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Evaluation of the RDM Index, a GIS composite indicator for identifying optimal areas for sustainable rural development: case studies from Vietnam and Kenya.

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Abstract

Sustainable rural development is essential for achieving global sustainable development goals, and geospatial technologies can play a vital role in this effort. This thesis evaluates the Rural Development Model Index (RDMI) for identifying areas suitable for sustainable rural development. The RDMI uses publicly available, high-resolution datasets with global spatial coverage to provide a comprehensive and accessible tool for non-profits and governmental agencies to plan for sustainable development. However, this study identifies several limitations that must be addressed.

The study recommends including additional indicators that measure key criteria for the RDM programme, particularly indicators related to access to electricity and poverty levels, and continuing to research and review new high-resolution datasets. The effects of variations in the model parameters and variables on the RDMI scores and classes are analysed through quantitative measures and visual maps The findings indicate that when only three dimensions are present, using the median as the dimension level aggregation method is not recommended. Instead, using the arithmetic or weighted average may be better choices. However, the average is more prone to being influenced by extreme values, and some countries may be more sensitive to weight selection, especially when outliers are present. Therefore, implementing indicator thresholds could be beneficial in addressing extreme data values.

The study recommends removing Normalised Difference Vegetation Index (NDVI) as a variable due to the risk of targeting more developed areas in countries where marginalized communities live in arid areas. Furthermore, the effects of including nitrogen dioxide (NO_2) as a variable need further research, and it is not advised to aggregate NO_2 with renewable energy resources.

Overall, the study highlights the potential of the RDMI as a tool for identifying suitable areas for sustainable rural development. However, further development and exploration are needed. The study's contributions can inspire further research and development of the RDMI and similar tools, ultimately contributing to the goal of sustainable rural development around the world.

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List of Abbreviations

CI - Confidence interval

DHS - Demographic and Health Survey

EO - Earth Observation

EW - Equal weighting

GDP - Gross domestic product

GIS - Geographic Information System

GRDI - Gridded Relative Deprivation Index

HDI - Human Development Index

LP - Lotus Project

MC - Monte Carlo

MICS - Multiple Indicator Cluster Surveys

ML - Machine learning

MPI - Multidimensional Poverty Index

NDVI - Normalised Difference Vegetation Index

NO_2 - Nitrogen dioxide

PV - Photovoltaic

RDM - Rural Development Model

RDMI - Rural Development Model Index

SDG - Sustainable Development Goals

SRDI - Sustainable Rural Development Index

SSA - Sub-Saharan Africa

UN - United Nations

UNDP - United Nations Development Programme

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Chapter 1 Introduction

Rural development is a crucial challenge for many countries, especially in regions where poverty and social inequalities are rampant. In recent years, geospatial technology and composite indicators have emerged as powerful tools for identifying areas with high potential for sustainable rural development. The Rural Development Model Index (RDMI) is one such composite indicator, which combines multiple datasets related to environmental, social, and geographical factors to identify optimal areas for rural development.

This thesis aims to evaluate the effectiveness of the Rural Development Model Index in identifying such areas, using case studies from Vietnam and Kenya. High-resolution geospatial data is used extensively in this study to provide detailed spatial information on various factors that affect rural development, such as population density, clean energy resources, and pollution levels.

The research questions that guide this study are: (1) To what extent does the RDMI reflect the key criteria for an optimal area for the RDM programme? (2) How do variations in the RDMI affect the index outputs for each country? To answer these questions, this thesis is divided into seven chapters which will be outlined in section 1.1.

1.1 Structure of the Paper

Chapter 1 of this paper introduces Lotus Project, the Rural Development Model, and the RDM Index. The introduction also outlines the research aims and objectives of the study, and it provides an overview of the case study countries, Vietnam and Kenya. In Chapter 2, a literature review is conducted on composite indicators and the use of geospatial data for measuring and estimating factors related to sustainable rural development.

Chapter 3 introduces the high-resolution datasets used in this study and the methodology used to calculate the RDMI. Chapter 4 outlines the methodology of the study, including interviews with Kenyan GIS experts, RDMI indicator and RDM criteria mapping analysis, exploratory data analysis, and sensitivity and uncertainty analysis.

In Chapter 5, the results of the sensitivity and uncertainty analysis are presented, including comparisons of the RDMI scores and classes, visual comparisons of maps, and comparisons of model outputs for pilot sites. Chapter 6 discusses the results of the study in the context of the two research questions, and it provides recommendations for future work on the further development of the index. Finally, Chapter 7 provides a conclusion summarising the key findings of the study and their implications.

1.2 Lotus Project and the Rural Development Model

This research project was carried out in collaboration with an organisation called Lotus Project which operates sustainable development programs in Vietnam. Their work is supported by their Rural Development Model (RDM) which is a framework for rural development with the goal of achieving self-sustaining growth. RDM is a five-phase plan for development where the initial steps involve identifying suitable communities that have limited access to electricity and then providing electricity to these villages by implementing a reliable and affordable microgrid-based system. The following stages in the model include training the community members on how to operate and maintain the off-grid systems and introducing a community-based development model with the goal of transitioning the community into a state of self-sustained growth (see Figure 1.1). There are numerous criteria for the ideal location for this type of development programme. For example, optimal villages or locations would be in underdeveloped, low-populated rural areas with limited economic activity and low to medium accessibility by road, and there should be an abundance of at least one renewable energy resource (wind, solar power, etc.).

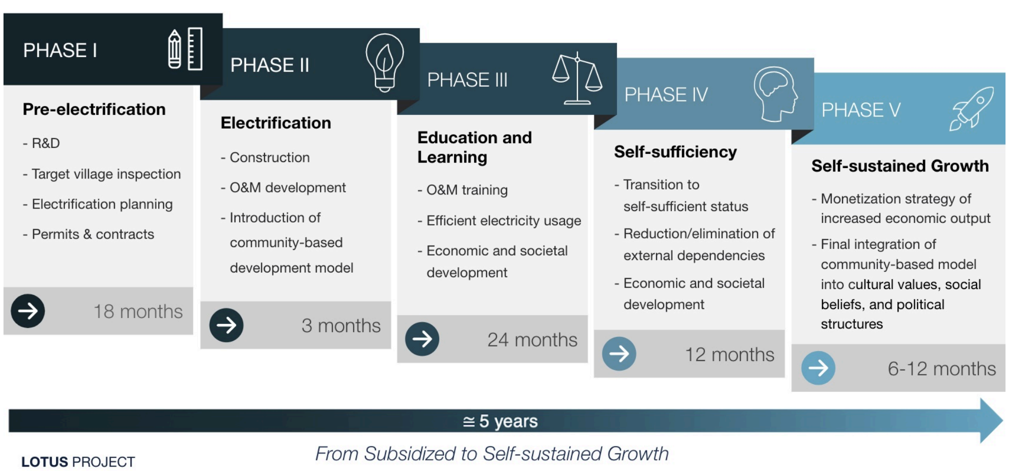


Figure 1.1 Diagram of the Rural Development Model five-phase framework

Lotus Project is currently conducting two pilot projects of the RDM programme in remote villages located in the Chi Lang and Van Quan districts of the Northern Vietnam mountains, near the border of South China (refer to Figure 1.2). As part of this research, the RDMI outputs for these two sites will be compared to assess whether their suitability level for the RDM programme, as indicated by the index, changes based on variations in the model.

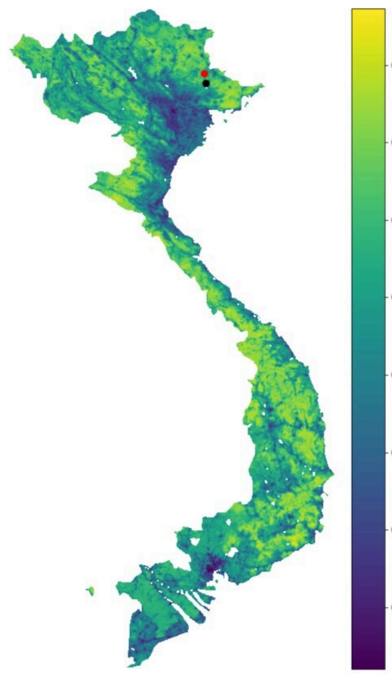


Figure 1.2 RDMI map of Vietnam showing Chi Lang (black dot) and Van Quan (red dot) villages (lotus-project.org). Areas closer to yellow in colour are more suitable for the RDM programme according to this index.

1.3 Rural Development Model Index

To identify areas that Lotus Project should target and prioritise in the future, the organisation has created an index called the Rural Development Model Index (aka the RDM Index or RDMI). The RDMI is an aggregation of data from three dimensions: environmental, social, and geographical. Currently, the environmental dimension includes data sources related to wind power, solar power, and air pollution levels (considered for inclusion). The social dimension consists of population density data, while the geographical dimension uses the Normalised Difference Vegetation Index (NDVI). All data used to calculate the RDMI come from public, open-source datasets and are geospatial data in the form of

GeoTIFF files. The index ranges from 0 to 1, with higher values indicating higher suitability for the programme.

While the RDMI has only been used in Vietnam, where Lotus Project operates its pilot projects, the organization aims to make the RDMI outputs available to other non-profit organizations and governmental agencies interested in rural development and electrification through clean energy. Consequently, Lotus Project plans to develop and publicize RDMI datasets for every country to enable its global use.

The RDMI is still under development, and Lotus Project intends to include more relevant indicators in the index in the future. This project aims to investigate additional indicators and geospatial data sources that can enhance the RDMI's effectiveness. Additionally, this research seeks to evaluate the RDMI's robustness and reliability using two case study countries.

1.4 Research Aims and Objectives

1.4.1 Research questions

The overall aim of this research project is to assess the quality and robustness of the RDM Index and to compare the outputs for the pilot country (Vietnam) with the outputs for a country in a different geographical region (Kenya).

In order to meet this aim, the study investigates the following research questions:

- **To what extent does the RDMI reflect the key criteria for an optimal area for the RDM programme?**

- **How do variations in the RDMI affect the index outputs for each country?**

Overall, this study seeks to provide valuable insights into the suitability of the RDMI as a tool for identifying optimal areas for rural development programs. By exploring the research questions and comparing outputs between the pilot country and a different region, the study aims to offer recommendations that can improve the index and make it more reliable and robust for use by non-profit organisations and governmental agencies globally.

1.4.2 Specific Objectives

To answer the research questions, the project has the following objectives to meet:

- Conduct an initial review of the RDMI map in the context of Kenya through interviews with GIS experts and use their feedback to inform the rest of the study.
- Develop a list of key and desirable criteria for the RDM programme, map the RDMI indicators to the criteria, and identify data gaps to suggest potential datasets to bridge them.
- Compare the relationships between the RDMI and each indicator using data from the case study countries by calculating correlations and generating visualizations to analyse the relationships between the RDMI and each dimension.
- Conduct a sensitivity analysis of the RDMI to determine the significance of the index's input parameters and variables by systematically varying each parameter and variable and observing how it affects the RDMI outputs. Conduct an uncertainty analysis to investigate how much uncertainty is associated with different forms of aggregation methods that could be used to calculate the RDMI.
- Test the effects of changing the different variables and parameters used for the index on the outputs for the two pilot sites where Lotus Project currently runs the RDM programme.

1.5 Case Study Countries

Two case study countries from different regions of the world were chosen to assess the RDM Index. The first country is Vietnam., which was chosen as a case study as this is where the Lotus Project was founded and the RDM Index was originally created using Vietnam as the prototype country. The organisation currently runs pilot projects in two districts in Northern Vietnam, and it plans to continue to work in this region, thus it is important to assess how effective the RDMI would be at supporting the organisation to identify new sites in the future.

The second case study country is Kenya which was primarily chosen due to it being in the sub-Saharan region. According to the latest data from the World Bank, only 48% of people in sub-Saharan Africa (SSA) have access to electricity (2020a), and in rural areas access to electricity drops to only 25% of the population (2020b). Furthermore, SSA is the poorest region in the world, and it is estimated that 38.3% of the population were living below the $1.90 per day poverty line in 2019 (World Bank, 2019). Although extreme poverty rates in this region have been slowly declining over the past two decades, in many sub-Saharan countries the number of people experiencing multidimensional poverty has actually been increasing due to population growth (Schoch and Lakner, 2020) Therefore, there is a huge need for rural electrification and poverty alleviation programmes in this region, and there are many organisations and governments that could potentially benefit a great deal from using the RDMI mapping tool to identify areas that are suitable for sustainable development programs (based on the RDM criteria). Moreover, Lotus Project is interested in possibly extending its operations to SSA in the future, and so, all these factors make it the ideal region to use as a case study for evaluating the RDMI.

1.5.1 Country Profile - Vietnam

Vietnam, officially known as the Socialist Republic of Vietnam, is a long and narrow country located at the eastern edge of mainland Southeast Asia. It shares borders with Laos and Cambodia to the west and China to the north. Vietnam had a population of around 97.5 million people in 2021 (United Nations, 2022) and covers an area of approximately 331,210 square kilometres, with a coastline of 3,260 kilometres along the South China Sea. Its capital Hanoi lies in the north of the country, while its largest city Ho Chi Minh is in the south. Its geography is diverse, featuring highlands, mountains, deltas, plains, and its long coastline. Its land cover is also highly varied, with forests, agricultural lands, wetlands, and urban areas.

Vietnam has undergone significant economic reforms that have propelled the country from being one of the poorest in the world to a middle-income country with the highest Human Development Index score among lower-middle-income economies. In the span of a generation, Vietnam's gross domestic product (GDP) per capita increased by 3.6 times between 2002 and 2021, and poverty rates (US$3.65/day, 2017 PPP) fell from 14% to 3.8% between 2010 and 2020 (World Bank, 2022a). Infrastructure services have also improved dramatically, with access to electricity increasing from 14% of the population in 1993 to 100% in 2020 (World Bank, 2020a). However, despite significant progress, access to clean water in rural areas remains limited, although it has increased from 17% in 1993 to 51% in 2020 (UNICEF, 2020).

The Vietnamese government is aiming to continue its rapid development and become a high-income country by 2045. However, the country recognizes the importance of sustainable development and has committed to reducing methane emissions by 30% and halting deforestation by 2030 (World Bank, 2022a). As a result, there is a growing emphasis on green growth and sustainable development in Vietnam's policy agenda, with the government promoting renewable energy and sustainable agriculture practices (Tran, 2020). Such initiatives are crucial for Vietnam's future growth and development and are aimed at balancing economic development with environmental protection and social well-being.

1.5.2 Country Profile - Kenya

Kenya, officially the Republic of Kenya, is a country in Eastern Africa by the Indian Ocean that borders Tanzania, Uganda, Somalia, Ethiopia, and South Sudan. As of 2021, Kenya had a population of approximately 53 million people, according to the United Nations (2022). The country covers an area of approximately 582,650 square kilometres, making it one of the largest countries in East Africa. Its capital and largest city is Nairobi, which is located in the southern part of Kenya, on the eastern edge of the Great Rift Valley and close to the geographic centre of the country. Other major cities include Mombasa, located on the coast, and Kisumu City, situated inland by Lake Victoria. The country has a diverse geography with a variety of landscapes that include fertile highlands, a coastal plain with golden beaches, an extensive semi-arid plateau in the north, and the Great Rift Valley which bisects the north and the south of the country (Ouma, 2019). Most of the population lives in the highlands, where it is cooler and more suitable for food production, or in coastal regions (UNDP, 2019).

Kenya has made significant progress in economic growth in recent years, and according to the World Bank, the Kenyan economy grew at an average rate of 5.7% per year between 2010 and 2019, making it one of the fastest-growing economies in the region. However, the COVID-19 pandemic had a significant impact on the economy in 2020, with the economy contracting by an estimated 0.1% (World Bank, 2022b).

Agriculture is the backbone of the Kenyan economy, accounting for over 30% of the country's GDP and employing around 75% of the population (World Bank, 2022b). The country is a major exporter of tea, coffee, and flowers, and is also a significant producer of horticultural products, including fruits and vegetables. However, the country is also vulnerable to drought and other climate-related challenges, which can have a significant impact on agricultural productivity. In recent years, the Kenyan government has been working to diversify the economy and reduce its reliance on agriculture. There has been a focus on developing the manufacturing sector, with the government implementing policies to attract foreign investment and promote local industries. The country has also seen significant investment in infrastructure, including the construction of new roads, railways, and ports, which has helped to improve the country's connectivity and competitiveness.

Despite this progress, Kenya still faces significant challenges in terms of poverty and inequality. The country has a high level of income inequality, and many Kenyans still live in poverty. According to data from World Bank's Poverty and Inequality Platform, the poverty rate in Kenya was 27.2% in 2019, with higher rates of poverty in rural areas and among certain ethnic groups (World Bank, 2022c). To address these challenges, the Kenyan government has implemented various programs and policies aimed at promoting inclusive growth and reducing poverty. These include social safety net programmes, such as cash transfer programmes and food subsidies, as well as policies aimed at improving access to education, healthcare, and other social services.

1.5.3 Comparison of Case Study Countries

When comparing Kenya and Vietnam as case study countries, it becomes clear that they have taken different paths towards achieving economic growth and social development. Kenya, a lower-middle-income country with a GDP per capita of $1,819 in 2021, is heavily reliant on agriculture and tourism, and faces significant challenges such as corruption, political instability, and income inequality (World Bank, 2022b). On the other hand, Vietnam, also a lower-middle-income country with a GDP per capita of $3,756 in 2021, has a more diversified economy, with a strong manufacturing sector and a growing services sector (World Bank, 2022a). It has made significant progress in reducing poverty and improving access to education and healthcare, ranking higher than Kenya on the Human Development Index (UNDP, 2022). Vietnam also performs better than Kenya on indicators such as access to clean water and sanitation, maternal and child health, and literacy rates (World Bank, 2022d).

In terms of renewable energy resources, Kenya has significant potential for geothermal, wind, and solar power generation, and has already made significant strides in the development of renewable energy. It is the largest producer of geothermal energy in Africa and has the continent's largest wind farm. Vietnam, however, has been relatively slow in developing its renewable energy capacity, despite having significant potential for hydropower generation. Nonetheless, the Vietnamese government has recently set ambitious targets for increasing its renewable energy capacity, including a target of generating 10% of its electricity from renewable sources by 2030 (World Bank, 2022a).

Overall, these differences highlight the importance of considering the unique context and challenges faced by each country when designing and implementing development strategies. While both Kenya and Vietnam face challenges such as corruption and income inequality, they have taken different paths towards achieving economic growth and social development. As such, it is crucial for development strategies to be tailored to each country's unique context and potential, including its renewable energy resources, to ensure sustainable and equitable development.

Table 1.1 A comparative table of development indicators for the two case study countries.

Development Indicator	Vietnam	Kenya
Human Development Index Score/Rank*	0.703/115	0.575/150
Life expectancy at birth*	73.6 years	61.4 years
Mean years of schooling*	13.0 years	6.7 years
Gross national income (GNI) per capita (2017 PPP $) *	$7,867	$4,474
Multidimensional Poverty Index**	0.008	0.171
Population in multidimensional poverty**	1.9 million	19.5 million
Access to electricity (rural population) ***	100%	62.7%
Rural population (% of total population) ****	62%	72%

* UNDP (2022), ** UNDP (2021), *** World Bank (2020b), **** World Bank (2021)

1.6 Summary of Introduction

This introductory chapter provides a comprehensive overview of the paper, introducing its main research aims and objectives. Firstly, it presents Lotus Project, a sustainable rural development initiative aimed at improving the livelihoods of rural communities. Its five-phase framework called the Rural Development Model guides the implementation of the initiative. Additionally, the chapter introduces the RDM Index, a tool used to assess the potential of areas for the Rural Development Model, and which will be evaluated in this study.

Furthermore, this chapter compares Vietnam and Kenya, two lower-middle-income countries with unique challenges and opportunities for sustainable rural development. This comparison highlights the importance of considering a country's context and potential when developing a tool like the RDM Index. Overall, this chapter sets the foundation for the subsequent chapters by providing an in-depth introduction to the main concepts and themes that will be explored throughout the paper.

Chapter 2 Literature Review

2.1 Introduction

The Rural Development Model (RDM) is a framework for sustainable socio-economic development that was created by a UK-based NGO called Lotus Project[1] that runs pilot projects in Northern Vietnam. RDM is a five-phase plan for development where the initial steps involve identifying suitable remote communities and then providing electrification to these villages (Bellis, 2020). To identify areas that Lotus Project should target and prioritise in the future, the organisation has created a composite indicator called the RDM Index (RDMI). Composite indicators are a method of quantifying multi-dimensional concepts that cannot be captured by just one indicator, and they are constructed by aggregating multiple indicators to form one simple index. This metric can then be easily communicated to stakeholders, and it allows for direct comparison or ranking of countries or areas in relation to the chosen concept (Freudenberg, 2003). In the case of the RDMI, the index values are displayed on a heatmap of the country, and this data visualisation can be used to easily compare areas within a country and to identify which have the most potential for the RDM programme. The index is on a scale of 0 to 1, and the higher the RDMI value, the more suitable the area is for development.

At present, the RDMI is made up of three different dimensions: environmental, social, and geographical (Verma, 2021). Population density data is the only indicator in the social category, and the Normalised Difference Vegetation Index (NDVI) is used for the geographical category. The environmental group is composed of indicators related to wind power and solar power. Lotus Project anticipates adding more relevant indicators in the future, and one of the aims of this project is to investigate other potential indicators and data sources that could enhance the index.

All the data currently being used to calculate the RDMI are types of high-resolution geospatial data. Geospatial data is locational data that describes a feature, object, or phenomena on or near the surface of the Earth (Stock and Guesgen, 2016). This type of data comes in two different forms, vector data and raster data. Vector data is composed of points, lines, and polygons that represent features on the Earth's surface, and examples include roads, rivers, and administrative boundaries. Whereas raster data represent geographical features through pixels, and types of raster data include satellite imagery, digital elevation models, and land cover maps. The data used for the RDMI are all forms of raster data. Different types of geospatial technologies are used to gather and analyse geospatial data, the most common being Geographical Information Systems (GIS), Remote Sensing (RS) and Global Positioning Systems (GPS)

[1] https://www.lotus-project.org/

(Reed and Ritz, 2004). While in the past geospatial data was mostly used by the military, intelligence agencies, and transportation companies, today it is an increasingly important element of every industry and sector in the world, including the development sector (Behm et al., 2018).

The aim of this literature review is to first explore how composite indicators have been used to quantify different dimensions of development, the issues that have arisen when constructing these kinds of indexes, and the techniques that can be applied to evaluate the quality of composite indicators. Next, the review will discuss the use of geospatial data in monitoring, evaluating, and planning development around the world. Specifically, it will explore the use of geospatial technologies to measure indicators that are related to the 2030 UN Sustainable Development Goals and indicators that are of particular interest to the RDMI, such as poverty levels, renewable energy resources, and rural development.

2.2 Composite Indicators

2.2.1 Composite Indicators in Development

Due to the complex nature of social, environmental, and economic development, composite indicators are frequently used to attempt to summarise these concepts (Bandura, 2011; Booysen, 2002), and some of the most well-known examples include the Human Development Index (HDI), the Gender Inequality Index (GII), the Global Hunger Index (GHI), and the Environmental Sustainability Index (ESI) (Yang, 2014). Composite indicators are popular in development as they are easy to communicate to the public and policymakers, they are useful for comparing and ranking different countries/states in terms of multidimensional concepts, and they make it easier to spot trends compared to looking at many indicators individually (Saisana and Tarantola, 2002; Saltelli, 2007). However, some key criticisms of the use of composite indicators are that there is uncertainty as to what extent they capture the concept, there is a risk that the decisions made by the developers could affect their quality and objectiveness, and that they have the potential to oversimplify complex issues (Saltelli, 2007).

