68	0.623 769
Kaduna	Kauru	Makami	10.58 723	8.064 289	1,200	0.2069	0.14 29	0.00 00	0.83 37	0.84 21	0.623 769
Kano	Warawa	Danbagiwa	11.80 092	8.775 857	10,571	0.2024	0.92 86	0.00 00	0.88 59	0.92 11	0.990 506
Kano	Dawakin Tofa	Dawaki East	12.11 289	8.345 582	23,003	0.2024	0.85 71	0.12 50	0.87 97	0.93 68	0.990 506
Kano	Garum Mallam	Garun Malam	11.67 67	8.347 889	19,885	0.2024	0.42 86	0.00 00	0.88 34	0.91 58	0.990 506

Kano	Dawakin Kudu	Dawaki	10.32 355	9.860 227	99,231	0.2024	0.28 57	0.12 50	0.81 20	0.88 95	0.990 506
Kano	Dawakin Kudu	Tsakuwa	11.69 219	10.20 386	32,735	0.2024	0.07 14	0.00 00	0.89 48	0.93 16	0.990 506
Katsina	Bakori	Barde/Kwantakwaran	11.59 89	7.566 06	30,331	0.2011	0.07 14	0.00 00	0.60 11	0.91 05	0.804 852
Katsina	Ingawa	Doro	12.62 408	8.051 39	31,130	0.2011	0.14 29	0.00 00	0.46 53	0.96 84	0.804 852
Katsina	Daura	Mazoji A	12.99 876	8.263 312	11,404	0.2011	0.14 29	0.00 00	0.31 67	0.98 42	0.804 852
Katsina	Dan Musa	Dan Musa A	12.25 739	7.332 733	28,515	0.2011	0.00 00	0.00 00	0.44 57	0.92 11	0.804 852
Katsina	Kafur	Kafur	11.67 745	7.676 751	40,876	0.2011	0.14 29	0.00 00	0.51 56	0.92 11	0.804 852
Katsina	Mai 'Adua	Mai\Adua \B\	13.17 834	8.270 513	25,937	0.2011	0.07 14	0.00 00	0.53 09	0.98 95	0.804 852
Kebbi	Arewa-Dandi	Kangiwa	12.57 496	3.843 717	32,546	0.2000	0.07 14	0.00 00	0.21 91	0.87 89	0.908 579
Kebbi	Augie	Augie South	12.91 458	4.601 244	5,152	0.2000	0.07 14	0.00 00	0.27 15	0.90 00	0.908 579
Kebbi	Koko/Besse	Koko Magaji	11.41 136	4.525 113	19,348	0.2000	0.07 14	0.00 00	0.22 15	0.77 89	0.908 579
Kebbi	Sakaba	Tudun Kuka	11.25 123	5.447 044	13,404	0.2000	0.14 29	0.00 00	0.91 85	0.76 84	0.908 579

Kebbi	Wasagu/Danko	Wasagu	11.42 482	5.800 782	60,376	0.2000	0.00 00	0.00 00	1.00 00	0.81 58	0.908 579
Kebbi	Bagudo	Lolo/Giris	11.60 399	3.593 384	44,970	0.2000	0.14 29	0.00 00	0.43 29	0.79 47	0.908 579
Kebbi	Birnin Kebbi	Maurida/Karyo/Ung. Mijin-Nan	12.58 318	4.157 782	27,475	0.2000	0.21 43	0.00 00	0.24 90	0.87 89	0.908 579
Kwara	Kaiama	Kaiama 11	9.583 544	3.934 218	13,705	0.1976	0.07 14	0.00 00	0.78 99	0.62 63	0.988 045
Kwara	Pategi	Lade 11	8.639 399	5.539 068	16,424	0.1976	0.07 14	0.00 00	0.81 62	0.52 11	0.988 045
Kwara	Edu	Lafiagi 11	8.755 291	5.400 134	31,060	0.1976	0.14 29	0.00 00	0.80 54	0.53 16	0.988 045
Niger	Katcha	Bisanti	9.328 754	6.212 533	10,974	0.2012	0.00 00	0.00 00	0.83 06	0.53 68	0.502 813
Niger	Magama	Tunga Jika	10.02 21	4.769 135	7,606	0.2012	0.07 14	0.00 00	0.85 14	0.63 68	0.502 813
Ogun	Ijebu East Central	Gbamu Gbamu	6.847 541	4.212 617	5,000	0.2015	0.07 14	0.00 00	0.72 39	0.16 84	0.978 551
Ondo	Okitipupa	Mahin Lv	6.422 032	4.59	7,314	0.1975	0.07 14	0.00 00	0.67 41	0.18 95	0.984 177
Ondo	Akoko South West	Oba li	6.080 96	6.822 152	50,174	0.1975	0.71 43	0.37 50	0.72 27	0.31 58	0.984 177
Osun	Aiyedade	Ijegbe / Oke-Eso/Oke-Owu Ijugbe	7.522 534	4.400 035	9,852	0.2003	0.00 00	0.12 50	0.73 57	0.24 74	0.984 177