One of the most famous composite indicators used in the development sector is the Human Development Index (HDI) which was introduced by the United Nations Development Programme (UNDP) in 1990 as a way of measuring development by more than just a country's GDP growth (UNDP, 1990). The indicators used to construct the HDI, as well as its calculation methods, have evolved over the years (Morse, 2014), and the most recent version of the HDI uses the geometric mean to aggregate four indicators related to three key dimensions of human development: a long and healthy life (measured by life expectancy), access to education (measured by average years of schooling and expected years of schooling) and a decent standard of living (measured by gross national income per capita) (UNDP, 2020). Despite it being one of the most important development indexes for policymakers, critics argue that there are still other core dimensions missing from the index, in particular a dimension related to environmental sustainability (Bhar and Dhara, 2021; Bravo, 2014; Sagar and Najam, 1998). For instance, Biggeri and Mauro (2018) propose enhancing the HDI by integrating two more dimensions related to the environment and human freedom to create the Sustainable Human Development Index (SHDI). The UNDP also continues to try to improve the HDI, and in response to the call for the index to factor in the environmental burden of economic growth, they have recently introduced the Planetary pressures-adjusted Human Development Index (PHDI) which considers countries' carbon dioxide emissions and material footprint (UNDP, 2020).

Another well-known composite indicator in the development sector is the Global Multidimensional Poverty Index (MPI) that was developed by the Oxford Poverty & Human Development Initiative and the UNDP in 2010 (Alkire and Santos, 2010). The MPI mirrors the HDI as it groups indicators into the same broad dimensions: health, education, and standard of living. However, while the HDI is available for nearly every country in the world, the Global MPI has only been calculated for 109 developing countries, and it uses micro data from household surveys such as Demographics and Health Surveys (DHS) to calculate its ten different indicators (including access to electricity, child mortality and child school attendance) (UNDP, 2021). Although it is more labour-intensive to collect this data, the MPI is a very useful composite indicator for development planning as it can be used to compare poverty levels not just between countries and regions, but also to analyse differences *within* countries between different areas and social groups. Data from the MPI can also be used by researchers to train models to predict outputs related to poverty and the indicators that make up the MPI (Pokhriyal and Jacques, 2017; Tingzon et al., 2019).

In recent years, there have been many new composite indicators developed due to the increasing need to consider sustainability in relation to different forms of development (García-Sánchez et al., 2015; Jeremic, Radojicic, and Dobrota, 2016; Sébastien and Bauler, 2013). For instance, Hashemi and Ghaffary (2017) propose an indicator called the Sustainable Rural Development Index (SRDI). They created this index as they found that while there are different indexes that measure local development, and there are indexes for evaluating the sustainability of tourism plans, there is an absence of measures that evaluate the effect tourism extension plans have on rural development. Therefore, just like other emerging indexes in development, including the RDMI, the SRDI was created based on the necessity to rank areas by a multidimensional concept that cannot be easily captured by a single indicator or by other existing composite indicators. Furthermore, the majority of development indexes that have already been created are intended for comparing different countries, whereas there are far fewer composite indicators which are used for comparing local areas, which is the intention of both the RDMI and the SRDI.

2.2.2 Constructing Composite Indicators

While the outputs of composite indicators are easy-to-understand, simple indexes, the construction process is a much more complicated affair. From selecting the appropriate data to choosing the most suitable type of aggregation, creating a new index is largely based on assumptions, and the decisions that developers make can radically affect the quality of the index (Freudenberg, 2003). To support developers to navigate the challenges involved in building a composite indicator, the Joint Research Centre-European Commission created the 'Handbook on Constructing Composite Indicators: Methodology and User Guide'. This OECD publication acts as a comprehensive guide on how to create indexes that are transparent, robust, and reliable (Joint Research Centre-European Commission, 2008). The handbook discusses ten steps in the construction process, including data selection, treatment of missing values, normalisation, weighting, and aggregation. For this part of the review, we will briefly discuss some studies which explore different approaches to several of these steps.

Choosing the most appropriate data to aggregate is a key decision to be made by researchers, and the OECD handbook recommends choosing data based on their 'analytical soundness, measurability, country coverage, relevance to the phenomenon being measured and relationship to each other' (Joint Research Centre-European Commission, 2008, p. 15). A common strategy involves reviewing the relevant literature and consulting with domain experts. For example, Rogelj et al. (2020) took this approach when exploring which economic indicators are most suitable for measuring sustainable development, and they concluded that the two most prominent indicators are unemployment rate and availability of agricultural infrastructure. However, other researchers have advocated for a more data-driven approach, such as Verma et al. (2020) who experimented with using clustering techniques to objectively select indicators for development indexes.

In addition to the challenge of deciding which indicators to include in the composite indicator, the robustness of an index depends a great deal on how the indicators are weighted and aggregated (Burgass et al., 2017), and there is a large and growing body of research that investigates different methods of calculating composite indicators (Becker et al., 2017a; Dobbie and Dail, 2013; Greco et al., 2019). The most common weighting system for indexes is equal weighting (EW), where all indicators are given the same weight (Joint Research Centre-European Commission, 2008). While EW is thought to be the most transparent and simplest method of weighting, Paruolo et al. (2013) suggest that EW may come with a large oversimplification cost depending on the type of aggregation used, and Greco et al. note that 'equal weights miss the point of differentiating between essential and less important indicators by treating them all equally' (2019, p. 66). There are many studies which apply and evaluate alternative weighting systems, such as data envelopment analysis (Chen et al., 2019; Lucas et al., 2021; Mohanty et al., 2021), principal component analysis (Jiang and Shen, 2013), the analytic hierarchy process (Chakraborty and Joshi, 2016) and budget allocation processes (Dur and Yigitcanlar, 2015; Zhou et al., 2012). In the first edition of the OECD handbook, Nardo et al. (2005) discussed the advantages and disadvantages of these various weighted methods, while Greco et al. (2019) provides a more recent review of weighting systems and current trends of methodological approaches to composite indicator construction. Furthermore, to aid with decision-making regarding weighting systems, Becker et al. (2017b) have introduced a set of three different tools to allow developers to analyse the importance of the weights they assign to indicators during the aggregation process.

Aggregation is the final step in forming a new index, and the OECD handbook discusses three different types of aggregation: linear, geometric, and multi-criteria (Joint Research Centre-European Commission, 2008). While linear and geometric methods are simpler forms of aggregation, they are criticised for their compensatory nature (particularly for linear aggregation). When these types of techniques are used, the weights no longer represent the importance of their associated variable (Munda, 2005). If it is crucial that the weights retain their importance or that a high score in one dimension should not be allowed to compensate for a low score in another (e.g., not allowing the population density indicator of the RDMI to compensate for low scores in the environmental dimension), then non-compensatory methods should be used such as the multi-criteria approach (MCA). This type of approach finds a compromise between different goals, however it can be computationally costly, especially when the number of instances is high, as is the case in the RDMI (Munda and Nardo, 2005). Because of the issues associated with both traditional compensatory and non-compensatory techniques, some researchers have experimented with creating hybrid methodologies to create relatively simplistic aggregation methods that still penalise substitutability between indicators and dimensions (Ács et al., 2014; Fusco, 2015; Mazziotta and Pareto, 2016).

2.2.3 Evaluation of Composite Indicators

Once a composite indicator has been developed, it should be evaluated to assess its accuracy and reliability as composite indicators involve several sources of uncertainty, such as data errors, methodological choices, and subjectivity. Failure to address these sources of uncertainty can lead to biased conclusions, and a thorough evaluation of new indexes can help justify decisions made during the construction process and make the composite indicator more transparent and its outputs more defendable. To conduct a proper evaluation, it is recommended to conduct statistical analyses, such as sensitivity and uncertainty analyses, to compare how sources of uncertainty affect the index and to explore how alternative methods of constructing the index affect its performance. (Saisana et al., 2005; Huergo et al., 2006; Joint Research Centre-European Commission, 2008).

A sensitivity analysis involves testing the robustness of the composite indicator results to changes in the underlying variables or parameters used in the construction of the composite indicator. A sensitivity analysis can be conducted using a variety of techniques, including one-way or univariate analysis, where one variable or weight is varied while others are held constant, or multi-way analysis, where multiple variables and weights are varied simultaneously (Saisana et al., 2005).

While a sensitivity analysis can help to identify which variables or weights have the most significant impact on the composite indicator results and inform decisions on how to improve the composite indicator, an uncertainty analysis aims to assess the impact of this uncertainty on the overall composite indicator score. One of the most common methods used in uncertainty analysis is the Monte Carlo method (MCM), or Monte Carlo simulation, which is a type of computational technique that uses random sampling to model the probability of different outcomes. MCM was developed by Stanislaw Ulam and John Von Neumann during World War II, and it is now used in a broad range of applications including physical sciences, computational biology, engineering, and financial modelling (Kroese et al., 2014). MCM is commonly employed to understand the impact of risk and uncertainty, and the use of MCM to assess the uncertainty present in a composite indicator involves assigning multiple random values to uncertain variables and running the composite indicator model numerous times to obtain multiple results. These results are then aggregated to obtain an estimate of the composite indicator score and a measure of the uncertainty associated with that score.

The OECD handbook recommends conducting both a sensitivity and uncertainty analysis, and a typical example of this sort of analysis can be seen in a study by Tate (2012) where an uncertainty analysis was performed to measure the robustness of various social vulnerability indexes, and a sensitivity analysis was applied to investigate which decisions in the construction process most influence the stability of the outputs. Or if we consider the HDI again as an example, Aguña and Kovacevic (2010) used uncertainty and sensitivity analyses to evaluate the robustness of this composite indicator and found that the controversial equal weighting system it uses proves to be robust. While Permanyer (2012) used an uncertainty analysis to demonstrate a new method they developed for comparing the different rankings that are produced by indexes when the weights are altered. Some studies have also evaluated the reliability of a new composite indicator by comparing the outputs of a new index to other types of indicators that are measuring a similar concept to check if there is any correlation (Nasierowski, 2016). Alternatively, or perhaps complementarily, qualitative analysis is another option in which experts or key stakeholders can be consulted to give opinions on the scores or rankings outputted by the index. An example of this is a study by Dr. Michaela Saisana and colleagues (2018) which aimed to increase the reliability and transparency of the Global Attractiveness Index (GAI), and their research paper illustrates how indexes can be evaluated through both qualitative research (reviews with internal and external experts) and quantitative analysis (statistical coherence checks, uncertainty and sensitivity analyses, and comparing ranking outputs of the GAI to ranking from other similar indexes). For the uncertainty analysis the researchers used MCM to calculate over 4,000 different simulations that were based on different treatments of missing values, using the arithmetic average versus the geometric average to aggregate at the pillar level of the index, and generating random weights for these pillars. This paper, along with the OECD handbook, has been an extremely useful guide on how to conduct a comprehensive evaluation of the RDMI for this research project. However, their methodology needed to be adapted somewhat as they utilise country rankings in their analysis, whereas this project evaluates the RDMI in relation to scores and classes of areas within a country.

2.3 Geospatial Data for Measuring, Evaluating and Planning Development

2.3.1 Monitoring the UN Sustainable Development Goals

The United Nations Sustainable Development Goals (SDGs) are a set of 17 goals that were adopted by the UN member states in 2015 for the 2030 Agenda for Sustainable Development. All these countries, both developed and developing, have committed to taking action between 2016 and 2030 towards ending global poverty, reducing inequalities, and allowing people to live peaceful and prosperous lives, while also protecting the Earth's biosphere and preserving natural environments like forests and oceans (Morton, Pencheon and Squires, 2017). The goals are based on the overwhelming evidence that there is a dire need for development to be more sustainable to ensure the world remains inhabitable in the future, and they incorporate the three dimensions of sustainable development: environmental protection, economic growth, and social inclusion (Griggs et al., 2013). There are 196 targets for the 17 overarching goals that include ending poverty, zero hunger, climate action, and sustainable cities and communities. Thus, tracking the progress towards the SDGs is a massive undertaking and a huge priority.

The UN has recognized the tremendous potential of using Big Data to both monitor and help make progress towards the SDGs (UN, 2018), and one of the data sources that was noted as having the most relevance is Earth Observation (EO) data, which is a subset of geospatial data. Geospatial data refers to any data that has a geographic location or spatial component, while EO data specifically refers to data collected from satellites or other platforms to observe the Earth's surface and atmosphere. A report by the UN Task Team on satellite imagery and geospatial data found that using EO data to monitor SDGs allows for more timely reporting on indicators, greater disaggregation of data for decision-making, and it can reduce the cost of reporting for nations without compromising on data impartiality, accuracy, or integrity (UN, 2017). Likewise, Anderson et al. (2017) highlight the myriad of benefits of using EO data as a source of evidence for assessing SDG indicators, such as the cost-effectiveness, accessibility, consistency, frequency, and scope of this type of data, and they believe it is especially valuable for tracking development in low-income countries which may not have the resources for other forms of data acquisition.

Andries et al. (2019) have developed a Maturity Matrix Framework to evaluate how applicable EO-derived data is to each of the 232 SDG indicators, and the resulting dashboard shows high potential for EO data to be used to monitor indicators for SDGs such as renewable and clean energy, life on land, and sustainable cities and communities. While Holloway et al. (2018) propose three main requirements for using EO data to measure sustainable development indicators. Firstly, the indicator needs to be seen or can be extracted from a satellite image. Secondly, there needs to be analysis-ready satellite imagery available for the selected location - this is satellite data that has been pre-processed and corrected to a standard format, allowing for easy and efficient analysis. And thirdly, there should be some validation data (or ‘ground truth’ data) available to test the statistical outputs from modelling the satellite imagery data. If this kind of data is not available, they recommend incorporating spatial information into the model, such as the spatial relationships that exist in this type of data, like autocorrelation (the idea that pixels close to each other are more likely to be similar than pixels that are far away). Machine learning (ML) is a subset of artificial intelligence that involves building algorithms that enable computers to learn from and make predictions or decisions based on input data without being explicitly programmed. And

Holloway et al. believe that there is a need to adapt current ML techniques to become better at modelling these types of spatial relationships. Similarly, a review by Ferreira, Iten and Silva (2020) on the use of EO data and ML techniques to monitor SDG progress concluded that as the availability of EO data increases, there is a growing demand for ML techniques which are suitable for analysing huge and varied datasets such as EO. They assert that these new ML methods are essential for extracting the most important features of the data, and therefore those which are most relevant to SDG indicators.

Lotus Project, like most development non-profits, aligns its work with the SDGs. The primary goals that the RDM programme addresses are ‘Goal 1: No Poverty’, ‘Goal 7: Affordable and Clean Energy’, and ‘Goal 8: Decent Work and Economic Growth’. The studies that were just mentioned have shown the potential for using high-resolution geospatial data, such as those used in the RDMI, to measure sustainable development goals. The next section will review studies that have used geospatial data to predict and measure indicators relevant to these SDGs, with a focus on core and desirable criteria for a future site for the RDM programme. For instance, the ideal area should have high levels of poverty, low economic activity, potential for rural development, suitability for off-grid electrical systems, poor access to electricity, and low levels of pollution. These criteria will be further discussed in Section 4.2.

2.3.2 Mapping Poverty and Economic Activity

In order to maximise the impact of the RDM programme, Lotus Project’s aims to target communities living in the most underserved and most disadvantaged areas in a country. And two of the key criteria for a future site for the RDM programme is that there should be high levels of poverty and limited existing economic activity. While concepts such as poverty can be difficult to measure through geospatial data due to the complex nature of this topic, poverty maps are an important tool for policymakers and researchers to understand the distribution of poverty across different regions of the world. Furthermore, mapping poverty helps NGOs and governments to target the people who are most in need and it informs decision-making regarding resource allocation and development planning from local to national levels (Akinyemi, 2010). However, the development of global poverty maps has been limited due to several challenges in data collection and analysis. One challenge is the lack of reliable and consistent data on household consumption and income. Many countries do not have regular surveys or censuses that collect detailed information on household income or consumption, and even when they do, the quality of the data can be questionable due to issues such as underreporting or recall bias (Ravallion, 2015). In addition, many of the poorest households may be missed by traditional surveys or censuses, as they may not be registered with local authorities or may be difficult to reach in remote or conflict-affected areas (Chen & Ravallion, 2010).

Another challenge is the lack of standardisation in poverty measurement. Different countries and organisations use different poverty lines and definitions of poverty, making it difficult to compare poverty rates across different regions and time periods (Chen & Ravallion, 2010). Even when a standard poverty line is used, there may be discrepancies in how poverty is measured, such as whether to use income or consumption data, or how to account for non-monetary aspects of poverty such as health or education (Ravallion, 2016).

Despite these challenges, there have been efforts to develop poverty maps using various methods and data sources, and many researchers have experimented with creating models to predict poverty using different forms of geospatial technologies (Jean et al., 2016). For example, Elvidge et al. (2009) created a poverty map based on a poverty index they formed by aggregating LandScan population counts and nighttime light data. They evaluated the resulting map by comparing it to country level poverty data from the World Bank. Similarly, Xu et al. (2021) used geospatial data including land cover usage, city accessibility, nighttime light, and Digital Elevation Model (DEM) data to map the integrated poverty index (IPI) for an extremely poor area of southwest China.

Household survey data and other national statistical data is often combined with geospatial data to train ML models that predict socio-economic indicators, or they can be used to validate such models (Jean et al., 2016). For example, a study done by Tingzon et al. (2019) employed a satellite-based deep learning approach (an approach that uses artificial neural networks with many layers to process and analyse complex data) to predict wealth levels, access to electricity and water, and years of education in the Philippines. They also created an alternative model that was trained on nighttime light data and geospatial data from OpenStreetMap (OSM - a collaborative, free, and open-source mapping project that allows users to create and edit maps of the world's geographic features) and found that the models achieved the same predictive performance when validated against the Philippine Demographic and Health Survey (DHS), with the latter model being much more cost-effective than the satellite-based model. Building on the previous study, Ledesma et al. (2020) explored how regression techniques can be used to predict levels of asset-based wealth using a combination of social media advertising data, remote sensing data and volunteered geographic data from OSM as inputs. Their research also focused on the Philippines and used DHS data as ground truth to validate their results. The study resulted in a model that is more interpretable and slightly more accurate than the deep learning model in the previous study, however at present this model has limited use globally as the data from Facebook and OSM is not complete or available for all areas yet.

In these types of studies, nighttime light is frequently used as a proxy for economic activity (Mellander et al., 2015). However, this kind of data is less effective at distinguishing differences in economic activity in areas with populations living near and below the international poverty line (Jean et al., 2016). And emerging technologies have the potential to become even better at predicting poverty and economic activity. For instance, Engstrom, Hersh and Newhouse (2017) found that by using computer vision to extract features (such as density of buildings, length of roads, roof materials, etc.) from high-resolution satellite imagery of districts in Sri Lanka, they could create a simple linear regression model that explains almost 60% of poverty headcount and consumption rates, whereas the models that they created using nighttime light imagery only explained 15%.

While Lotus Project is aiming for the RDMI to be a comprehensive index for measuring sustainable development, it currently lacks an indicator to estimate poverty or economic activity levels at a sub-national level. Despite promising studies on using geospatial data to measure poverty, there is still a dearth of datasets with global spatial coverage that are relevant to the RDMI. Nonetheless, two potential datasets have been identified during this literature review. The first is the Global Subnational Atlas of Poverty (GSAP) developed by the World Bank, which provides subnational poverty data for approximately 1,800 subregions across 166 economies (Nguyen et al., 2021). The second dataset is the Global Gridded Relative Deprivation Index (GRDI) developed by the Center for International Earth Science Information Network (CIESIN) at Columbia University. The GRDI measures relative deprivation at a high resolution for the entire world, by calculating the difference between an area's socioeconomic status (SES) and the SES of its surrounding areas using a Bayesian hierarchical framework that combines survey data, census data, and remote sensing data (CIESIN, 2022). The SES measure is based on a range of indicators, including household income, education level, and access to basic services. Both of these datasets have the potential to be included in the RDMI to address the data gap in poverty-related measures.

2.2.3 Rural Development Planning

Geospatial data is frequently used to support rural development studies as it gives planners access to the spatial data infrastructure of geographical areas, which is crucial for planning and decision-making at all levels of administration (Poi et al., 2018). It also helps planners to understand the interconnectedness of environmental, cultural, economic, and demographical considerations around certain resources which can be visualised through thematic map layers (Sarkar, 2018). Thus, geospatial data is ideal for measuring many of the criteria that LP considers when identifying a new site for their rural development programme.

For example, a key requirement for a potential RDM site is that it meets the criteria of being rural with low population density. The Degree of Urbanisation (DEGURBA), which has been endorsed by the UN Statistical Commission, is one potential way of determining whether an area is rural, and it was developed to create a universally applicable and unbiased method that relies mainly on population size and density thresholds applied to a 1 km x 1 km population grid (OECD and European Commission, 2020). The method classifies settlements into three categories based on these criteria. Cities consist of adjacent grid cells with a population density of at least 1,500 people per square kilometre or are at least 50% built-up, and a minimum population of 50,000. Towns and semi-dense areas consist of adjacent grid cells with a density of at least 300 people per square kilometre and at least 3% built-up, with a minimum total population of 5,000. Rural areas encompass all grid cells that are neither cities nor towns and semi-dense areas, and most of these cells have a population density below 300 people per square kilometre. Ideally this method is applied to geo-coded census data, which shows the location of every person and household. This type of data has only been published for a limited number of countries, but many countries are preparing for censuses that will collect this data, while some countries have already gathered this information. For instance, the latest census conducted in Kenya geolocalized all households (Dijkstra et al., 2021).

While this is a promising development for census data, gridded high resolution population datasets are often preferred over census data for development planning for several reasons (Stevens et al., 2015). First, gridded population datasets provide population estimates at a finer spatial resolution, which is essential for rural areas with small and dispersed populations. Second, gridded population datasets can be updated more frequently than census data, allowing for more up-to-date population information. Finally, gridded population datasets are more accessible and easier to integrate into analytical workflows than census data, which can facilitate rural development planning and decision-making. While there are a variety of gridded population datasets available (including those from Population of the World version 4 (GPW4), Global Human Settlement (GHS), and LandScan), one of the most widely used datasets is from WorldPop, and many comparative studies have found it to be one of the accurate means of estimating population density (Yu et al., 2021). For these reasons, LP has chosen to measure population density using a high-resolution dataset from WorldPop, and this is discussed in more detail in section 3.1.2.

Another desirable quality of a target site for the RDM programme is the availability of land that is suitable for future agricultural and development activities, and GIS data is frequently used for assessing this kind of land suitability. For example, by following guidelines from the FAO on land suitability mapping, Ahmad and Goparaju (2017) used geospatial technology to create an agroforestry suitability map with multiple weighted thematic layers, such as nutrient availability, slope, rainfall, and elevation. In a study by Oakleaf et al. (2019), the researchers created development potential indices to visualise areas which would be optimal for sustainable development on a global land suitability map. These thirteen indices relate to renewable energy, mining, fossil fuels and agriculture, and they were formed through the application of spatial multi-criteria decision analysis techniques, which assessed the resource potential and how feasible it is to develop. Uncertainty and sensitivity analyses were used to evaluate the robustness of the indices, and the researchers validated the map by comparing it to areas of planned development. While Rout et al. (2012) employed a participatory rural approach (PRA) in their study that utilised geospatial data and local knowledge to create action plan maps for land resource and water resource development in the catchment area of Ansupa lake in Orissa, India. They used remote sensing data to evaluate the natural resources available and created thematic maps based on satellite imagery and cadastral sheets, such as maps showing land use, land capability, etc. They then consulted with local communities which resulted in extensive ground truthing of the maps and a micro analysis of the development plans at a village level. Lotus Project takes a similar approach with the RDM programme, whereby high potential areas are first identified through heatmaps of the RDMI, and then community members from villages within these areas are consulted to determine the next steps for development planning.