Oyo	Ibarapa North	Igangan I	7.641 232	3.169 418	4,335	0.2022	0.00 00	0.00 00	0.78 86	0.28 95	0.985 935
Oyo	Iwajowa	Iwere-Ile li	8.122 759	3.059 76	30,351	0.2022	0.00 00	0.00 00	0.83 25	0.32 11	0.985 935
Plateau	Shendan	Demshin	8.687 958	9.446 555	5,000	0.1928	0.00 00	0.00 00	0.85 02	0.67 89	0.873 066
Sokoto	Wurno	Marafa	12.49 02	4.211 956	35,089	0.2012	0.28 57	0.00 00	0.28 58	0.84 74	0.908 579
Sokoto	Goronyo	Goronyo	13.40 39	5.710 65	30,771	0.2012	0.07 14	0.00 00	0.76 91	0.93 68	0.938 115
Sokoto	Goronyo	Rimawa	13.42 306	5.947 317	43,797	0.2012	0.00 00	0.00 00	0.31 01	0.95 26	0.938 115
Sokoto	Gwadabawa	Gigane	13.46 578	5.209 774	37,936	0.2012	0.14 29	0.00 00	0.32 27	0.93 16	0.938 115
Sokoto	Gwadabawa	Gwadabawa	13.37 834	5.252 97	69,691	0.2012	0.28 57	0.00 00	0.24 89	0.91 05	0.938 115
Sokoto	Isa	Isa South	13.16 803	6.389 847	35,546	0.2012	0.14 29	0.00 00	0.28 51	0.93 16	0.938 115
Sokoto	Kware	Kware	13.21 132	5.267 209	25,385	0.2012	0.42 86	0.12 50	0.23 02	0.91 05	0.938 115
Sokoto	Silame	Katami North	12.96 783	4.710 069	12,000	0.2012	0.07 14	0.00 00	0.22 92	0.88 95	0.938 115
Sokoto	Tangaza	Tangaza	13.40 159	4.870 232	40,683	0.2012	0.07 14	0.00 00	0.21 26	0.93 16	0.938 115

Sokoto	Gada	Kyadawa/Holai	13.75 659	5.545 371	60,404	0.2012	0.07 14	0.00 00	0.76 79	0.95 26	0.938 115
Sokoto	Gudu	Kurdula	13.57 568	4.365 783	4,000	0.2012	0.00 00	0.00 00	0.91 10	0.94 74	0.938 115
Zamfar a	Zurmi	Birnin Magaji	12.62 833	6.889 928	28,287	0.1990	0.00 00	0.00 00	0.60 56	0.92 11	0.488 045
Zamfar a	Bakura	Birrintudu	12.72 648	5.982 344	22,397	0.1990	0.00 00	0.00 00	0.08 59	0.88 95	0.488 045
Zamfar a	Gummi	Birrintudu	12.02 886	5.279 145	45,985	0.1990	0.07 14	0.00 00	0.26 11	0.84 74	0.488 045
Zamfar a	Maru	Dan Sadau	11.40 958	6.591 979	135,366	0.1990	0.00 00	0.00 00	0.70 65	0.81 58	0.488 045
Zamfar a	Bukkuyum	Bukkuyum	12.18 274	5.494 694	26,248	0.1990	0.07 14	0.00 00	0.31 31	0.84 74	0.488 045
Zamfar a	M aradu n	Janbako	12.80 208	6.134 407	27,689	0.1990	0.00 00	0.00 00	0.69 36	0.90 00	0.488 045
Zamfar a	Shinkafi	Shinkafi South	13.05 891	6.510 498	33,286	0.1990	0.14 29	0.00 00	0.63 57	0.92 11	0.488 045
Zamfar a	Talala Mafara	Jangebe	12.19 514	6.067 638	30,151	0.1990	0.07 14	0.00 00	0.87 54	0.87 37	0.488 045
Zamfar a	Birnin Magaji	modomawa east	12.56 397	6.804 771	14,980	0.1990	0.07 14	0.00 00	0.37 01	0.92 63	0.488 045