Road access is a critical factor for rural development, as it enables access to essential services such as markets, healthcare, and education. However, rural road infrastructure is often poorly developed, leading to limited connectivity and poor road conditions. To determine the suitability of an area for the RDM programme, Lotus Project would ideally also consider road access. An ideal area should be accessible by road but not too well-connected, as high connectivity is often associated with higher levels of development. Currently, the RDMI lacks an indicator for road access, but the Rural Access Index (RAI) could be a useful tool for this purpose. The RAI is a widely used indicator for measuring transport sector development, originally developed by Roberts, KC, and Rastogi in 2006. The original RAI was based on household surveys and calculated as the proportion of people with access to an all-season road within 2 km of walking distance. However, this method faced limitations such as cost, limited spatial representativeness, and comparability issues across countries. To address these limitations, a new RAI method has been developed that uses high-resolution population distribution data and digitised road network data, which allows for more efficient and accurate calculation of RAI without relying on household surveys (World Bank, 2019). This new method is more comparable across countries, as it uses standardised data sources and techniques. However, the RAI is not yet available at a sub-national level for all countries, but it could be a valuable indicator to include in the index once it becomes available.

In the meantime, another factor that could be considered when integrating measures into the RDMI is the level of remoteness of an area, which is determined by its distance from urban centres and is associated with road access and rurality. Nelson et al. (2019) have developed a suite of global travel-time accessibility indicators for the year 2015, providing useful measures of current access to resources and opportunities across a range of settlement sizes. Their study validated the travel-time estimates against journey times from a Google driving directions application, demonstrating good agreement and highlighting the potential utility of these indicators in measuring and improving access to remote areas. Importantly, the researchers have made the suite of nine high-resolution accessibility datasets freely available to the public online[2], which could enable their integration into future versions of the RDMI.

2.2.4 Measuring Clean Energy Resources and Identifying Areas for Rural Electrification

Rural electrification is crucial for socio-economic development as it can help to improve living standards, reduce poverty, and increase access to education and healthcare (Cook, 2012). Thus, one of the first steps in the RDM programme is to provide the community with reliable electricity through the installation of a microgrid system that is run on clean energy. In order to ensure that there is both a demand and supply for this rural electrification, it is essential that potential sites have poor or limited access to electricity, and there should be a high availability of renewable energy resources. Geospatial data has been crucial for supporting this type of rural electrification planning for decades (Domínguez and Amador, 2007; Isihak, Akpan, and Bhattacharyya, 2022). For example, a study done by Muselli et al. in 1999 determined the most suitable electricity systems for remote areas in Corsica by considering geospatial variables such as the distance between houses and the electrical network grid. Similarly, Monteiro et al. (1998) used the levelling electric cost (LEC) and the Solargis tool to evaluate which forms of rural electrification were most appropriate for different areas of Cape Verde. The LEC also featured in a study by Amador and Domínguez (2005) where they used GIS methodologies to assess whether rural areas were more suitable for conventional or renewable energy technologies. The researchers identified areas with a high potential for renewable energy systems by considering the LEC which they calculated by using rural population

[2] https://figshare.com/articles/dataset/Travel_time_to_cities_and_ports_in_the_year_2015/7638134/3

density, solar radiation, average wind speed and the distance of connection to the Medium-Voltage grid-MV. After first identifying optimal areas for renewable energy, certain areas were selected to validate the detected potential through higher resolution maps. In a more recent study, Schmitter et al. (2018) used multi-criteria analysis to map suitable areas for solar photovoltaic water pumps. This required them to consider not only solar radiation, but also the availability of water resources and access to local markets.

While these studies focus more on the supply of energy, Kaijuka (2007) discusses how GIS maps can be used to examine patterns of energy demand and to identify areas for investment. This study took a demand-side approach, and they created an energy benefit points system based on local conditions and needs assessments, with points being rewarded based on geospatial data related to the population and infrastructure.

While all these studies demonstrate how helpful GIS data is for planning for electrification at a sub-national level, it is difficult to create global datasets for suitability as there are so many local factors to consider when planning for rural electrification. There are two renewable energy potential datasets already included in the index, photovoltaic power potential and wind power density, and these datasets are discussed in more detail in section 3.1. However, these datasets focus more on the supply side and do not account for the LEC or demand for electrification. There are some existing datasets that provide estimates of the cost of rural electrification in different countries. For example, the Global Electrification Platform (GEP)[3] is an online, open-access and interactive platform that provides an overview of investment scenarios related to electrification in selected countries. While the International Energy Agency (IEA) also provides data on rural electrification and access to modern energy services in its World Energy Outlook reports. However, these datasets may not have high-resolution data for all countries or provide detailed cost estimates for each country. Therefore, there is still a need for a more comprehensive and consistent dataset that provides high-resolution data on the demand and cost estimates for rural electrification in every country.

2.4 Literature Review Conclusion

The purpose of this literature review was to gain more understanding of existing research related to the research questions. This review has covered some of the advantages and disadvantages of using composite indicators like the RDMI to express complex topics, as well as the challenges involved with

[3] https://electrifynow.energydata.info/

constructing these indexes and approaches that can be used to evaluate their robustness and reliability. The last topic is especially pertinent for the study as the overall aim is to evaluate the RDMI and assess how it can be enhanced. The use of geospatial technologies to monitor, measure and predict development indicators has also been outlined briefly in this review. Section 4.2 will further explore the relevance of current data and indicators used to calculate the RDM Index and consider additional geospatial variables that could be included in the index to make it a more comprehensive measure of suitability for sustainable rural development.

Chapter 3 Data

The RDMI was developed in 2020 by a group of volunteer data scientists working for the Lotus Project, and they plan to continue to develop the index based on the findings of this research and the availability of new datasets that could enhance the index. This section will discuss the original datasets that they have chosen to include in the index, as well as the new dataset that they are proposing to add, and it will also explain the steps involved in pre-processing the data and constructing the index. This methodology was developed entirely by the Lotus Project team, and it was only altered slightly for this project to adapt to new issues arising in the latest datasets (as noted in section 3.2.), as well as to change the variables and parameters to create the test models, which will be discussed more in Chapter 4.

3.1 Datasets

The RDMI is currently an aggregation of four geospatial indicators that come from a range of data sources, and Lotus Project is proposing to add one more indicator (nitrogen dioxide) in the coming months. All the data that is used for calculating the RDMI is in a GeoTIFF[4] file format, which is similar to a regular TIFF file but has additional georeferencing information such as the type of projection used. While the data come from different sources, they are all open data that are available online and are free to access and use for research, education, and non-commercial purposes. They are also available for every country, which is an important criterion for inclusion in the index as it allows for the RDMI to be used worldwide.

3.1.1 NDVI

The indicator currently used in the geographical dimension is the Normalised Difference Vegetation Index or NDVI which is a measure of the amount of green vegetation present in an area. NDVI is calculated by subtracting the near-infrared light (which vegetation strongly reflects) from the red band (visible light, which vegetation absorbs) and then dividing the result by the sum of the two bands as shown in Figure 3.1 (Weier & Herring, 2000). NDVI values range from -1 to +1, with higher values indicating more vegetation. If there are negative values, it is likely there is water present, compared to areas that have values closer to +1 that are likely to have an abundance of dense, green vegetation. Areas that have values close to zero lack green leaves and may be urban or very arid areas.

NDVI is used in a variety of applications, including crop monitoring, land cover mapping, and environmental monitoring. NDVI can be used to monitor changes in vegetation over time, as well as to

[4] https://www.ogc.org/standard/geotiff/

detect areas of drought, deforestation, and desertification, and it can also be used to identify areas of high or low agricultural productivity. Studies in Vietnam have used NDVI to map large-area rice cropping systems (Guan et al., 2016) and to study how rice crop patterns vary by administrative units (Nguyen et al., 2012). While Tran, Xu, and Liu (2019) used an NDVI-based classification system to study the effect of rapid urbanisation on urban land cover in Hanoi.

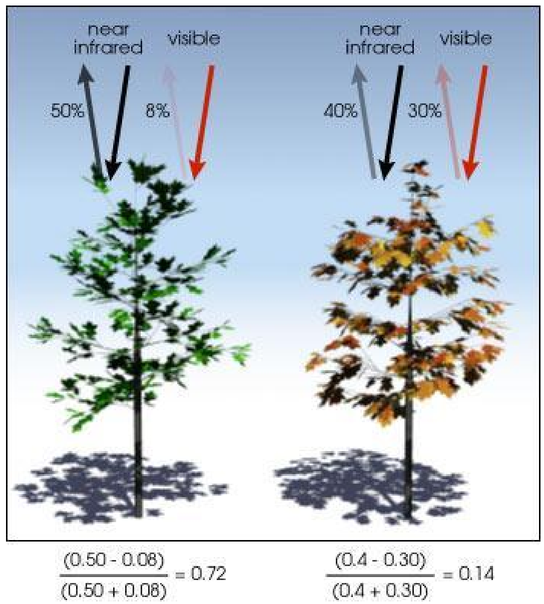


Figure 3.1 Diagram demonstrating how NDVI is calculated using the reflected visible and near-infrared light by vegetation. Credit: Robert Simmon

In sub-Saharan Africa, NDVI has also been utilised to monitor agricultural production of crops such as maize, but it is also frequently used in studies which are more concerned with predicting drought, water availability and desertification. Other studies have investigated how NDVI can potentially be used as a measure of poverty and other health and development indicators, including the relationship between NDVI and levels of malaria (Fastring and Griffith, 2009). While investigating the inter-spatial relationship between NDVI and poverty in West Africa, Sedda et al. (2015) found that there is a significant association between poverty, health, and vegetation cover in the study area. Specifically, areas with higher levels of poverty had lower levels of vegetation cover, and these areas were also associated with higher rates of malnutrition and poor health outcomes. The study also found that the relationship between poverty, health, and vegetation cover varies depending on the specific country and region within West Africa.

The NDVI data for the RDMI was sourced from Google Earth Engine (GEE) which is a cloud-based platform that provides users with access to a vast amount of satellite imagery and geospatial data. This data is made available through the GEE data catalogue, which includes datasets on various topics, such as land use, climate, and biodiversity. The data was collected by Landsat 8, a satellite mission operated by NASA and the United States Geological Survey (USGS) and is designed to provide global coverage of the Earth's land surface. Launched in February 2013, Landsat 8 is the latest satellite in a series of missions that have been providing high-quality, long-term observations of the Earth's surface since 1972. The Operational Land Imager (OLI) sensor on the satellite collects data in eight spectral bands, including four bands in the visible to near-infrared range (bands 1-4) and four bands in the shortwave infrared and near-infrared range (bands 5-7 and band 9) (Vermote et al, 2016). To create the datasets for Vietnam and Kenya in the Google Earth Engine code editor, bands 4 and 5 were used to calculate the NDVI by taking the difference between the near-infrared reflectance and the red reflectance, and dividing by their sum:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

where NIR is the reflectance in the near-infrared band (band 5) and Red is the reflectance in the red band (band 4).

The date range was adjusted to get the median of the data collected from 01/11/2017 to 01/11/2022. Originally the cloud cover parameter (the percentage of an image that is covered by clouds or cloud shadows) was set to 10%, and this is the value that was used for the Vietnam dataset. However, upon first examining the RDMI map for Kenya, it was observed that part of the southern coastal region of the country (where the city of Mombasa is located) was not displayed upon the map. Further investigation revealed that the NDVI file was missing a tile due to there not being data available with cloud cover below 10%, and thus the parameter needed to be increased to 15%. This parameter is likely to have to be adjusted in the future based on the quality of data available for each country.

3.1.2 Population Density

Population data is essential for rural development planning as it helps identify areas with high or low population density, and accurate population data can inform decisions about the allocation of resources, such as the construction of schools, healthcare facilities, and other infrastructure (IFAD, 2011). The data for the population density indicator in the social dimension of the RDMI comes from gridded high-resolution population datasets that are sourced from the website of WorldPop[5], a research group that focuses on enhancing the quality and use of spatial demographic data for health and development applications. WorldPop offers a range of different gridded population estimate datasets, and the one that is used for the RDMI is the 'Unconstrained individual countries 2000-2020 UN adjusted: Population density' dataset. The datasets for Vietnam and Kenya have approximately 100m spatial resolution and have been produced by using an 'top-down' unconstrained estimation modelling approach which was developed by Stevens et al. (2015). This approach uses census data and covariates such as nighttime lights data and landcover data with an iterative Random Forest model to estimate the number of people in each pixel. This number is adjusted to reflect the country's total population from United Nation population estimates and is then divided by the pixel surface area to estimate population density.

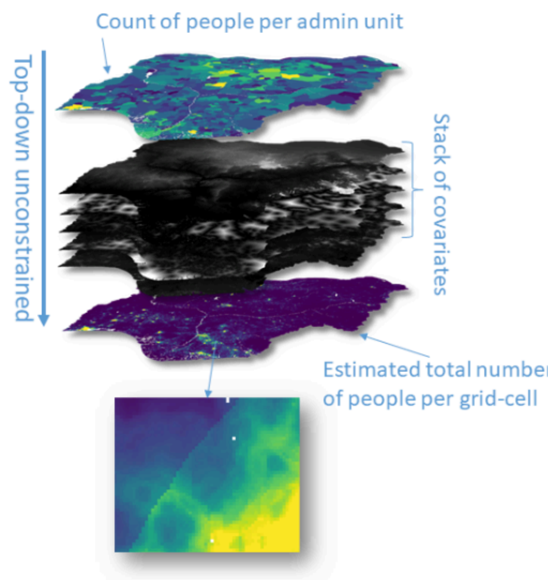


Figure 3.2 Diagram showing the unconstrained estimation modelling approach to calculating population density as developed by Stevens et al. (2015). Source: worldpop.org

3.1.3 Photovoltaic Power Potential

Photovoltaic (PV) power is a form of renewable energy that is generated from sunlight, and PV systems are composed of solar cells that convert sunlight into electricity. These systems can be used in off-grid

[5] https://www.worldpop.org/

applications, such as remote villages or islands. PV systems can be also used to supplement existing grid-connected systems, and they can be used in combination with other renewable energy sources, such as wind and hydro. As the availability of renewable energy resources is very important for the RDM programme, one of the two indicators in the environmental dimension is PV power potential which refers to the amount of electricity that can be generated by using solar panels to convert sunlight into electrical energy. PV power potential is calculated by considering the theoretical potential, the system configuration, and external factors such as the air temperature affecting the system performance, topographic and land-use constraints (ESMAP, 2020). By analysing these factors, experts can estimate the amount of electricity that can be generated by a PV system in a particular location. This information is useful for planning and designing PV systems, as well as for evaluating the economic and environmental benefits of using solar energy.

The PV power potential datasets that are used in the RDMI calculation are sourced from the Global Solar Atlas 2.0[6] which is an online tool that provides information on solar energy potential for different locations around the world. This tool is published by the World Bank Group, funded by ESMAP, and the data is prepared by Solargis. The datasets refer to the average daily output, the unit of measurement is kilowatt-hours per square metre per day (kWh/m²/day) and the datasets for the case study countries have a spatial resolution of 1km.

3.1.4 Wind Power Density

The second indicator in the environmental dimension is wind power density data which is a measure of the energy available in the wind at a particular location and is dependent on the wind speed and air density. Wind power density can be used to estimate the potential energy output of a wind turbine at a given location. The datasets were downloaded from the website of Global Wind Atlas (GWA), a free, online tool created by the World Bank Group and the Technical University of Denmark (DTU Wind Energy) that is intended to be used to identify high-wind areas around the world. To create the GWA, researchers used large-scale global meteorological datasets and downscaled the data to high-resolution wind resource datasets through generalisation and microscale modelling (Badger et al., 2015). The public datasets that were used to calculate the GWA include those related to topography, orography, land use to roughness length and bathymetry. It is a continuous process to validate the GWA, and Vietnam is one of the five countries which have been validated thus far. The unit of measurement for wind power density is watts per square metre (W/m²) and the datasets have a spatial resolution of 250m.

[6] https://globalsolaratlas.info/map

3.1.5 Nitrogen Dioxide

Nitrogen dioxide (NO_2) is a colourless, highly reactive gas that is a major air pollutant which is formed when nitrogen and oxygen combine in the presence of sunlight and is a major component of smog. High levels of NO_2 can have negative effects on human health and the environment, such as respiratory problems, acid rain, and damage to vegetation. Therefore, it is important to avoid areas with high NO_2 levels when planning for rural development to ensure that the development does not exacerbate existing environmental problems or negatively impact human health. By selecting areas with low NO_2 levels for rural development, the development can contribute to improving the overall environmental quality and sustainability of the region. And so, Lotus Project is proposing to add NO_2 levels as an additional indicator for the environmental dimension of the RDMI.

The NO_2 dataset that is used in this study is also sourced from GEE and is derived from the TROPOMI instrument onboard the Sentinel-5 Precursor (S5P) satellite, which was launched by the European Space Agency (ESA) in 2017. The S5P TROPOMI instrument provides high-resolution data on atmospheric pollutants, including NO_2, with a global coverage and daily revisit frequency.

The NO_2 dataset available on GEE is based on Level 2 data from the S5P TROPOMI instrument, which provides vertical column densities of NO_2 in units of mol/m². The data is processed using the Sentinel-5P Level 2 Data Processor, which applies a range of corrections and quality filters to the raw instrument data. The final product is a high-quality dataset of NO_2 vertical column densities with a spatial resolution of approximately 7 km x 3.5 km at nadir, and the datasets used for this study are the median of data collected from 01/01/2021 - 01/01/2023.

There is offline and online NO_2 data available from S5P and the difference between these types of data is related to the way the data is processed and the timeliness of the data. This study uses the offline data as it is validated and corrected for any errors before being released to the public, while the online data is processed in near-real-time and is released shortly after it is acquired by the satellite, making it more suitable for quick monitoring of NO_2 concentrations, such as during air quality emergencies.

3.1.6 Summary of Datasets

In conclusion, the RDMI is composed of four indicators from various data sources, with the potential addition of nitrogen dioxide in the near future, and a summary of these datasets is shown in Table 3.1. The data are all in a GeoTIFF file format and are accessible online for research, education, and non-commercial purposes. The NDVI and NO_2 data were sourced from satellite data available on Google Earth Engine. The population density data were obtained from WorldPop, and the PV power potential and wind power density datasets were downloaded from the Global Solar Atlas and the Global Wind Atlas respectively, both of which are initiatives funded by the World Bank. For the datasets that were sourced on GEE, the date ranges were manually adjusted and the median or mean was obtained for this time period. The cloud cover parameter for the NDVI data was set to 10% for Vietnam, but it had to be increased to 15% for Kenya due to the lack of data available. Overall, the datasets utilised in the RDMI provide reliable and accurate information that can be used to evaluate many factors related to rural development in different regions around the world, thanks to their global availability, high resolution, and free accessibility.

Table 3.1 Summary table of RDMI datasets.

Indicator	Dimension	Unit	Dates	Spatial Resolution	Source	Polarity
Population Density	Social	Number of people per square kilometre	2000-2020	100m x 100m	WorldPop	Decreasing
Normalised Difference Vegetation Index	Geographical	Index value	Median of data collected from 01/11/2017 to 01/11/2022	30m x 30m	Google Earth Engine Data Catalogue – USGS (Landsat 8 Level 2, Collection 2, Tier 1)	Increasing
Photovoltaic Power Potential	Environmental	Kilowatt-hours per square metre per day ($kWh/m^2/day$)	1994-2018	1km x 1km	Global Solar Atlas	Increasing
Wind Power Density	Environmental	Watts per square metre (W/m^2)	Based on 10 years of mesoscale time-series model simulations	250m x 250m	Global Wind Atlas	Increasing
Nitrogen Dioxide	Environmental	Molecules per square centimetre (mol/cm^2)	Median of data collected from 01/01/2021 - 01/01/2023	7 km x 3.5 km	Google Earth Engine Data Catalogue – European Union/ESA/Copernicus (Sentinel-5P)	Decreasing

3.2 RDMI Calculation Methodology

This section will detail the calculation methodology of the RDMI, which was developed entirely by the Lotus Project team. The researchers felt it was important that the methodology used to calculate the RDMI was kept rather simple so that it would allow new indicators to be easily added to the index in the future. For this project, the original calculation methods were retained except for including some minor changes made to the loading functions as detailed below. The calculations were also altered for Model 2, where the arithmetic average was used instead of the median for the dimension level aggregation, and for Model 3 where the maximum was used instead of the median for the sub-dimension level aggregation. The calculations are programmed in Python script.

3.2.1 Loading

The Rasterio[7] Python package is used to load the GeoTIFF files, which allows the pixel data in the files to be loaded as a NumPy masked array[8]. This is done as some of the files contain invalid or null values for pixels that lie outside of the country borders and loading the data as masked arrays means only the valid values are accessed.

Each of the datasets have their own loading functions which specifies which values should be masked, for example as outliers are common in NDVI files, the top and bottom 2.5% of values are also masked. Originally all zero values for NDVI were also masked as the datasets that were first used for this indicator had zero values for pixels that were outside the country borders, however the latest dataset has null values instead of zero values for pixels outside of the borders. Furthermore, the Kenya dataset contains pixels which have valid zero values for NDVI. And so, to avoid masking valid values within country boundaries, a modification was made to the original NDVI loading function by removing the masking feature, which was deemed unnecessary for areas outside the country borders.

[7] https://rasterio.readthedocs.io/en/stable/index.html

[8] A NumPy array is a multidimensional array that provides fast, efficient, and optimised operations on arrays and matrices. A NumPy masked array is a subclass of the NumPy ndarray that allows elements to be masked or hidden for a variety of reasons, such as representing missing or invalid data. It provides a convenient way to perform operations on arrays while ignoring masked elements.

3.2.2 Imputation

One of the main challenges with combining the different geospatial data is that they have different levels of resolution, for example the population density file has a spatial resolution of 100m whereas the wind power density data has a resolution of 250m. To overcome this issue, the Rasterio package has been used to directly change the resolution of the datasets by changing the height and width of the files. In order to change the resolution in this way, a resampling method must be specified, and the Lotus Project team chose to use the bilinear method as they found it to be the most appropriate method for the non-linear and continuous data that the RDMI is made up of. The dimensions of the population density data were chosen as the standard height and width that all GeoTIFF files would conform to.

3.2.3 Scaling

It is crucial to ensure that the metrics used for comparison are on a comparable scale, especially since they originate from various datasets with their own intrinsic scales. It is also important to minimise the number of mathematical transformations applied to the data, as using a unique transformation for each new metric can increase the complexity of the scaling process indefinitely. To address this, three different mathematical transformations are used to scale the data - log_10 (base 10 logarithm), identity (do nothing), and bi-symmetric log transformation. If the data does not contain zeros or positive and negative values at the same time, then the log is applied, otherwise the bi-symmetric log is more appropriate. The bi-symmetric log is also applied when the data is spread over orders of magnitudes, which is the case for NDVI data. If the orders of magnitude are within a reasonable scale, then no transformation is applied. After the most appropriate algorithm has been selected automatically and applied, each data point is z-scored to normalise the data and make them comparable to each other.

3.2.4 Polarity

An important next step in the RDMI calculation is making sure that the polarity of each indicator matches the aim of the RDMI. Higher values for certain indicators may mean potential sites are more desirable, whilst the opposite could be true for other indicators. For example, high PV power potential makes a site more suitable for the RDM programme, whereas high population density makes it less desirable. Therefore, in the polarity column of Table 3.1, those labelled ‘increasing’ are the metrics which increase with increases in RDMI, and ‘decreasing’ decrease with increases in RDMI. In the former case, no polarity transformation needs to be applied, but in the latter case the indicator values are multiplied by -1.

The Lotus Project team are aware that the relationship between an indicator and its suitability for the RDM programme may not always be monotonic, e.g., having low population density makes an area more suitable for the programme, but if the density falls below a certain level it would make the area unsuitable as there needs to be a certain number of people living in the vicinity. However, this pre-processing step does not yet account for these types of non-monotonic relationships.

3.2.5 Application of Sigmoid Function

The next step in transforming the data is to ensure that each of the metrics are in a bounded range, as not doing so means that the values of each dataset after applying the scaling and polarity transformation are potentially infinite. One option would be to normalise each dataset by the minimum and maximum pixel values. However, one of the issues with this is that each country's data would be standardised using different values, and it could be problematic if either of these values were an outlier.

Considering these issues, the Lotus Project team decided to use the sigmoid function as a normalisation method, which is defined as:

$$\sigma(X) = \frac{1}{1 + e^{-x}}$$

The function takes an unbounded domain to output data in the range of 0 and 1, and it has the advantage of providing the same function regardless of the particular details of the dataset. Hence it is possible to compare values across indicators and countries, and the function is also not as sensitive to outliers as compared to using the min-max standardisation.

3.2.6 Weighting and Aggregation

The final step in constructing a composite indicator is weighting and aggregation. At present, there is no weighting scheme used for the RDMI dimensions as the index is formed by calculating the median of the dimensions (and each dimension is the median of each of its sub-dimensions). One of the main advantages of using the median is that it is robust to outliers, meaning that extreme values do not have a disproportionate effect on the final result. However, the median does not consider the magnitude of the values, and therefore may not reflect the relative importance of different components of the composite indicator.

For the sensitivity analysis, the original aggregation functions were altered for Model 2 (the arithmetic average was used to aggregate the dimensions) and Model 3 (the maximum values of the two indicators in the environmental dimensions was calculated to form the values for that dimension), and for the uncertainty analysis weighted averages were used for the Monte Carlo simulations. Details of the weighting scheme will be discussed further in section 4.5.

3.2.7 Summary of RDMI Calculation Methodology

In conclusion, the RDMI calculation methodology (displayed in Figure 3.3) is a simple yet effective approach that enables the incorporation of new indicators in the future. The methodology involves loading and masking of datasets using Python's Rasterio package, imputing data to a common resolution through bilinear resampling, scaling with logarithmic, identity, or bi-symmetric log transformations, and adjusting polarity with the use of a sigmoid function for normalisation. The final step in creating a composite indicator is weighting and aggregation. Currently, the RDMI dimensions do not have a weighting scheme as the median of the dimensions is calculated instead. This is advantageous as the median is robust to outliers but may not consider the importance of different components due to not taking into account the magnitude of values.

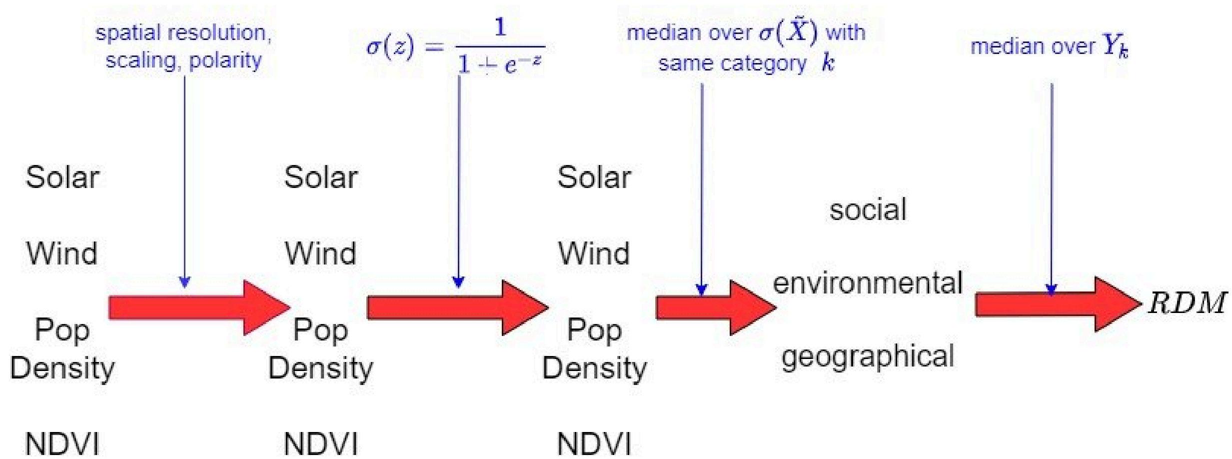


Figure 3.3 Diagram summarising the RDMI calculation methodology. Source: lotus-project.org.

Chapter 4 Methodology

To assess the effectiveness of the RDMI for the two case study countries, a mixed-methods approach was employed. This approach involved collecting and analysing both qualitative and quantitative data to gain a comprehensive understanding of the RDMI's performance and potential. The qualitative component involved conducting interviews with GIS experts to gather insights and feedback on the RDMI map of Kenya. The quantitative component included sensitivity and uncertainty analyses to determine the impact of variations in parameter values on the suitability scores. This section provides a detailed description of the methods used in the study, including expert interviews, indicator/criteria mapping analysis, exploratory data analysis, and robustness analysis.

The research methodology consisted of the following steps:

1. As an initial step in the study, GIS experts working in Kenya were interviewed to gather expert feedback on an interactive RDMI map of Kenya. The objective of these interviews was twofold: first, to obtain their perspectives on the accuracy of the RDMI map, and second, to identify any opportunities for improving it.

   During the initial development of the RDMI, the RDMI map for Vietnam was reviewed by the organisation's board of management, which includes Vietnamese professionals, and it has since been used for identifying areas for development in the country. However, this was the first time the RDMI map for Kenya was being reviewed by individuals outside of the organisation. Hence, this step was critical in informing the rest of the study as it was crucial to consult experts in Kenya to identify any immediate concerns and gather information to guide the rest of the study.

2. After establishing the criteria for high RDM suitability, an indicator-criteria mapping analysis was conducted to ensure that the selected indicators are both relevant and reliable for measuring an area’s suitability for the RDM programme, and that they adequately reflect the underlying criteria. The analysis also involved identifying any gaps and consulting the literature to determine which datasets could be included in the index in the future, either on a country-by-country basis or more broadly.

3. Exploratory Data Analysis (EDA) was performed using Python and ArcGIS to explore the data and determine which parameters to test in the subsequent sensitivity and uncertainty analysis. The data was first examined by creating maps of the raw datasets and comparing them for the two countries, providing a better understanding of their similarities and differences for each indicator. Next, after pre-processing the raw data using the RDMI pre-processing steps detailed in section

3.2, maps of the three dimensions (environmental, social, and geographical) were compared to the map of the overall RDMI outputs for each country, and differences between the RDMI maps for Kenya and Vietnam were examined. Finally, a correlation analysis was conducted to explore the relationships between the RDMI, its dimensions and sub-dimensions, and the results for each case study country were compared.

4. A sensitivity analysis was conducted to assess the impact of variations in the model on the RMDI outputs and maps, guided by observations made in the previous steps. For each model, the index scores were compared, and the continuous output data was classified into five different levels of suitability. The analysis investigated how changes in input parameters and variables affected the distribution of these suitability classes in Kenya and Vietnam, enabling identification of the factors with the greatest influence on index values and corresponding suitability levels. Additionally, scores were calculated for the coordinates of two pilot sites where Lotus Project operates in Vietnam, and these scores were compared across different models to assess the stability of the sites' suitability levels.

5. Finally, an uncertainty analysis was performed using Monte Carlo simulations to address the uncertainty associated with using the median as the method of aggregation to construct the index. Specifically, 1,000 simulations of the weighted average using random weights were conducted to generate a range of possible outcomes. The results of the simulations were then compared to the outputs of the RDMI using either the median or arithmetic average as the aggregation method.

By following these steps, a comprehensive evaluation of the RDMI was achieved and potential areas for improvement were identified. The next subsections will explain the research methodology in detail, and the results will be presented in Chapter 5 and discussed in Chapter 6.

4.1 Interviews with Kenyan GIS Experts

4.1.1 Purpose of Interviews

To initiate the research, interviews were conducted with three GIS experts who are currently working in Kenya. These interviews were conducted to gather feedback on the RDMI map for Kenya, and the insights gathered from these interviews informed the subsequent development of the research methodology and approach. Specifically, the experts were asked to evaluate the accuracy of the map and provide recommendations on how it could be improved in general, as well as how it could be enhanced in the context of Kenya. To facilitate discussions, an interactive map was created (see Figure 4.1), which displays the average RDMI value for groups of pixels when the user hovers over an area. This allows users to easily identify areas of high suitability through the overall colour scheme of the map (the areas in yellow have the highest suitability) and view individual values for each area.

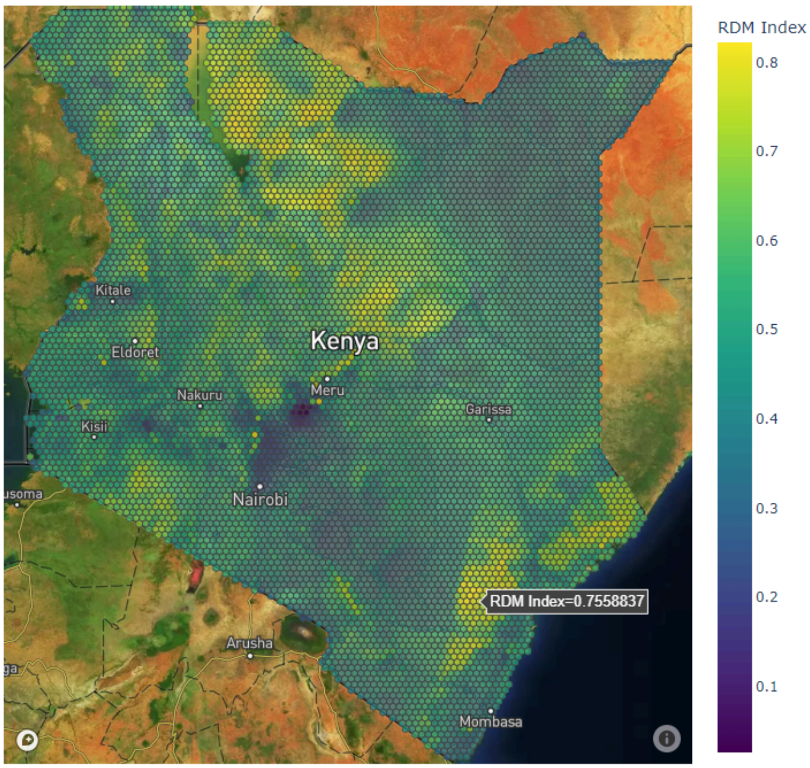


Figure 4.1 Interactive map of Kenya's RDMI scores (created by author)

4.1.2 Participant Selection and Interview Process

Participants were contacted through the Women in Geospatial+ professional network and community. This network is dedicated to promoting and supporting women and gender minorities in the geospatial industry, and it was deemed an appropriate source for identifying potential interviewees. The selection criteria for participants included having educational backgrounds in GIS, geography, or related fields, as well as extensive professional experience in GIS in Kenya. Participants were informed of the purpose and nature of the study and were asked to provide informed consent prior to the interviews. The interviews were conducted over the Microsoft Teams platform and were recorded for accuracy and reference purposes. After the interviews, participants were sent a summary of the discussions in order to ensure that any misunderstandings could be rectified.

One of the limitations of the interviews was the lack of prior relationship with the interviewees. Due to cultural differences, it is possible that the interviewees may not have felt comfortable being overly critical of the RDMI or the map that was being evaluated. Additionally, another limitation was the small sample size, as interviews were only conducted with three GIS experts in Kenya. This may limit the generalizability of the findings to other areas or contexts, such as Vietnam. Considering the possibility of issues arising when applying the RDMI to a new country, it is advisable to have an expert review the RDMI map of that country to identify any potential concerns or deviations.

4.1.3 Interview Findings

According to the interviewees in this study, the RDMI map of Kenya is fairly accurate to very accurate and is indicative of the areas typically identified for rural development by local authorities. However, all three experts noted that the northeast region of the country has unexpectedly low RDMI values compared to other parts of the north, and they felt it should also be considered highly suitable for rural development. It was observed that the yellow area of the map in the north, with the highest RDMI values, is arid, sparsely populated, and deserted. While one expert felt that all indicators currently integrated in the index play important roles, others predicted a possible correlation between certain indicators such as population density and nitrogen dioxide (although this indicator was not included in the RDMI version that they were shown, but they were informed it may be integrated in the future).

The interviewees understood that the inclusion of indicators in the RDMI requires global availability, hence why all indicators are derived from satellite data. Nevertheless, the experts suggested that the map could be improved by incorporating more localised and socially relevant features such as health centres, schools, and churches, as factors like healthcare and education are critical in the planning of rural development. And sub-national level data on healthcare and educational facilities in Kenya are readily available from governmental websites - although they acknowledged that this may not be the case for all countries.

The interviewees also identified several other potential layers that could be added to the RDMI map to make it more effective for identifying areas for rural development. Firstly, adding information on road access, particularly in the north where there is only one main highway, would be valuable. Secondly, borders of national parks should be included in the map, such as in the Kibwezi area where two large national parks are located. In addition, including information on water bodies, such as rivers and lakes, would be helpful in areas where data is missing due to lakes, which may not be clear to someone unfamiliar with the country. Access to water, such as checking for available aquifers, could also be beneficial. And temperature data, specifically land surface temperature (LST), could be added as a layer to differentiate between bare and populated areas. Land use land cover (LULC) data would be complementary to this feature.

Furthermore, data on poverty, income, and spending at a village level could be integrated from the Kenya National Bureau of Statistics to better understand the economic status of districts. While nighttime light data could possibly serve as an indicator of electricity connection, which is important as most rural areas in Kenya are not connected to the grid. Finally, telecommunications and internet access data could be added to the map to demonstrate connectivity, and this type of data may be available on a global scale.

Along with these recommendations, the experts made several additional comments regarding the RDMI map of Kenya. They noted that Mount Kenya appears as the darkest area on the map, indicating the lowest RDMI values. The experts also pointed out that some rural areas are very green in Kenya, while others are dry and arid. One interviewee expressed uncertainty about whether NDVI should be considered a geographical dimension, although they believe it would make sense as an environmental dimension. They mentioned that in many sub-Saharan African countries, there may be rural areas that are agricultural and green, while others are marginalised and dry. And so, NDVI may work as a proxy for ruralness for some countries without large arid areas, but for Kenya, this may not provide accurate results because some areas are arid. The experts also noted that air pollution is generally higher in cities and lower in rural areas, so if it is integrated into the index, it may be correlated with population density. Additionally, NDVI in urban areas should be low, indicating a possible correlation with population density in these areas.

4.1.4 Summary of Feedback from Interviews

In conclusion, while the interviewees felt the RDMI map was moderately successful at identifying areas for rural development, they expressed concerns that the central north was being scored too highly compared to the northeast of the country which is also very suitable for development and in need of poverty alleviation activities. Furthermore, it was concluded that the use of NDVI as a proxy for ruralness needed further investigation, particularly in arid areas like Northern Kenya. Moreover, the results indicate that there is a need to include additional indicators in the RDMI or as additional layers on top of the RDMI map (see Figure 4.2). In particular the organisation should consider adding indicators related to social factors (e.g., access to healthcare and education), road access, land use/land cover, poverty data, access to water, nighttime light data, and telecommunications/internet access. These dimensions could provide a more comprehensive understanding of an area's suitability for rural development and improve the accuracy of the RDMI map for Kenya and other countries in the region.

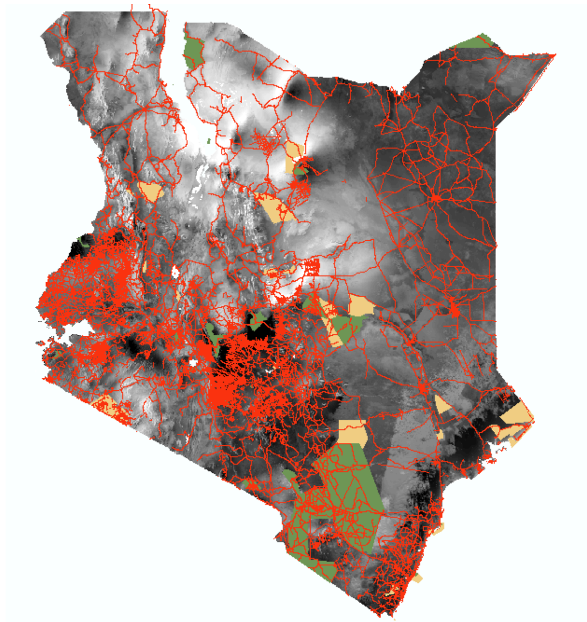


Figure 4.2 Example of how the RDMI map for Kenya could be visualised with additional layers such as road networks (red) and protected areas (green and yellow). Image created by author using ArcGIS.

4.2 RDMI Indicators and RDM Criteria Mapping Analysis

One of the most important steps in evaluating the effectiveness of a composite indicator is examining its theoretical framework and how the data relates to this framework. This helps to evaluate if the RDMI can accurately measure the factors that are important for rural development and to provide useful insights for further development of the index. To do this, discussions were held with the Lotus Project team and a review was conducted of the RDM programme's theory of change[9]. Based on this, a list was created with the core criteria that comprise the profile of an ideal area for the RDM programme, as well as additional criteria that would enhance the area's desirability. Each of the RDMI indicators was then mapped to these criteria to identify which criteria are measured by the index and which ones are not.

[9]A theory of change is a tool used in programme planning, evaluation, and implementation that describes the causal pathways through which a programme is expected to achieve its intended outcomes and impact. It typically includes a series of necessary steps or conditions that must occur for the desired change to take place, along with the underlying assumptions and evidence that support the proposed approach.

4.2.1 RDM Criteria

The core criteria are those that must be met for an area to be considered suitable for the programme. The first core criterion is that the area must be rural, and it should also be sparsely populated - criteria that one could assume would be strongly correlated, as rural areas are usually defined as areas with low population. In addition, there should be limited access to electricity or unreliable grid access, and the area should also have a high availability of unused renewable energy resources with low levels of pollution. High levels of poverty and limited economic activity are also critical factors for consideration in selecting an area for the programme, and again it seems that there is potentially an overlap between these two concepts, and a measure for one may be correlated with a measure for the other.

There are also several potential criteria that, while not essential, would make the area more desirable for the programme. These include consideration for suitability of the land for development activities, accessibility by road, and access to markets and any other types of infrastructure that could be beneficial for the programme. Additionally, having an ethnic minority population in the area is another potential criterion that could be considered. Ideally by considering both core and desirable criteria, the RDMI would identify areas that are most suitable for the RDM programme objectives and help to ensure successful implementation.

4.2.2. Mapping of Criteria to Indicators

Table 4.1 provides a mapping of each RDM criterion to its corresponding indicator(s) in the current index, where available. Out of the seven core criteria, four have at least one indicator. However, there is concern regarding the appropriateness of the indicator currently used to measure rurality (NDVI), which will be discussed in section 4.2.3.

In addition, Table 4.1 highlights significant data gaps in the index, indicating the need for integration of other indicators to measure all the RDM criteria and ensure the completeness of the index. To address these gaps, potential future data sources are also mapped to the RDM criteria in the table. These will be discussed further in section 4.2.4.

Table 4.1 Mapping of RDMI Criteria to Indicators and Potential Data Sources

Core Criteria	Current indicator	Potential future data sources
The area is rural.	**NDVI (Google Earth Engine, Landsat 8)**	• Degree of Urbanisation • Population density • Global travel-time accessibility indicators (Nelson et al., 2019)
There is poor or no access to electricity or unreliable grid access.	**None**	• Global Electrification Platform (GEP) • High-resolution gridded dataset to assess electrification for SSA (Falchetta et al., 2019) • Nighttime light data • Household survey data
There is a high availability of unused renewable energy resources.	**Photovoltaic Power Potential (Global Solar Atlas)** **Wind Power Density (Global Wind Atlas)**	• Datasets related to other forms of clean energy
The area is sparsely populated.	**Population Density (WorldPop)**	• Population Density (Facebook/Data for Good at Meta) • Degree of Urbanisation
There are low levels of pollution.	**Nitrogen Dioxide (Google Earth Engine, Sentinel-5P)**	• Global Annual PM2.5 Grids from MODIS, MISR, and SeaWiFS Aerosol Optical Depth (AOD)
There are high levels of poverty.	**None**	• Global Gridded Relative Deprivation Index (GRDI), v1 (2010–2020) • World Bank's Global Subnational Atlas of Poverty (GSAP) • Household survey data

		• Nighttime light data
There is limited economic activity.	**None**	• Household survey data on employment rates, income, and household consumption • Nighttime light data
Desirable Criteria	**Current indicator**	**Potential future data sources**
The area is suitable for development activities.	**None**	• Land cover/land use maps
The area is accessible by road.	**None**	• Rural Access Index (World Bank, 2016) • Global travel-time accessibility indicators (Nelson et al. 2019)
The area has good access to markets.	**None**	• Household survey data • Rural Access Index (World Bank, 2016)
There are social amenities in the area that would also benefit from the micro-grid.	**None**	• Administrative data from government ministries
There is an ethnic minority population.	**None**	• Census data

4.2.3 Suitability of Indicators

The indicators used in the RDMI are generally well-suited to measuring their corresponding criteria. The PV power potential and wind power density datasets are appropriate for measuring an area's renewable energy availability, which is essential for the success of microgrid electrification systems. Furthermore, the World Solar Atlas specifically designed the PV power potential dataset to evaluate an area's suitability for a solar power system. Population density is effectively measured using high-resolution, gridded datasets from WorldPop, which provides detailed estimates of the population in an area. The Sentinel-5P remote sensing data is an ideal choice for measuring nitrogen dioxide levels, a key indicator of air pollution. Overall, these indicators are well-aligned with the RDMI's objective of assessing an area's suitability for the RDM programme.

On the other hand, the suitability of NDVI as an indicator for measuring rurality is not entirely clear. In countries like Vietnam, where lush tropical vegetation covers much of the countryside due to forestation or rice farming, there may be a strong correlation between rurality and high levels of green vegetation, making NDVI a potentially useful indicator for measuring rurality. However, as noted in section 4.1, GIS experts from Kenya have raised concerns about the applicability of NDVI for measuring rurality in areas like sub-Saharan Africa where the presence of vegetation does not necessarily indicate rural areas. In such areas, there may be large arid regions that are highly rural but lack green vegetation. Therefore, the suitability of NDVI as an indicator for measuring rurality depends on the specific context and may require careful consideration.