D.3 Results Appendix

D.3.1 BAU case results

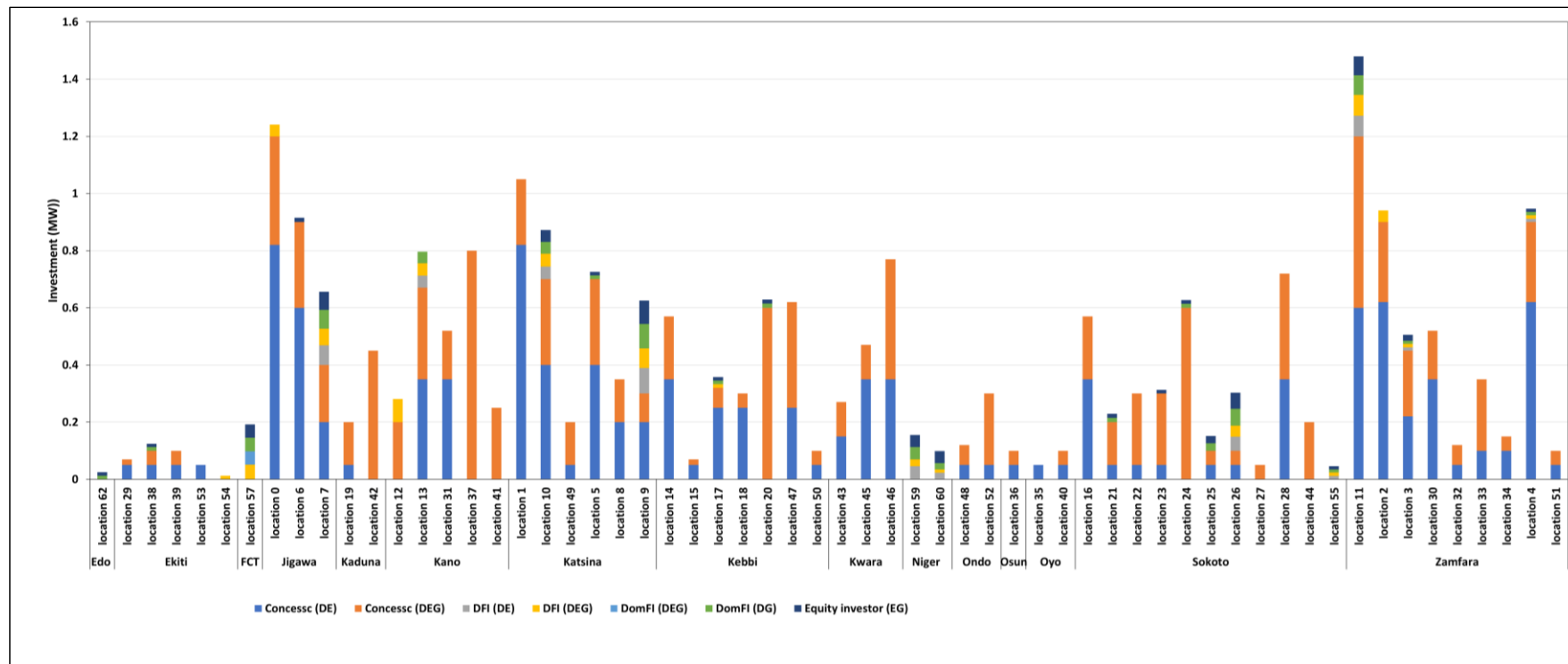


Figure D-2 Total investment for each location and