4.2.4 Data Gaps in the RDMI

The RDMI currently does not measure all of the RDM criteria, as indicated in Table 4.1. While the table highlights potential datasets that could be considered in the future, it is important to note that the selection of datasets was based on a high-level literature review. As such, it would be advisable for Lotus Project to perform a more in-depth review of available datasets during future development of the index. This is particularly important given the rapidly increasing availability of high-resolution datasets, which could greatly enhance the completeness of the RDMI. Since the RDMI was first developed in 2020, there have been numerous new datasets released that could provide valuable insights into rural development challenges. Therefore, ongoing review and incorporation of new data sources will be crucial to ensure the continued relevance and accuracy of the index. Most of the datasets suggested in the table have already been discussed in Chapter 2, and the rest of this subsection will briefly discuss some of the key data gaps that Lotus Project could address in the future to enhance the comprehensiveness of the RDMI.

One important criterion for the RDM programme is the lack of access to electricity or unreliable access, which is not directly measured by any of the indicators in the RDMI. This is due to the limited availability of global datasets that capture this requirement. However, the Global Electrification Platform, mentioned in Chapter 2, could potentially provide data to measure this criterion in the future. Additionally, high-resolution gridded datasets such as the one developed by Falchetta et al. (2019) to assess electrification in sub-Saharan Africa could also be valuable for inclusion in the RDMI. Moreover, in the absence of such datasets, some studies have used nighttime light data as a proxy for electricity access.

Nighttime light data has also been used in studies to estimate levels of poverty and economic activity, which are two other important and related criteria that are not currently measured in the RDMI. As discussed in the literature review, compared to environmental and geographical phenomena, development indicators such as these can be difficult to quantify and capture using geospatial data alone. For example, measuring poverty levels or access to markets requires detailed information about households and communities, which is not always available in geospatial data. Also, development indicators are often measured at a more granular level than environmental and geographical indicators, which can make it more challenging to collect accurate and reliable data. However, if the RDMI is to be used for identifying areas that are most in need of rural development, it is crucial that the gaps related to these criteria be addressed. And so, Lotus Project could consider adding data from datasets such as the Global Gridded Relative Deprivation Index (GRDI), World Bank's Global Subnational Atlas of Poverty (GSAP) or, nighttime light data. These datasets have already been discussed in Chapter 2, and they are available for most countries.

Household surveys, such as the Multiple Indicator Cluster Surveys (MICS) and Demographic and Health Surveys (DHS), could also be valuable sources of data to address some of the gaps in the index. By integrating such data into the RDMI, it would be possible to create a more comprehensive and nuanced picture of the development challenges facing different regions and communities around the world. However, the availability of such data is not uniform across countries and regions, and there may be challenges related to data quality, comparability, and representativeness that need to be addressed when integrating household survey data into the RDMI. If Lotus Project wanted to experiment with adding household survey data as it has the potential to help the index to identify the people most in need, there are a couple of options they could explore. One option would be to integrate the household data into the index for just the countries that have this data available, although then the index outputs would not be comparable across countries. However, as this index is intended to compare areas within a country, this may not be an issue. Alternatively, the index could be kept as it is, so it is consistent across countries, but indicators from household survey data could be added as layers to the RDMI maps of countries that have this extra data.

4.2.5 Summary of Indicator and Criteria Mapping Analysis

While the availability of high-resolution, global datasets related to geography and environment has increased significantly in recent years, thanks to initiatives such as Google Earth Engine and ESMAP, there is still a significant lack of such datasets for social and economic indicators, and as a result not all of the criteria for the RDM programme are currently being measured. Many countries continue to rely on household survey data to measure and monitor these types of indicators. However, despite that survey data can be a very good source of data for a wide range of development indicators, it is not available for all countries, and it may be outdated, as it is costly and labour-intensive to collect data through these data methods. Nevertheless, when the appropriate data is available, it could be layered on top of the map or even integrated as an additional indicator for just that country. Furthermore, as the availability of global, high-resolution datasets related to development is rapidly increasing, the organisation should continue to research and review newly published datasets that could be suitable for measuring the RDM criteria that is not included in the index yet. The organisation should also consider finding a replacement for using NDVI as a measure of rurality, as the research indicates that it is not a suitable measure of this quality in all parts of the world. That said, as population density is already included in the index, it may not be necessary to have a separate indicator for rurality as these two criteria are so closely linked. In conclusion, this step was very important in evaluating the effectiveness of the RDMI, as it helped to identify the data gaps and to explore potential datasets and sources that could address these data gaps in the future so the RDMI can provide a more comprehensive profile of an ideal area for the RDM programme.

4.3 Exploratory Data Analysis

In this section, the exploratory data analysis steps undertaken in the study will be outlined. Initially, raw datasets for both case study countries will be presented in map format and analysed for similarities and differences. Next, the RDMI and its dimensions will be mapped and assessed for any discernible patterns. Finally, the findings of the correlation analysis conducted on the RDMI, its dimensions and sub-dimensions will be discussed.

4.3.1 Comparison of Raw Datasets

Population Density

Vietnam is a much more populous country than Kenya with a total population of 97.5 million compared to 53 million in Kenya (United Nations, 2022). It also has almost triple the number of people per square kilometre, with Kenya having a mean population density of 96 people per km^2 while Vietnam has an average of 297 people per km^2 (see Table 4.4).

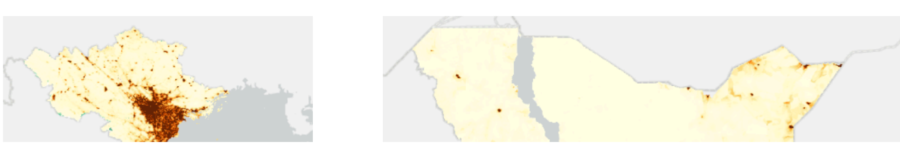


Figure 4.3 Maps of raw population density datasets for Vietnam (left) and Kenya (right).

These maps of population density for both countries are showing areas with 1000 people per km2 or more in the darkest brown colour. The most populated areas in Vietnam can be found in the country's capital, Ho Chi Minh in the south of the map (approx. 9 million) and in Hanoi in the north (approx. 5 million), as well as the 49 smaller cities in the country which have between 100,000 and 1 million people, many of which are found along the coast, as evident by the dark brown line representing high population density that runs along the coastline of the country. The Mekong Delta in the southeast of the country is also quite densely populated, with 20% of the Vietnamese population living in this area, however the majority of these people live in rural areas (Olson, 2022).

As is clear from the map, the majority of Kenya is quite sparsely populated, and most Kenyans live in scattered, rural settlements. The most densely populated areas include the largest city Nairobi that is in the cooler highlands, the second largest city Mombasa at the coast, and the central west of the country close to Lake Victoria, where there are many urban areas including the port town of Kisumu and Eldoret, the principal town in the Rift Valley region.

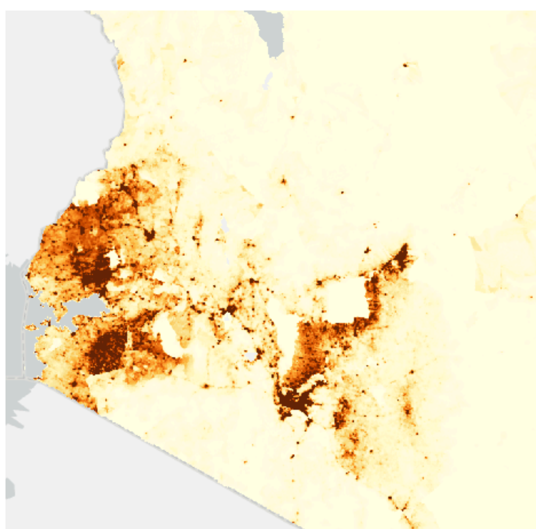


Figure 4.4 Western section of population density map of Kenya that shows areas of very high and very low areas of density next to one another.

By examining the map of Kenya's population density data, we can see that there are some areas that have very low populations that are in sharp contrast to the surrounding areas with much higher population density. This is not a noticeable issue in the Vietnam map, and it occurs in Kenya as there are many national parks and protected areas, such as Mount Kenya National Park, therefore there is a clear outline of which areas in densely populated regions where people are not permitted to live unless they are in tribal settlements (see Figure 4.4).

Table 4.1 Summary statistics for raw population density datasets.

Population density	Min	Max	Mean	Std. dev
Vietnam	0.55	82298.9	296.89	1299.38
Kenya	0	167454.4	96.01	661.10

Normalised Difference Vegetation Index

Upon examining the maps of the raw datasets for NDVI in Figure 4.5, viewers can clearly see that there is a stark difference in the amount of green vegetation present in Vietnam compared to Kenya. In Vietnam, the majority of the rural areas are forestland or used for agricultural purposes such as growing rice crops, thus these areas have an abundance of green vegetation. Furthermore, most areas with low NDVI values seem to mirror the areas with high population density as seen in the map of Vietnam in Figure 4.3. Therefore, there seems to be a noticeable relationship between low NDVI values and high population density in Vietnam, and one might assume that in this context, if an area has high NDVI values, it is likely to be a rural area.

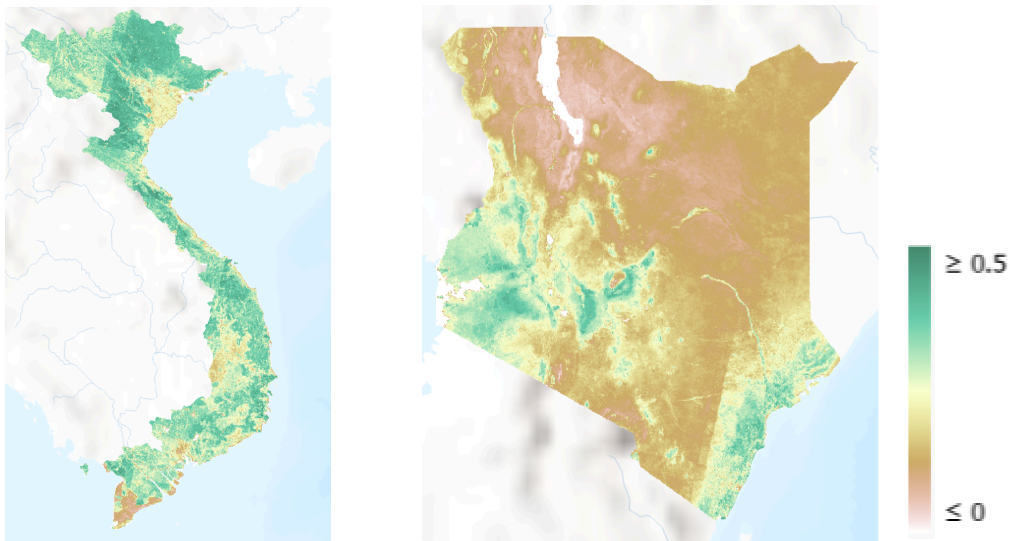


Figure 4.5 Maps of raw NDVI datasets for Vietnam (left) and Kenya (right).

In Kenya, most of the country has quite low amounts of green vegetation, and the map indicates that the central north of the country seems to have the least amount of vegetation present. This is not surprising, as GIS experts pointed out that this area is extremely arid. The greenest areas can be found on the coast and in the areas with the highest population density (the highlands and central west of the country). A land cover/land use (LCLU) map was also consulted to give more context to the NDVI data. The LCLU map showed that the area in the north is indeed bare land, and the densely populated areas with high levels of green vegetation are croplands. These areas have some of the most fertile land and/or best climatic conditions for agriculture, and therefore they are also the areas where people tend to live more, which increases both the population and the intensity of agriculture in these areas.

From visualising and comparing the maps of population density and NDVI, it appears that there is a very different relationship between these two indicators for the case study countries. The assumption that NDVI can be used as a proxy for 'ruralness' does not hold true for Kenya, while in Vietnam it is a very reasonable assumption to make.

Another interesting discovery was made while comparing the summary statistics of the two NDVI datasets. Even though Vietnam is mostly covered in green vegetation and the majority of Kenya is not, the mean NDVI value for Vietnam is actually lower than the mean value for Kenya. We can also see that the minimum value for Vietnam is below zero, which indicates the presence of water. Those very low values are likely to have affected the overall average value for the country, and they are present in the southern tip of the Mekong Delta, which can be seen in brown at the bottom of the map. This area consists mainly of swamps, mangrove forests, and rice paddy fields, and many parts of this low-lying region are flooded for months of the year, therefore it has extremely low NDVI values due to the abundance of water.

Table 4.2 Summary statistics for raw NDVI datasets.

NDVI	Min	Max	Mean	Std. dev
Vietnam	-0.136	0.506	0.080	0.142
Kenya	-0.203	0.457	0.104	0.104

Photovoltaic Power Potential

Like the NDVI maps, there is also a considerable difference between the maps of the PV power potential for each of the case study countries (Figure 4.6), with Kenya having quite high solar power potential values throughout the country (3.31-5.30) and the greatest potential is shown in the west of the country. Whereas Vietnam has generally lower values (1.95-4.63), particularly in northern Vietnam and in highland areas. In contrast, in Kenya the highlands have higher solar power potential than the lowland areas, except for the mountain peak areas such as Mount Kenya which can be identified as the darkest purple spot in the centre of the map.

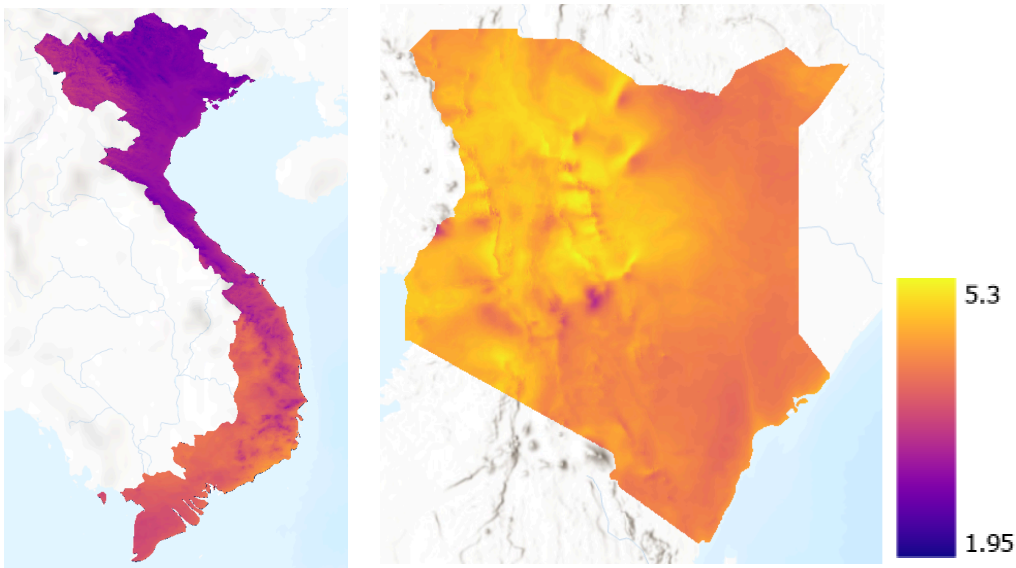


Figure 4.6 Maps of the raw PV power potential datasets for Vietnam (left) and Kenya (right).

Table 4.3 Summary statistics for raw PV power potential datasets.

PV Power Potential	Min	Max	Mean	Std. dev
Vietnam	1.95	4.63	3.42	0.49
Kenya	3.31	5.30	4.52	0.28

Wind Power Density

The wind power density datasets for Vietnam and Kenya are the most similar of all the indicators, and both countries have areas of high wind power potential, with similar mean values and both seem to have higher wind power density in areas that are at higher elevations (Figure 4.7). However, in Kenya there is also quite a distinct area at the south of Lake Turkana in the northwest that has the greatest wind power potential for the country. In fact, Kenya's main wind power station is located in this area just south of the lake. This area also has very high solar power potential, but it is very arid.

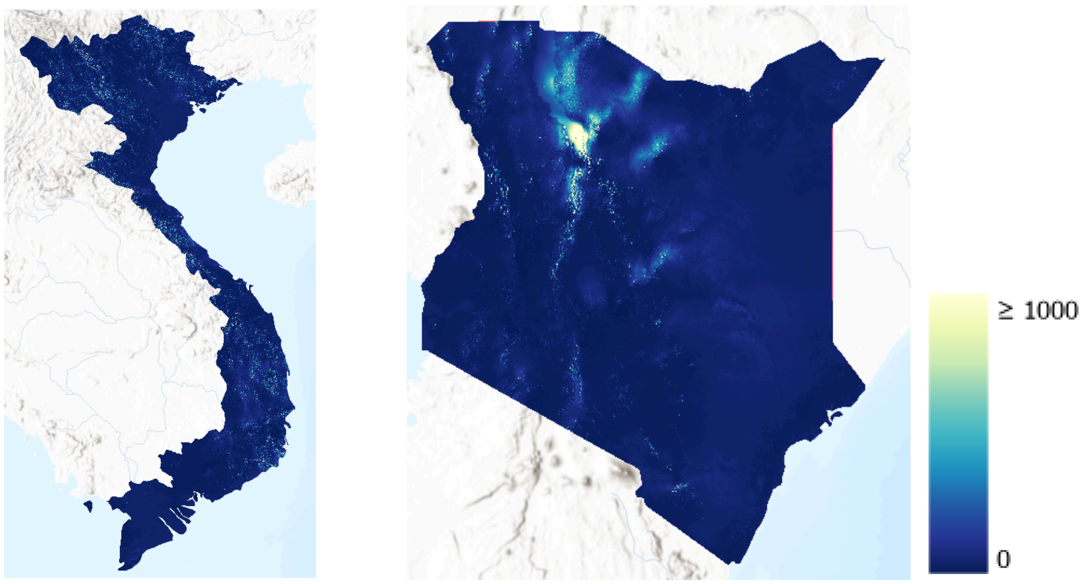


Figure 4.7 Maps of the raw wind power density datasets for Vietnam (left) and Kenya (right).

Table 4.4 Summary statistics for raw wind power density datasets.

Wind Power Density	Min	Max	Mean	Std. dev
Vietnam	0.000039	14041.87	61.48	129.99
Kenya	0.000331	13114.47	57.73	104.55

Nitrogen Dioxide

Finally, the raw datasets for the proposed new indicator nitrogen dioxide were visualised and the maps for each country were compared. The results showed that Kenya has significantly lower levels of nitrogen dioxide compared to Vietnam, with only a few relatively high values observed in the capital city of

Nairobi. The highest levels of nitrogen dioxide in Vietnam can clearly be seen in the highly populated areas in the north, especially near the coast, and Ho Chi Minh in the south.

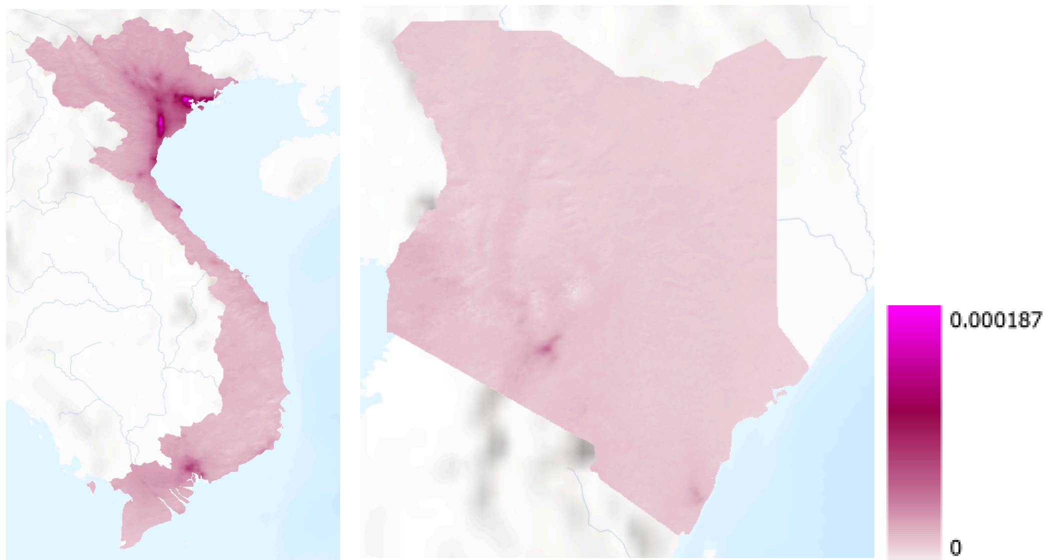


Figure 4.8 Maps of the nitrogen dioxide datasets for Vietnam (left) and Kenya (right).

Table 4.5 Summary statistics for the nitrogen dioxide datasets.

Nitrogen Dioxide	Min	Max	Mean	Std. dev
Vietnam	0	0.000187	5.71E-06	1.25E-05
Kenya	-3.42e-06	4.87e-05	4.79E-06	4.15E-06

Summary

A comparison of the raw datasets for the case study countries reveals significant differences between them. In Vietnam, a considerable portion of the rural area is dedicated to rice farming or covered by forests and jungles, resulting in high levels of vegetation. As a result, the rural areas with low population density have high values for (NDVI) in contrast to the urban centres. In Kenya, however, vast parts of the country, particularly in the Rift Valley in the north, have very low NDVI values due to the scarcity of green vegetation. These areas also have low population density but exhibit high values for both photovoltaic and wind power density. Overall, the two countries present distinct characteristics in terms of their natural and human-made environments, which should be considered when evaluating the RDMI.

4.3.2 Comparison of RDMI and its Components

After comparing the raw datasets for each of the indicators for both case study countries, the next step in the EDA was to generate country maps of the RDMI and each of its dimensions and compare these maps to investigate if there are patterns or anomalies. The maps of the dimensions show the datasets after they have been pre-processed (as outlined in the data calculation section), and in the case of the environment dimension show the median for the two sub-dimensions. The maps and results for Vietnam and Kenya will be examined and discussed separately before comparing the results.

Vietnam

When the RDMI map of Vietnam is examined, areas with the two largest cities are clearly marked as unsuitable areas, while the areas with the highest RDMI values include the northeast of the country near the border with China and the area between Da Nang city on the central coast and Ho Chi Minh city in the south. The maps of the dimensions do not show any unusual changes to the datasets after they have been pre-processed.

Comparing the RDMI map to the dimensions in Figure 4.9, it would appear that many of the areas which have the highest RDMI values also have the highest values for the geographical dimension (NDVI) and lowest values for the social dimension (as previously mentioned, the population density data was transformed so that high population density values show as low values for the social dimension, as it is more desirable for the RDM programme to have low population density). Thus, these two maps have many areas that look very similar to the RDMI map. However, it is more difficult to find similarities between the RDMI map and the map of the environmental dimension (which is the median of the PV power and wind power potential). This is especially true for the upper half of the map, for which there appears to be no identifiable pattern between the RDMI and the environmental dimension values. However, there seems to be more correlation between these two in the lower part of the map.

When the dimension maps are compared to each other, there is a clear relationship between the social dimension and the geographical dimension in the most populated parts of the country, which had already been identified while comparing the raw datasets.

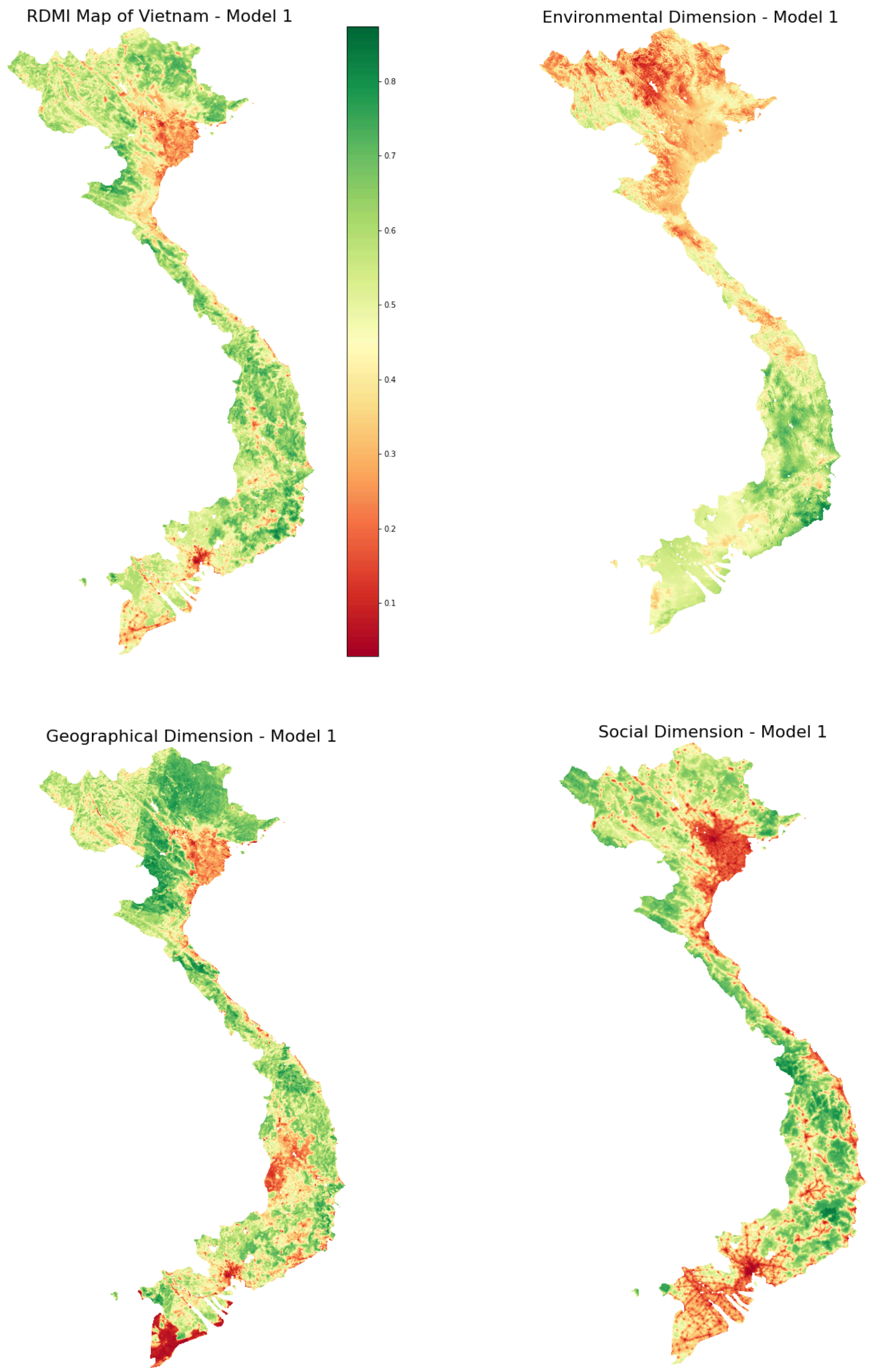
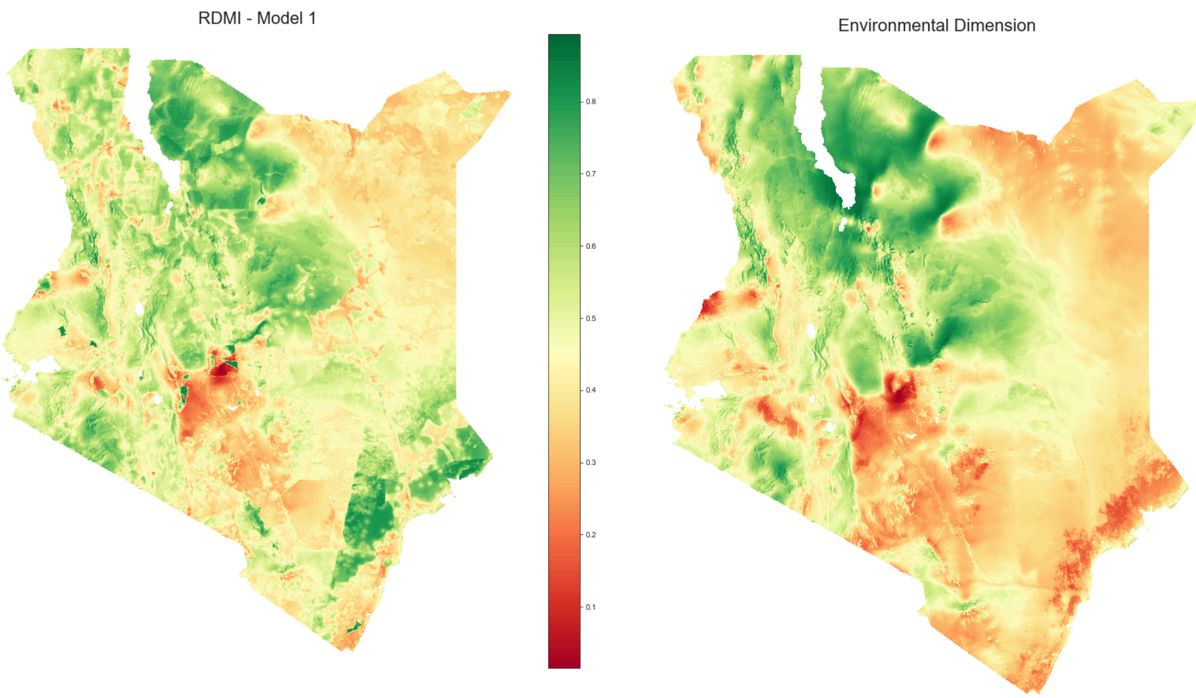


Figure 4.9 Map of the RDMI scores for Vietnam (top left) and scores for each of the index dimensions: environmental (top right), geographical (bottom left) and social (bottom right).

Kenya

Next, the maps of Kenya were analysed for patterns or anomalies. The RDMI map revealed that the central highlands between Nairobi and Mount Kenya (the darkest red spot in the centre of the map) were the least suitable areas for the RDM programme, while the central north of the country to the west of Lake Turkana and the southwestern coast north of Mombasa had the highest RDMI values. The missing patches in the map corresponded to water bodies such as lakes, which were masked out.

Further examination of the maps of the individual dimensions showed a significant difference between the pre-processed population density map in the social dimension and the raw dataset reviewed earlier (see Figure 4.3). The map of the social dimension revealed a sizable block of red in the lower part of the map surrounded by dark green areas, as well as other smaller patches of red on the map, some with adjacent dark green patches.



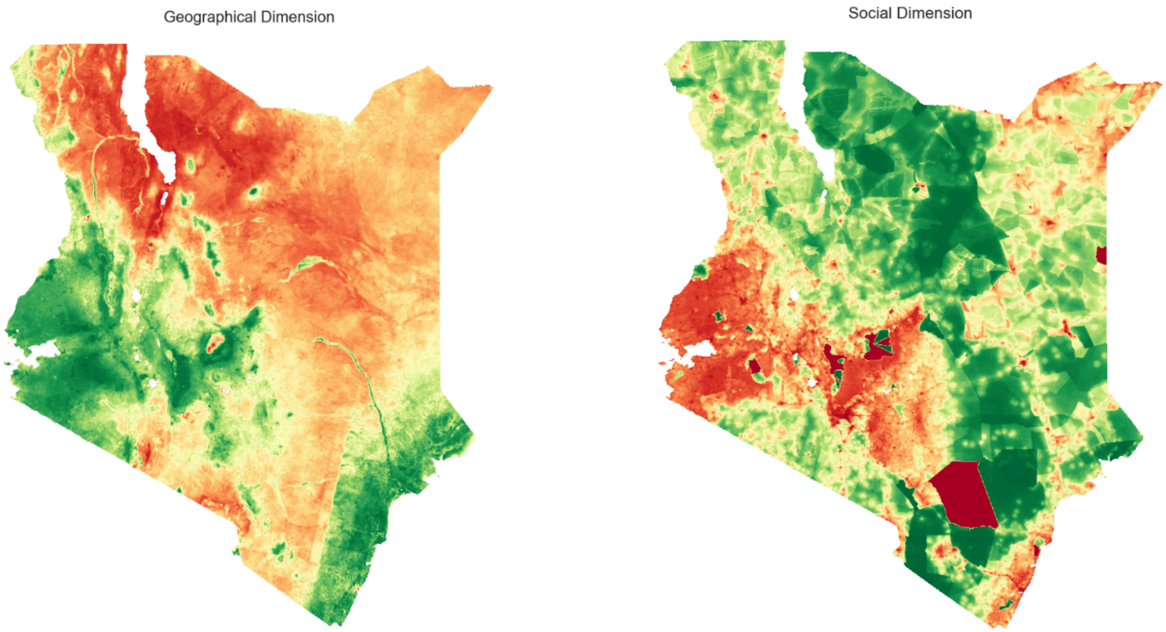


Figure 4.10 Map of the RDMI scores for Kenya (top left) and scores for each of the index dimensions: environmental (top right), geographical (bottom left) and social (bottom right).

Low population density is considered more suitable for the RDM programme than high population density in urban areas. Therefore, when the population density data is transformed, the final step involves multiplying the standardized values (between 0 and 1) by -1 to penalize high population and reward sparsely populated areas. Generally, areas in the social dimension map closer to red have high population density, while areas shown in green are sparsely populated. However, the map for Kenya shows this is not the case for areas with extreme values. In the raw dataset, these areas have zero or very low population density as they are special areas such as national parks or conservation areas. However, these areas are not marked specifically on the map, and they were only noticeable in the raw dataset map if they were surrounded by areas of high population density. Multiplying zero values by -1 had no effect on these values, resulting in these areas with zero population density values appearing as dark red on the map, as if they have extremely high levels of population density. However, all non-zero values for population are transformed correctly, and areas with extremely low population, such as those bordering Mount Kenya National Park, will show as dark green on the map (as shown in Figure 4.11).

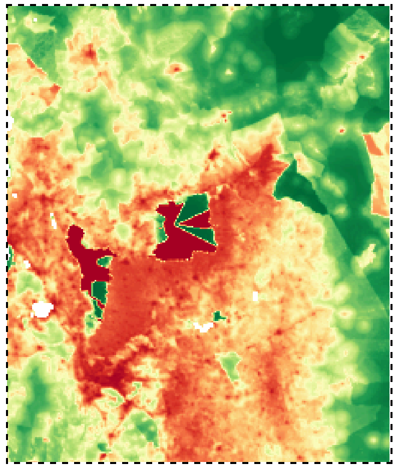


Figure 4.11 Section Kenya's map for the RDMI's social dimension that shows areas of very high (dark green) and very low (dark red) values next to one another.

This issue of zero population density is not an issue with Vietnam, and therefore up until this point the Lotus Project team had not considered this possibility. This discovery now highlights two different issues with the calculation of the index. Firstly, in the RDMI map, these areas with zero population are no longer evident as these values are too extreme to be chosen as the RDMI value for that pixel as the RDMI is the median of the three dimensions, thus the middle value will be chosen. This results in these areas appearing as if they are viable areas for development despite being restricted areas with no people living there. The second issue that is raised is that the RDMI is currently based on the assumption that the lower the value of population density, the more suitable it is for development, and there is currently no threshold for the minimum population density an area needs to have for it to be deemed suitable. It is essential that there are people living in an area for Lotus Project or any organisation to conduct community development programs there. And so, it could be more appropriate to set thresholds/bounds for the minimum and maximum values for population density, and areas which have values outside of these thresholds would be automatically assumed to be unsuitable for development, and therefore output a RDMI value of 0.00.

Next the RDMI map was compared to each of the dimension maps, and in this case the environment dimension appears to be the most similar to the RDMI map for nearly all of the country. The exception is the coastal region north of Mombasa which has some of the lowest values for the environmental dimension, but some of the highest values for the other two dimensions.

When the dimensions are compared to each other, there is again a clear relationship between the social dimension and the geographical dimension. However, in contrast to Vietnam, in Kenya there appears to be a negative relationship between these dimensions, with areas with high values for the geographical values mirroring areas with low values for the social dimension (apart from special areas with zero population).

Interestingly, in the northern part of the maps, the team found a pattern where areas that were very sunny and windy tended to have low levels of green vegetation and low levels of population. These areas in the central north are extremely arid, as noted from the interviews and the land cover map, explaining the pattern.

Vietnam vs. Kenya

After visually comparing each country's RDMI map with maps of its dimensions, it appears the social and geographical dimensions are the most similar to the RDMI map of Vietnam, while the environmental dimension seems to be the most dominant influence on the RDMI map of Kenya. To understand what might have caused the countries to have different dominant dimensions, and in general to understand why the RDMI map tends to mirror certain dimensions in certain places, rather than reflect the three dimensions overall, it is necessary to look at the distribution of the dimensions and how they are aggregated.

As already mentioned, the RDMI is formed by aggregating the dimensions using the median. The median was chosen over the average as it is less susceptible to possible outliers, however while there are still only three dimensions (more may be added in the future) this results in the RDMI taking on the value for the dimension which has a value that falls in between the other two values, the table below shows the percentage of pixels where the RDMI value is equal to each of the different dimensions.

Table 4.6 Proportion of pixels where the RDMI value equals the different dimension values.

% of pixels where RDMI value is equal to dimension value			
RDMI	**Environmental**	**Social**	**Geographical**
Vietnam	22.85%	**38.34%**	**38.88%**
Kenya	**48.23%**	29.54%	22.23%

When we look at the boxplots of the distributions for the RDMI and dimensions for each country, we can see that the median of the social dimension for Vietnam falls in between the median of the other two dimensions and it almost matches the median of the RDMI. For Kenya, the median for the environmental dimensions falls between the other two, and in fact its values are much more tightly packed in the centre of the range while the other two dimensions are more spread out below and above the centre, this may be why the environmental dimension was the median values for 48% of the pixels. Whereas for Vietnam, the social and geographical dimensions were the median values for 38% and 39% of the pixels respectively. The environmental dimensions for both countries have quite similar distributions and are both condensed around the centre, however in the case of Vietnam, the geographical dimension has much higher values in general, and as previously discussed it appears that these high values of NDVI are associated with high values of the social dimension. If there are two high values with one medium value, the median will be the lower of those high values, which may explain why the geographical and social dimensions are so dominant in the RDMI map of Vietnam.

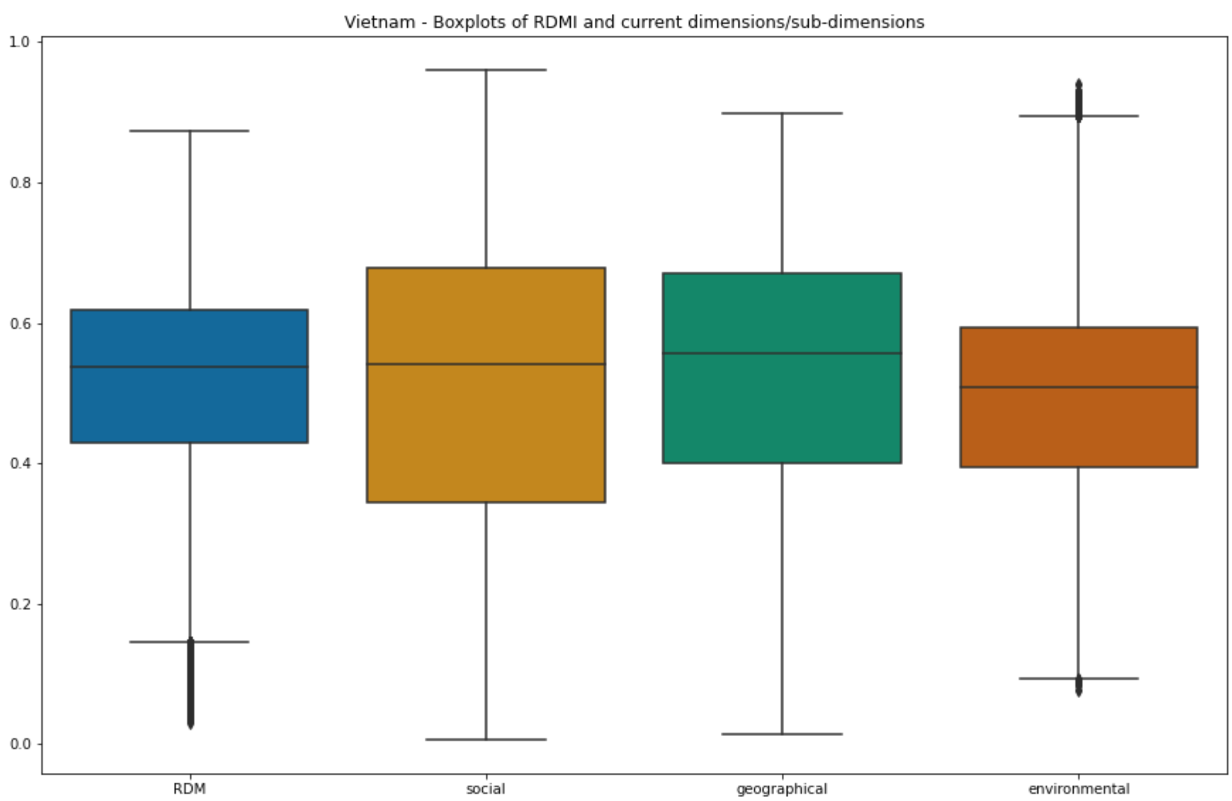


Figure 4.12 Boxplots with the distributions of the RDMI and its current dimensions for Vietnam.

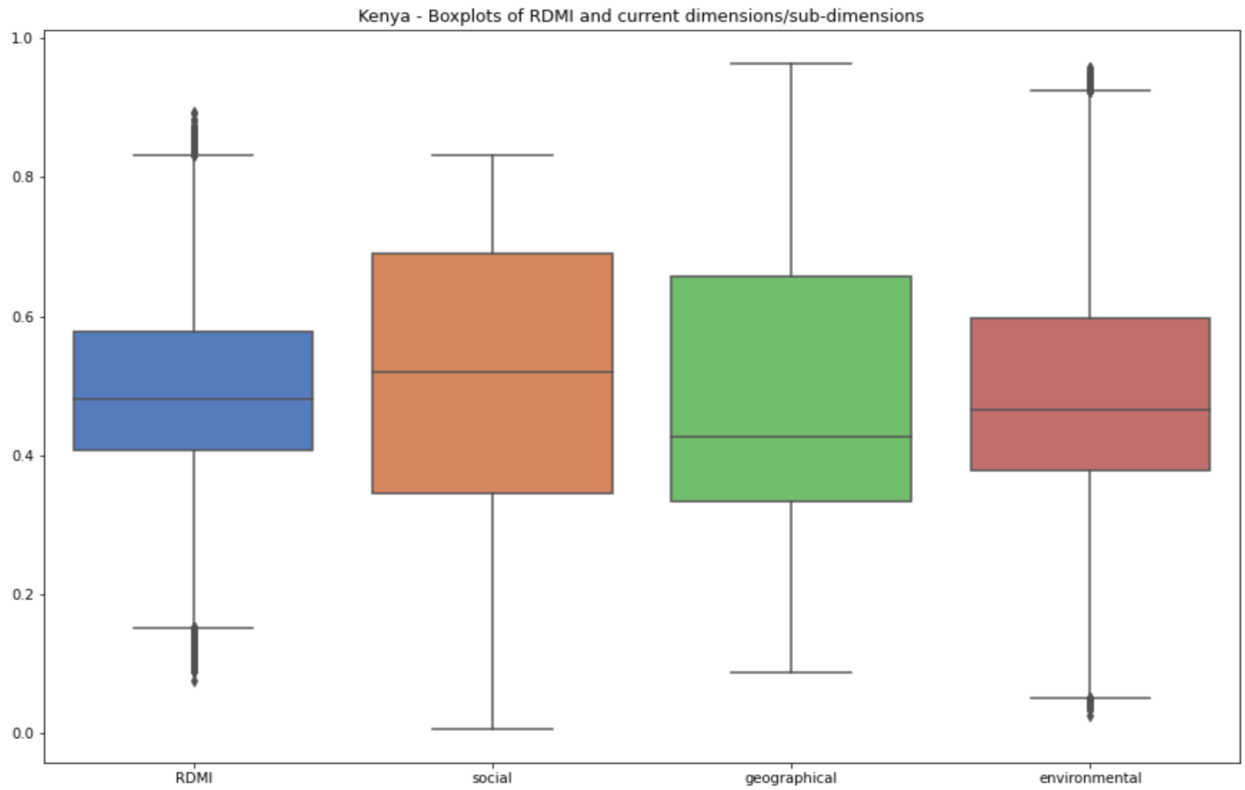


Figure 4.13 Boxplots with the distributions of the RDMI and its current dimensions for Kenya.

4.3.4 Correlation Analysis

Correlation analysis is an important tool for assessing composite indicators as it can help identify potential issues of multicollinearity among the individual indicators. Multicollinearity can lead to instability in the composite indicator and can distort the relationship between the CI and the underlying variables it is meant to represent. By using correlation analysis, this study examined the strength and direction of the relationships between the individual indicators and the RDMI, as well as between the individual indicators themselves. This can help to identify any redundancies or dependencies among the indicators and determine which indicators are driving the overall score.

The interviews with GIS experts and the results of EDA suggested that there may be multicollinearity in the RDMI. Specifically, there appears to be correlations between NDVI and population density, as well as population density and the proposed new indicator nitrogen dioxide. To test for these possible correlations, Pearson's correlation method was used for each dimension and sub-dimension, with the outputs visualised in heatmaps (see Figure 4.14 and Figure 4.15). Green indicates a positive relationship, whereas red indicates a negative relationship, and the darker the colour, the stronger the relationship.

For the Vietnam dataset, the correlation heatmap indicated a strong positive correlation between the overall index and the social and geographical dimensions (0.81 and 0.68 respectively), while the correlation between the environment and the RDMI was weak (0.18). This difference in strengths of relationship was expected after examining how the distribution of these dimensions influence the index. The heatmap also showed a positive correlation between the social and geographical dimensions (0.48), supporting the observation from the maps that high NDVI values in Vietnam seem to be correlated with low population density. Additionally, a negative correlation (-0.34) was observed between NDVI and photovoltaic power potential, and this may in part be due to the fact that the south of the country has more photovoltaic power potential than the north, and it also contains some of the lowest NDVI values due to some of the Mekong Delta being submerged under water.

Next the Kenya dataset was tested for correlation, but before doing so the rows with zero population were removed from the dataset as including them could affect the analysis. As expected from the observations in the previous section, a strong positive correlation (0.59) was found between the environmental dimension and the RDMI. The social dimension also had a strong positive correlation with the index, but there was no significant relationship between the geographical dimension and the index. In line with expectations, the geographical dimension (NDVI) was negatively correlated with the social dimension (-0.49), and the geographical dimension was negatively correlated (-0.5) with wind power density. Wind power density also had a positive correlation with the social dimension (i.e., a negative correlation with population density), suggesting that windier areas in Kenya tend to have lower population density.