investor type in 2030

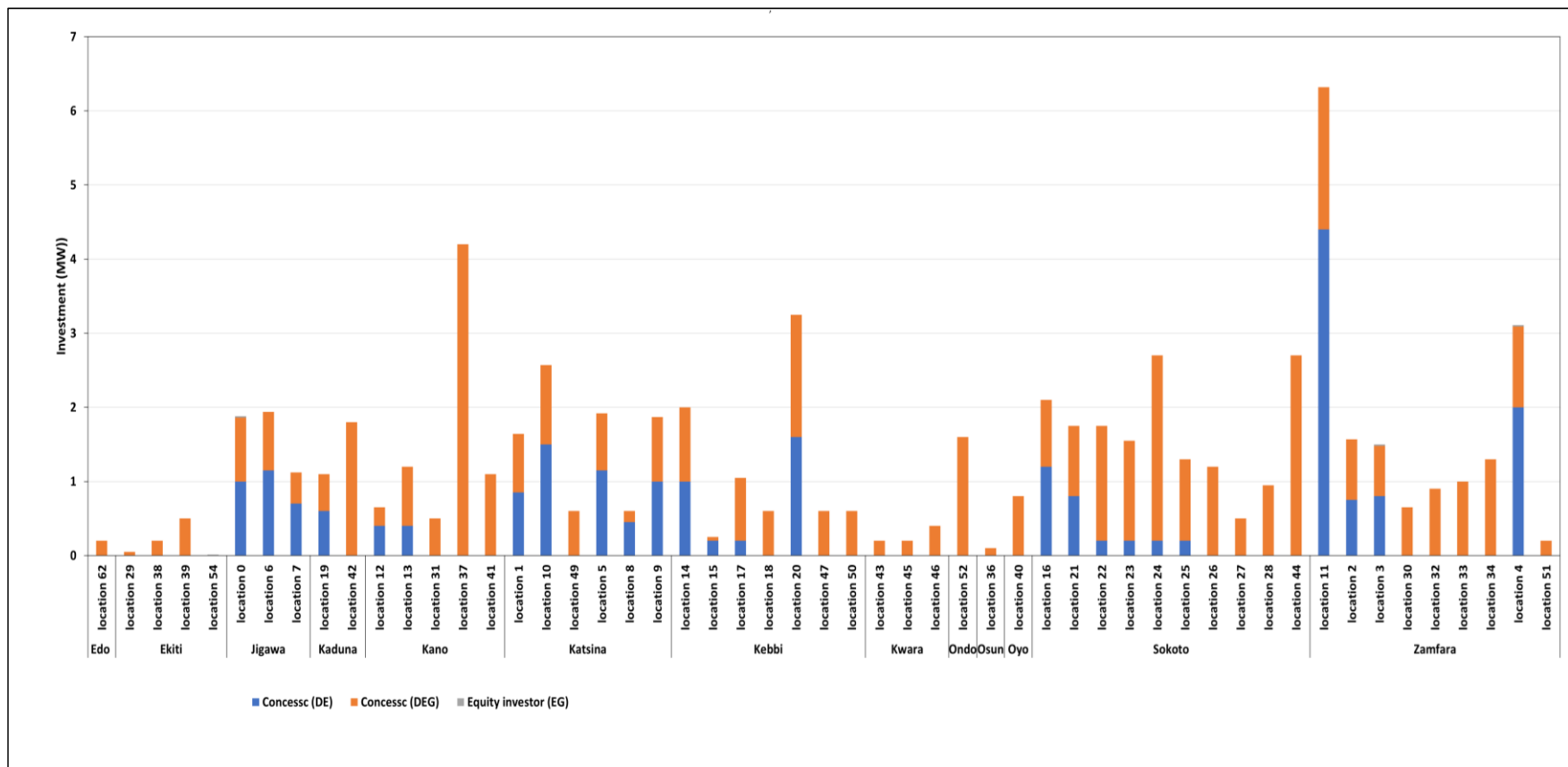


Figure D-3 Total investment for each location and investor type in 2040