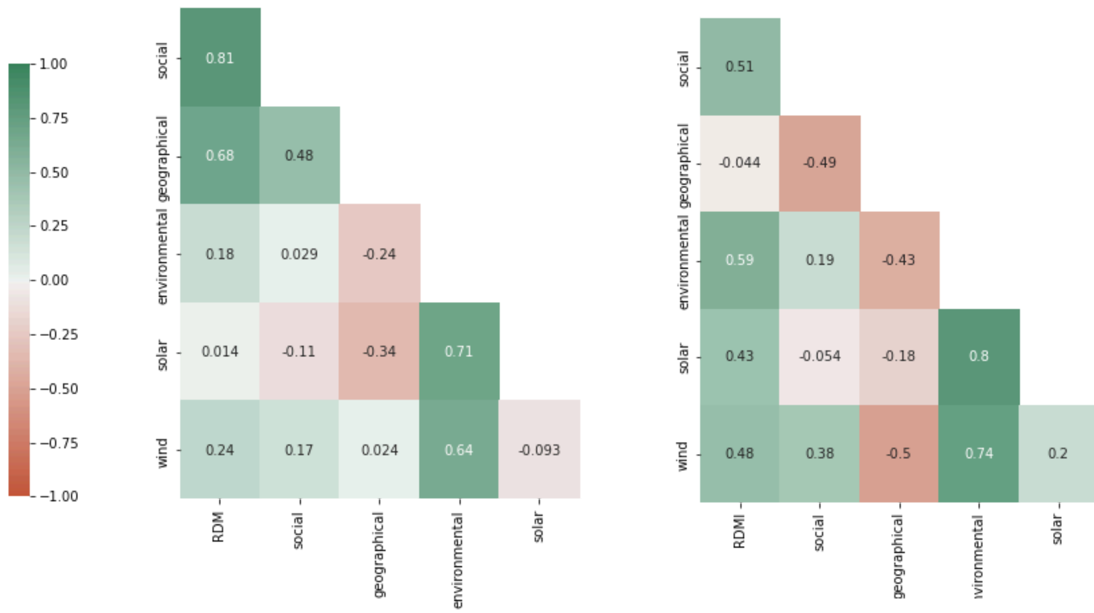


Figure 4.14 Correlation heatmaps for the RDMI and its dimensions and sub-dimensions (Vietnam on the left and Kenya on the right).

After integrating the proposed new air pollution indicator - nitrogen dioxide (NO_2) - into the RDMI, the correlation heatmaps were regenerated for both country datasets. The results show a positive correlation between NO_2 and the social dimension, indicating that areas with higher population density tend to have higher levels of air pollution, with moderate correlation coefficients of 0.52 for Vietnam and 0.41 for Kenya. For Vietnam, there is a very slight positive correlation between NO_2 and the geographical dimension (0.16), while for Kenya, there is a negative relationship between NO_2 and the geographical dimension (-0.37). This suggests that greener areas in Kenya tend to have higher air pollution levels, as NO_2 has a decreasing polarity, where higher values indicate lower levels of pollution after pre-processing. While this might seem counterintuitive, it makes sense given that greener areas in Kenya also tend to be more populous. Additionally, the inclusion of NO_2 strengthened the relationship of the RDMI with the environmental dimension for the Vietnam dataset, increasing the correlation coefficient from 0.18 to 0.41. This dimension had previously had the lowest impact on the RDMI for Vietnam, but now has more of an influence.

Figure 4.15 Correlation heatmaps for the RDMI and its dimensions and sub-dimensions, after nitrogen dioxide has been integrated into the index (Vietnam on the left and Kenya on the right).

4.3.5 Summary of EDA

In summary, the exploratory data analysis conducted in this study has highlighted significant differences in indicators between the case study countries, providing a better understanding of their unique profiles and the diverse relationships between the RDMI and its components. The findings of the EDA suggest areas for improving the index, including the need to address pre-processing issues, such as zero population values in some areas of Kenya. These results will inform the next steps in the study, as parameters and variables will be drawn from these findings. For instance, the use of the median as the dimension level aggregation method has led to some dimensions having too much influence in certain areas, indicating a need to explore other forms of aggregation. Additionally, the EDA has shown that while NDVI is negatively correlated with population density in Vietnam, the opposite is true for Kenya, suggesting that it is not a reliable proxy for ruralness in all regions. Therefore, it is necessary to investigate the effect of removing this indicator from the index, as well as to further test the impact of including nitrogen dioxide as a new indicator.

4.4 Sensitivity Analysis

A sensitivity analysis was conducted to investigate the effects of changes in both the model parameters and model variables on the output data of the RDMI for the two case study countries. In composite indicator analysis, model parameters refer to the choices made regarding aggregating or weighting the data. On the other hand, model variables refer to the indicators included in the index, which can be added or removed to improve the index's relevance and accuracy. The model parameters and variables to test were chosen based on observations from the previous steps in the research, including the interviews with experts and the Lotus Project team, the EDA, and the literature review. This section describes the methodology and approach taken for the sensitivity analysis, and the results of this analysis will be discussed in Chapter 5.

4.4.1 Univariate Approach

A univariate sensitivity analysis approach was used to test the sensitivity of the RDMI model to different variations. This type of analysis involves changing one variable or parameter at a time while holding all others constant. In contrast, multivariate sensitivity analysis involves changing multiple variables simultaneously to assess their combined effects on the outcome of interest. A multivariate approach was also experimented with to create models that combined two of these variations. The results of the multivariate analysis showed that the outputs were even more sensitive to combined variations. However, there were some issues with this approach due to the small number of variables used in the RDMI. For example, if one of the variations in the model is the exclusion of a variable, the remaining variables become more sensitive to changes in parameters, and each variable has a larger influence on the overall score of the composite indicator when there are fewer variables. Consequently, it was decided to focus more on the univariate analysis approach, which provided clear and transparent results that are easier to interpret and more relevant for practical decision-making.

4.4.2 Model Parameters and Variables

This subsection describes the four models created for the univariate sensitivity analysis and how they differ from the original RDMI model (Model 1), which served as the baseline for comparison.

The first alternative model, Model 2, uses a different method of aggregation at the dimension level compared to the base model. While Model 1 calculates the RDMI by obtaining the median of the three dimensions, Model 2 uses the arithmetic average. The use of the arithmetic average was tested as an alternative to the median, as the exploratory data analysis suggested that the median tended to create bias towards certain dimensions, particularly since the index currently only has three dimensions, resulting in two values being excluded when using the median.

The next alternative model, Model 3, focuses on sub-dimension level aggregation. While Model 1 also uses the median to aggregate indicators within a dimension to obtain the score for that dimension, it was not possible to test the use of arithmetic average over median for the environmental dimension (currently the only dimension in the RDMI with multiple indicators). This is because the environmental dimension has only two indicators - PV potential and wind power density - and therefore, both methods would produce the same output, as they will result in the middle value between the two indicators. However, since Lotus Project indicated that the organisation would more than likely only install one type of off-grid energy system at a time, it may be more appropriate to use the maximum value of these two indicators, instead of the median or arithmetic average. Thus, Model 3 tests the maximum as an alternative method of aggregation at the sub-dimension level.

The other variations in the models were related to the inclusion and exclusion of specific variables. Initially, NDVI was included in the index as an indicator of ruralness - areas with more vegetation were considered more rural. However, during the exploratory data analysis phase, it became apparent that this assumption did not hold true for sub-Saharan countries like Kenya, where the most rural areas could be arid while areas with more vegetation were more densely populated. Given these findings, the suitability of NDVI as an indicator for the RDMI was re-evaluated. Therefore, Model 4 excludes NDVI to investigate its impact on the RDMI outputs. This was done with a particular focus on comparing the results for the case study countries, given the significant differences in their vegetation profiles that became apparent when comparing their raw data for this indicator (as discussed in section 4.3.1).

Model 5 includes a proposed new variable, nitrogen dioxide (NO_2), as a new sub-dimension in the environmental dimension. Lotus Project suggested this addition due to the organisation's recognition of the importance of factoring in air pollution and other forms of pollution levels in an area before embarking on any development plans.

Based on these modelling parameters and variables, these four alternative models were created, and their outputs were compared to the base model (with NDVI included, NO_2 excluded, and the median used as the aggregation method for both the dimensions and sub-dimensions).

4.4.3. Comparison of RDMI Scores and Classes

After calculating the RDMI scores for each model, the RDMI scores were compared to the base model scores using paired t-tests to determine whether the distributions were statistically different. The goal was to assess whether the RDMI was robust and not highly sensitive to changes in the model's parameters or variables. If the paired t-tests showed no significant difference, it would suggest that the RDMI scores for the different models were similar, indicating that the model was not highly sensitive to changes in its parameters or variables.

Next, the continuous output data was classified into five equal-sized quantiles between the minimum and maximum values for each dataset, representing different levels of suitability for the RDM programme, namely very low, low, medium, high, and very high. Classifying the continuous data facilitated the interpretation of the impact of using different model parameters and variables. Additionally, it enabled a more direct comparison between the different models tested in the study, as well as the distributions of the output datasets for the two case study countries.

Although the use of quantiles ensured that the classes were comparable, it is important to note that the thresholds for the different classes varied slightly due to the different minimum and maximum values in each output dataset. As a result, the ranges of values represented by each class differed slightly between the datasets. However, this approach provided a consistent framework for the analysis, and was chosen because the results of the RDMI are always considered in the context of a particular country. Rather than using a fixed threshold to determine suitability for the RDM programme, the organisation looks for the most suitable sites which are in the top percentiles for the values within that country.

Overall, the transformation of continuous data into classified data provided a more interpretable and informative analysis of the data and its relationship to the RDM programme, which was further strengthened by using paired t-tests to compare the models. The combination of these approaches allowed for a more precise comparison of the models and a straightforward comparison between output datasets for different models and the two case study countries.

4.4.4 Visual Comparison of Maps

The RDMI outputs for the different models were also compared visually by creating maps of the classified data. By comparing the RDMI maps visually, it was possible to gain a deeper understanding of the impact of the variations in the models on the different countries, given the unique country profiles previously identified through the analysis of raw datasets and dimensions. This approach helped to contextualize the numerical output and provided a more comprehensive understanding of the RDMI results. Ultimately, the visual comparison of the RDMI maps served as a crucial step in the analysis process and provided a more nuanced understanding of the data.

4.4.5 Comparison of Model Outputs for Pilot Sites

The final step in the sensitivity analysis involved comparing the different model outputs for two specific locations in Vietnam. These locations correspond to the sites of the Lotus Project's pilot projects in the northern part of the country, where they are pioneering the RDM programme (see section 1.2).

When the original RDMI model was applied to these areas, they were found to be highly suitable for the programme which validated the decision to choose them as pilot project sites (the RDMI was created after they were selected). However, the last stage of the sensitivity analysis aimed to investigate whether their suitability changes when using different model parameters and variables. This comparison is important for ensuring that the RDMI can be used effectively in these areas, as well as for assessing the robustness of the RDMI model using a real-world application of the index.

4.4.6. Summary of Sensitivity Analysis Methodology

In conclusion, the sensitivity analysis conducted in this study provided a comprehensive evaluation of the RDMI model and its ability to predict suitable sites for RDM programmes in Vietnam and Kenya. A univariate approach was used to test the model's sensitivity to different variations, which was found to be more relevant for practical decision-making than the multivariate approach due to issues with the small number of variables used in the RDMI. This univariate analysis involved creating four alternative models, which incorporated variations such as different aggregation methods at the dimension and sub-dimension levels, exclusion of one indicator (NDVI), and inclusion of a new indicator (NO_2). And the scores for each model were compared to the base model using paired t-tests to determine if there is a significant difference in their distribution. The data was then grouped into five classes, and this classification into different suitability levels facilitated a more straightforward comparison of the model outputs and provided valuable insights into the potential impacts of using different model parameters and variables. Comparing the RDMI maps visually enabled the detection of spatial trends and patterns that may not be readily apparent from numerical data output alone. Finally, the comparison of model outputs for pilot sites tested the reliability of the RDMI model in predicting the suitability of specific locations for RDM programmes. In conclusion, the sensitivity analysis conducted demonstrated the extent to which the RDMI model is influenced by alterations in its input variables, thus assessing the robustness of the index.

4.5 Uncertainty Analysis

To further evaluate the results of the sensitivity analysis, an uncertainty analysis was employed to evaluate the reliability and robustness of the RDMI in terms of the aggregation method used at a dimension level. Furthermore, it provides a measure of the uncertainty associated with the results and assists in identifying areas in the construction of the index that may require further consideration. The methodology employed to conduct the uncertainty analysis includes the use of the Monte Carlo method to generate random weights for 1,000 simulations of calculating the RDMI using the weighted average, and the results of the analysis will be discussed in the following section.

4.5.1 Aggregation as a Source of Uncertainty

The choice of aggregation methods used to construct composite indicators is highly debated, and the RDMI's use of the median has resulted in biased output datasets towards certain indicators, rather than providing an overall evaluation of the different dimensions in each area. Using the arithmetic average or assigning weights based on importance could be alternatives, and the uncertainty analysis aimed to build on the sensitivity analysis and further compare the outputs of the index using the different forms of aggregation. Specifically, the investigation employed the Monte Carlo (MC) method to generate random weights, which were used to calculate the RDMI using a weighted average. The results of these 1,000 simulations for the weighted average were then compared to the outputs for the RDMI when calculated with two other models: the median (Model 1) and the arithmetic average (Model 2).

4.5.2 Monte Carlo Simulations and Weighting Schemes

Weights were assigned to the three dimensions of the RDMI in three steps. In the first step, the first weight was randomly selected from a uniform distribution centred around 0.33, representing equal weighting for each dimension. To account for the relative importance of each dimension, a range of 0.18-0.48 was used. In the second step, the weight was randomly selected again from a uniform distribution but depending on the value for the first weight, the range of the distribution may be further limited to ensure that the weights added up to 1. For example, if the first weight is 0.18, the second weight is selected from a distribution with a range of 0.34-0.48, because a lower threshold would make it impossible for the three weights to sum up to 1 as the third weight can be no larger than 0.48. Finally, the third weight was calculated as the difference between 1 and the sum of the first two weights. Before calculating the RDMI using the weighted average, the list of three weights was shuffled and a weight was assigned to each dimension.

4.5.3 Analysis of Results

Once the 1,000 simulations were completed, the results were compiled into a Pandas data frame and 250 random observations were extracted to create a sample data frame. The median of the MC simulations for each of the rows in the sample dataset was obtained, along with the 90% confidence intervals (CIs) for each simulation. The RDMI output for Model 1 and for Model 2 were calculated, and the results for the coordinates that were included in the sample data frame were joined to the data frame.

To compare the results of the MC simulations for the weighted average with the outputs of Model 1 and Model 2, several analyses were performed. Firstly, the results were visualised together in graphs to investigate how they compared to each other. Secondly, the proportion of times that the sample outputs for Model 1 and Model 2 fell within the 90% CIs for the weighted average simulations was calculated. Additionally, the average distance between the median of the MC simulations and the outputs for Model 1 and Model 2 for the two case study countries was compared using an independent t-test. The average size of the 90% CIs was also calculated for each country, and these were also compared to check if there was a statistical difference between them. Finally, Pearson's correlation coefficient was used to measure the strength of the relationship between the different outputs, providing further insights into the similarities and differences between the aggregation methods.

4.5.4 Summary of Uncertainty Analysis Methodology

The results of composite indicators are very influenced by the choice of aggregation method, as it may assign different weights to individual indicators, thus impacting the overall score. This uncertainty analysis aimed to provide insights into how the RDMI would perform under different aggregation methods, and to understand the impact of using alternative methods on the stability of the index.

Chapter 5 Results

Chapter 5 presents the results of the sensitivity and uncertainty analysis conducted for the RDM Index. The chapter is divided into two sections. The first section provides an overview of the sensitivity analysis results, including quantitative results for each model and a comparison of country maps with the base model. The stability of index values for pilot sites across different model variations is also discussed. In the second section, the findings of the uncertainty analysis are presented.

5.1 Sensitivity Analysis

The tables for each country below display the specifications of each model that was tested in the sensitivity analysis along with the summary statistics (mean, standard deviation, minimum and maximum) for each output dataset and the percentage of observations that moved up or down a class or two from the original class that was assigned to the observation for its output for Model 1.

Table 5.1 Sensitivity Results for Vietnam.

Model	NDVI	$N0_2$	Sub-Dimension Aggregation	Dimension Aggregation	Mean	Std. Dev	Min	Max	Moved 0 classes	Moved 1 class	Moved 2 classes
1	Yes	No	Median	Median	0.519	0.138	**0.029**	0.874	N/A	N/A	N/A
2	Yes	No	Median	**Average**	0.509	0.118	0.099	0.838	71.4%	28.5%	0.0%
3	Yes	No	**Max**	Median	**0.550**	**0.152**	**0.029**	**0.922**	78.5%	21.1%	0.4%
4	**No**	No	Median	Median	0.503	0.128	0.107	0.878	50.1%	**46.3%**	**3.6%**
5	Yes	**Yes**	Median	Median	0.518	0.141	**0.029**	0.841	**80.2%**	19.7%	0.1%

Table 5.2 Sensitivity Results for Kenya.

Model	NDVI	$N0_2$	Sub-Dimension Aggregation	Dimension Aggregation	Mean	Std. Dev	Min	Max	Moved 0 classes	Moved 1 class	Moved 2 classes
1	Yes	No	Median	Median	0.494	0.124	0.015	0.894	N/A	N/A	N/A
2	Yes	No	Median	**Average**	0.493	0.084	0.105	0.840	68.0%	31.8%	0.1%
3	Yes	No	**Max**	Median	**0.545**	0.128	0.016	**0.925**	73.4%	25.7%	0.9%
4	**No**	No	Median	Median	0.493	**0.151**	**0.008**	0.864	51.4%	**46.5%**	**2.2%**
5	Yes	**Yes**	Median	Median	0.497	0.126	0.016	0.884	**76.1%**	23.1%	0.8%

The findings from both case study countries suggest that variations in the model had a significant impact on the outputs of the RDMI. Paired t-tests were conducted to compare the RDMI mean for Model 1 with the mean of each subsequent model, and the null hypothesis was rejected in all cases. These results indicate that each variation in the model caused a change in the distribution of RDMI scores. This was true for both case study countries. Additionally, every change to the RDMI model prompted at least one fifth of the observations to either increase or decrease a level of suitability.

For both Vietnam and Kenya, Model 3 had the highest mean RDMI score (0.550 and 0.545, respectively), as well as the largest maximum RDMI values. These findings suggest that areas in both countries tend to score higher when only one renewable energy source is considered, rather than the median of both PV power potential and wind power density. However, it's worth noting that within the output datasets for Vietnam, Model 3 also has the largest standard deviation and the lowest minimum value. These variations indicate that there may be some outliers or extreme values that contributed to the overall RDMI score. Nevertheless, it's important to highlight that even after sub-dimension aggregation was changed to the maximum, the majority of observations (78.5% for Vietnam and 73.4% for Kenya) remained in the same suitability class. This il that the RDMI scores were still largely consistent even with this change in aggregation method.

Conversely, the removal of the Normalised Difference Vegetation Index (NDVI) had a significant impact on both countries, with 50% of the observations for Vietnam and 49% of the observations for Kenya moving into a different suitability class. Moreover, this change caused the standard deviation of RDMI scores to increase for both countries, with Model 4 exhibiting the largest variation within the output datasets for Kenya.

The next variation which had a significant impact on the class distributions was changing the dimension-level aggregation from the median to the arithmetic average, as observed in Model 2. For Vietnam and Kenya, this change resulted in 29% and 32% of the samples, respectively, moving to a different level of suitability. Moreover, the change to the model resulted in a decrease in variation within the RDMI output dataset, and Model 2 had the lowest standard deviation among all the output datasets for both countries. This suggests that the arithmetic average aggregation method may have led to a more consistent and stable RDMI score distribution for these countries.

Lastly, adding the proposed new indicator to the environmental dimension in Model 5 had the least impact on the levels of suitability. Even so, 20% (Vietnam) and 24% (Kenya) still moved to a different class level, and this model variation had almost the same effect as changing the environmental sub-dimension aggregation to the maximum, as observed in Model 3 where 21% and 27% of pixels moved to different classes.

5.1.1 Model 1 versus Model 2

Table 5.3 Summary of effects on RDMI classes for Model 2.

Model 1 to Model 2	Moved 0 classes	Moved 1 class	Moved 2 classes	% of moved observations that increased class	% of moved observations that decreased class
Vietnam	71.4%	28.5%	0.0%	28.3%	**71.7%**
Kenya	68.0%	31.8%	0.1%	33.6%	**66.4%**

Table 5.4 Comparison of class distributions between Model 1 and Model 2 (values show % of total).

Vietnam	Very Low	Low	Medium	High	Very High
Model 1	1.9	13.3	34.2	**44.0**	6.6
Model 2	1.6	15.7	**40.0**	38.4	4.2
Difference	-0.3	+2.4	**+5.8**	-5.6	-2.4
Kenya	Very Low	Low	Medium	High	Very High
Model 1	0.5	12.5	**55.4**	26.1	5.5
Model 2	0.4	13.3	**59.0**	26.9	0.3
Difference	-0.1	+0.8	+3.6	+0.8	**-5.2**

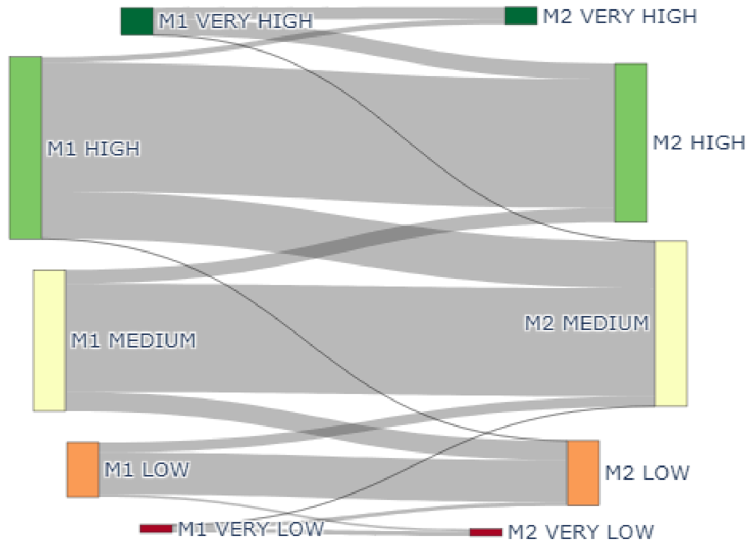


Figure 5.1 Sankey graph showing the direction of movement between classes from Model 1 to Model 2 for Vietnam.

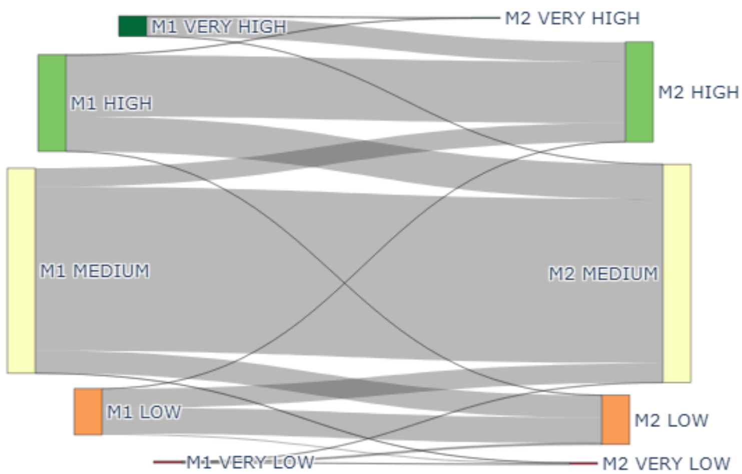


Figure 5.2 Sankey graph showing the direction of movement between classes from Model 1 to Model 2 for Kenya.

In Model 2, the dimension-level aggregation method was changed from the median to the arithmetic average. This change had a significant impact on the observations for Vietnam and Kenya, with 29% and 32% respectively being reclassified into a different suitability class. In both case study countries, the majority of the observations that moved to a different class were downgraded to a lower class, representing 72% and 66% of the total respectively. As shown in Figure 5.1, in the Vietnam dataset a considerable number of observations that were previously classified as 'high' suitability moved to the 'medium' class, resulting in the 'medium' class becoming the dominant one. For Kenya, the most significant change occurred in the 'very high' class, which dropped from 5.5% in Model 1 to only 0.3% in Model 2. The variation in Model 2 also resulted in a general increase in the number of observations classified as having medium suitability. The next step will involve examining maps to explore the spatial differences in the datasets.

Model 1 vs. Model 2 - Vietnam Maps

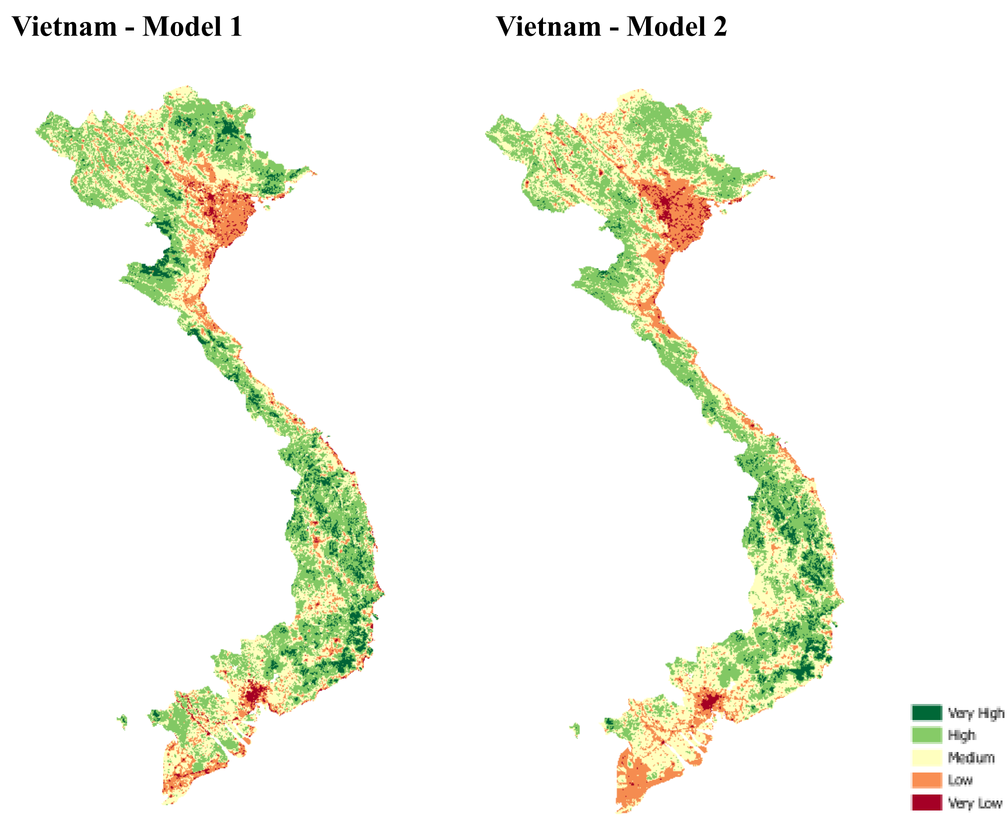


Figure 5.3 RDMI Maps of Vietnam - Model 1 (left) and Model 2 (right).

While comparing the maps of Vietnam generated by Model 1 and Model 2, some observable differences can be noted, although the contrast is not significant. Notably, areas in the north that were classified as having very high suitability using Model 1 have moved down to the next lower class in Model 2 when the RDMI is calculated. Additionally, extreme values for NDVI in the Mekong Delta have become more evident (as discussed in section 4.3.1), with this area now clearly classified as having low suitability, as shown in Figure 5.4. However, it is uncertain at this stage whether an area like this, with a high water content, would be unsuitable for the RDM programme, as it is still suitable for many water-based activities such as fishing, aquaculture, and rice cultivation.

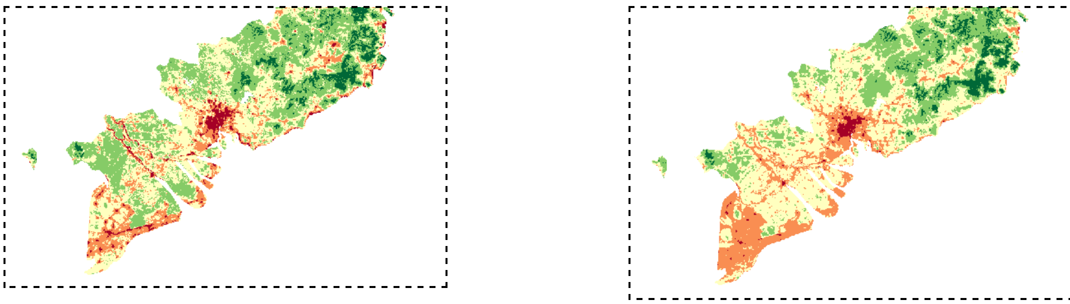


Figure 5.4 RDMI Maps of Mekong Delta area of Vietnam - Model 1 (left) and Model 2 (right).

Model 1 vs. Model 2 - Kenya Maps

Kenya - Model 1 **Kenya - Model 2**

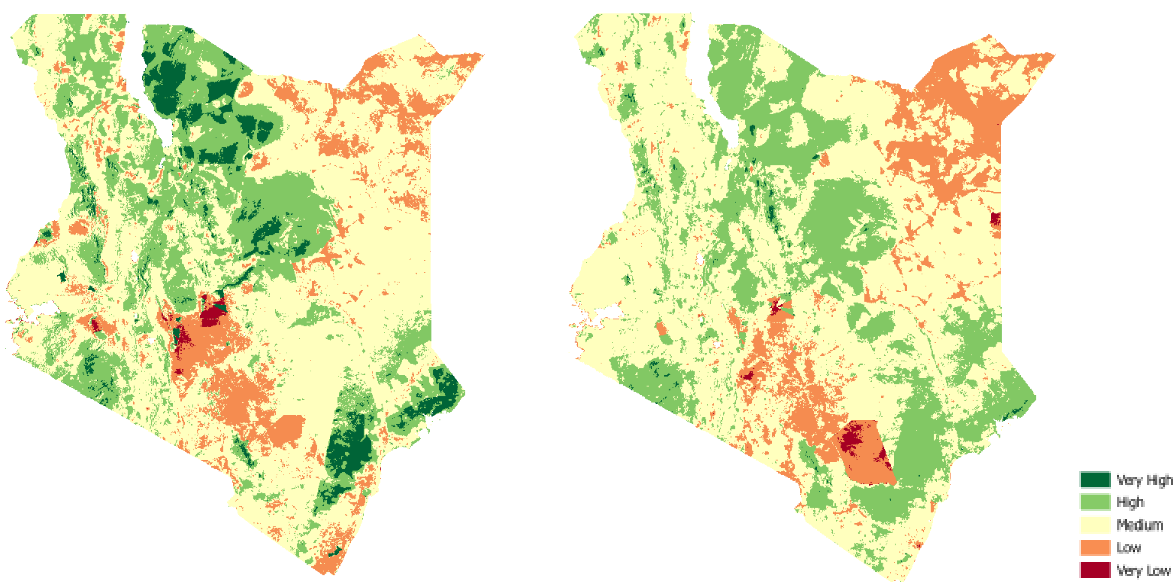


Figure 5.5 RDMI Maps of Kenya - Model 1 (left) and Model 2 (right).

Kenya's maps for Model 1 and Model 2 show a much greater difference compared to Vietnam. Almost all of the areas that were previously classified as having 'very high' suitability have dropped down a class, although they are still considered to have high suitability. In Model 2, nearly half of the pixels that were considered 'high' with the median are only classified as 'medium' when the average is used, indicating a general decrease in suitability in the map.

One of the most noticeable differences between the two maps is the clear visibility of the national park area in the lower part of the map for Model 2 (Figure 5.6). This could be due to the fact that extreme values for the social dimension, such as zero population, were not considered when calculating the median of the pixels. However, the average is more sensitive to outliers, making extreme values more discernible on the map. Despite the overall downward trend, some areas have increased in suitability, such as the southern coastal region where the city of Mombasa is located. This area no longer has low suitability despite its high population density.

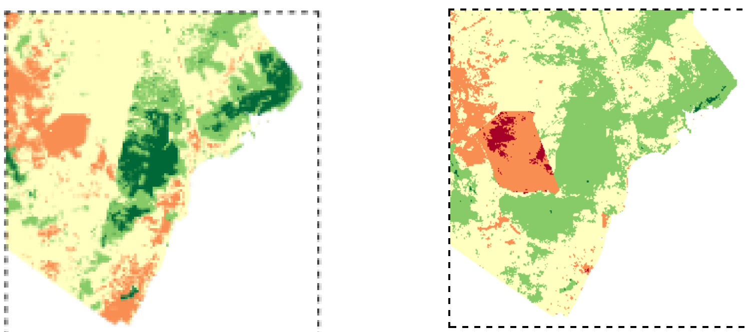


Figure 5.6 RDMI map for southeast coast of Kenya - Model 1 (left) and Model 2 (right).

5.1.2 Model 1 versus Model 3

Table 5.5 Summary of effects on RDMI classes for Model 3.

Model 1 to Model 3	Moved 0 classes	Moved 1 class	Moved 2 classes	% of moved observations that increased class	% of moved observations that decreased class
Vietnam	78.5%	21.1%	0.4%	**51.9%**	48.1%
Kenya	73.4%	25.7%	0.9%	**82.2%**	17.8%

Table 5.6 Comparison of class distributions between Model 1 and Model 3 (values show % of total).

Vietnam	Very Low	Low	Medium	High	Very High
Model 1	1.9	13.3	34.2	**44.0**	6.6
Model 3	2.2	13.5	32.4	**44.3**	7.5
Difference	+0.3	+0.2	**-1.8**	+0.3	+0.9
Kenya	Very Low	Low	Medium	High	Very High
Model 1	0.5	12.5	**55.4**	26.1	5.5
Model 3	0.3	9.1	**45.5**	38.6	6.5
Difference	-0.2	-3.4	-9.9	**+12.5**	+1.0

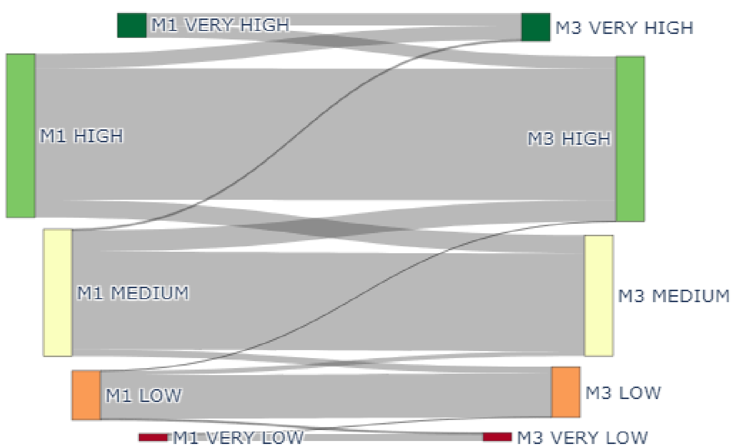


Figure 5.7 Sankey graph showing the direction of movement between classes from Model 1 to Model 3 for Vietnam.

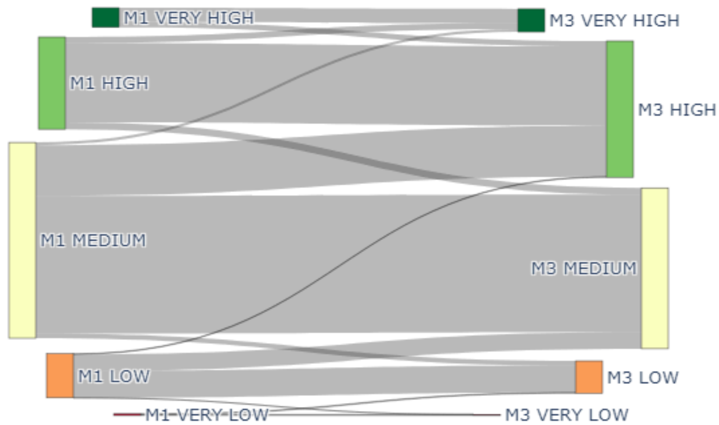


Figure 5.8 Sankey graph showing the direction of movement between classes from Model 1 to Model 3 for Kenya.

As discussed at the start of section 5.1, the use of Model 3 had a significant impact on the RDMI scores on average, resulting in an overall increase in the mean scores. Table 5.5 further reveals that of the 26% of observations for Kenya that moved to a different class as a result of using the maximum as the sub-dimension aggregation method, 82% of them moved up into a higher class. Figure 5.8 illustrates that most of these observations moved from the 'medium' class to the 'high' class. In contrast, the impact of this variation in the model on the class distributions for Vietnam was less pronounced. Both the table and Figure 5.7 show that roughly the same proportion of observations moved up as those that moved down to a lower class.

Model 1 vs. Model 3 - Maps of Vietnam

Vietnam - Model 1 **Vietnam - Model 3**

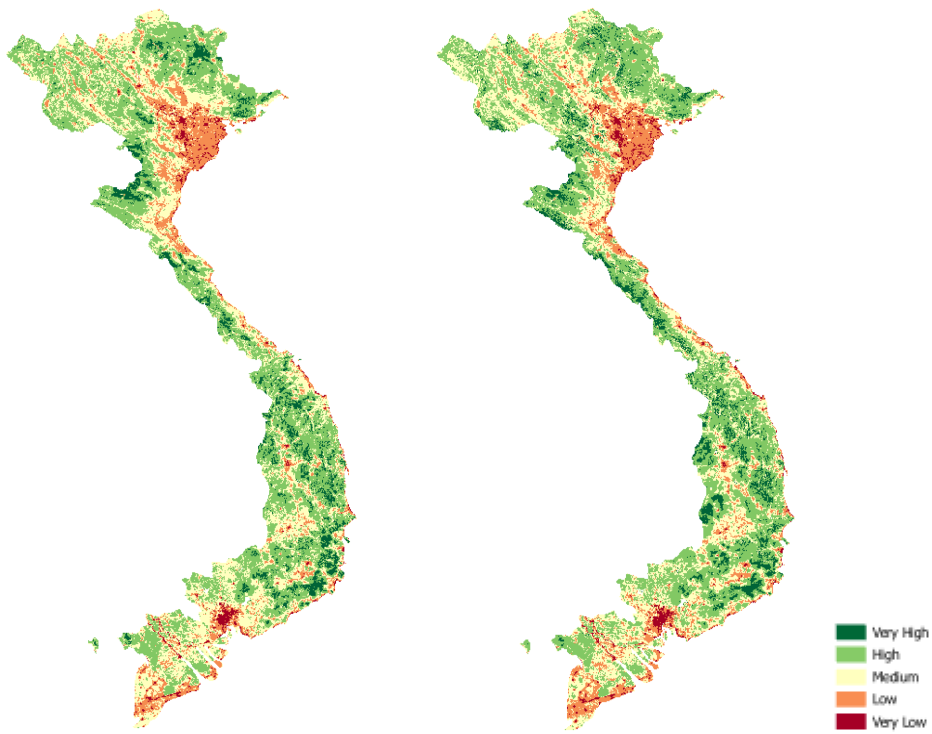


Figure 5.9 RDMI Maps of Vietnam - Model 1 (left) and Model 3 (right).

Like Model 2, there are no significant discrepancies between the maps for Vietnam for Model 1 and Model 3. However, Table 5.6 shows an increase in the number of pixels classified as having very high suitability. Upon close examination, it becomes evident that areas in the northern part of the map, particularly in the highlands along the border with Laos, have become more suitable for development, as illustrated in Figure 5.10. This is likely due to the fact that although these areas have low PV power potential, they have some of the highest values for wind power density, as discussed in section 4.3.1. Consequently, considering the maximum value of either renewable energy resource allows areas with sufficient potential for one of these resources to be deemed highly suitable.

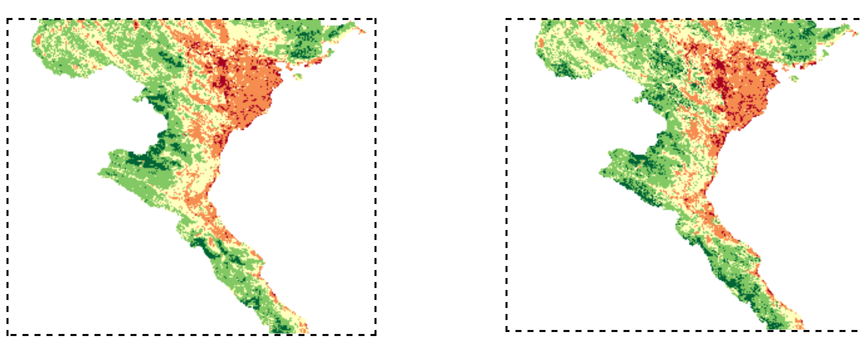


Figure 5.10 Maps showing that areas in Northern Vietnam in the highlands along the border with Laos have lower levels of RDM suitability in Model 1 (left) compared to Model 3 (right).

Model 1 vs. Model 3 - Maps of Kenya

Kenya - Model 1 **Kenya - Model 3**

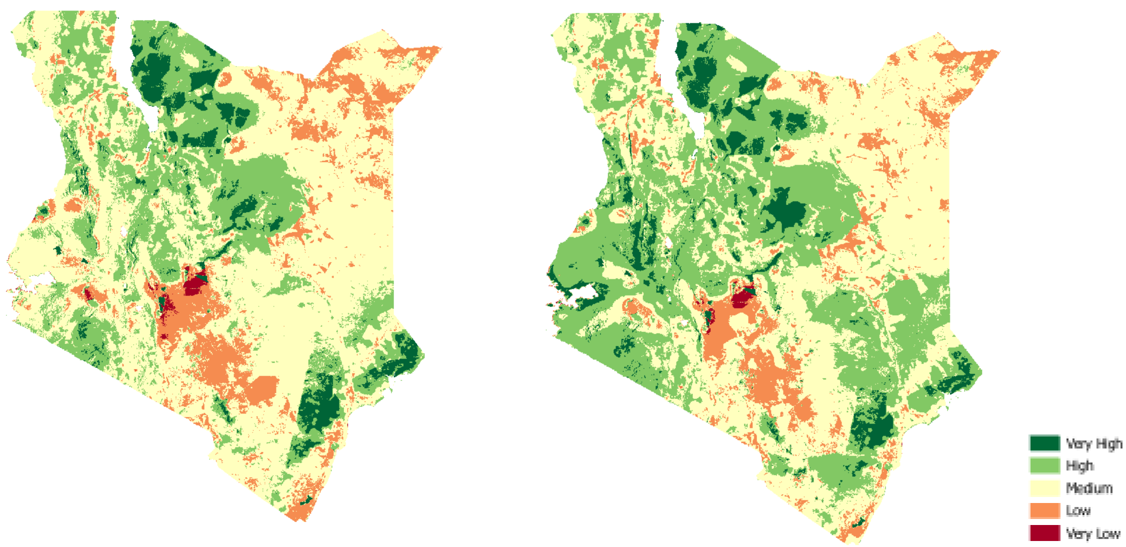


Figure 5.11 RDMI Maps of Kenya - Model 1 (left) and Model 3 (right).

There is a marked difference between Kenya's Model 1 and Model 3 maps, unlike Vietnam's maps. Generally, many areas that were previously considered medium suitability have increased to high suitability when the maximum renewable energy resources are considered. As indicated in section 4.3.1, Kenya has high solar power potential throughout the country, but the areas with very high wind power potential are mainly in the central north near Lake Turkana. By not prioritising areas with high values in both categories, more areas are now considered suitable for the programme. Thus, while the central and western parts of the map in the north changed minimally, other areas such as the central west near Lake Victoria showed a substantial increase in suitability due to abundant PV power potential but low wind power potential (see Figure 5.12). However, it is essential to note that most of these areas are unsuitable for the RDM programme as they have high levels of population density (as well as high levels of green vegetation). Nevertheless, both models use the median as the dimension-level aggregation method, which can lead to an overestimation of suitability in areas where one dimension, such as the social dimension, has a low value, while the other two dimensions have high values. As a result, some areas may appear more suitable than they truly are.

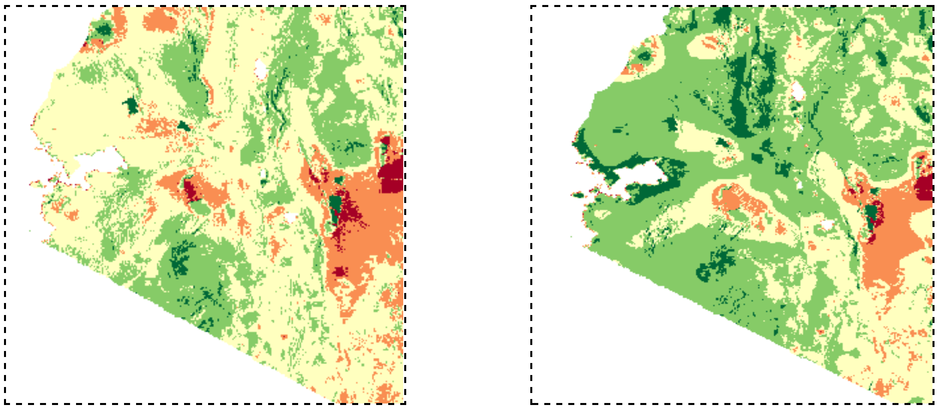


Figure 5.12 Maps showing that areas in Western Kenya have lower levels of RDM suitability in Model 1 (left) compared to Model 3 (right).

5.1.3 Model 1 versus Model 4

Table 5.7 Summary of effects on RDMI classes for Model 4.

Model 1 to Model 4	Moved 0 classes	Moved 1 class	Moved 2 classes	% of moved observations that increased class	% of moved observations that decreased class
Vietnam	50.1%	46.3%	3.6%	20.4%	**79.7%**
Kenya	51.4%	46.5%	2.2%	**59.3%**	40.7%

Table 5.8 Comparison of class distributions between Model 1 and Model 4 (values show % of total).

Vietnam	Very Low	Low	Medium	High	Very High
Model 1	1.9	13.3	34.2	**44.0**	6.6
Model 4	2.8	22.8	**42.3**	28.6	3.5
Difference	+0.9	+9.5	+8.1	**-15.4**	-3.1
Kenya	Very Low	Low	Medium	High	Very High
Model 1	0.5	12.5	**55.4**	26.1	5.5
Model 4	1.6	18.5	**35.3**	**35.3**	9.4
Difference	+1.1	+6	**-19.9**	+9.2	+3.9

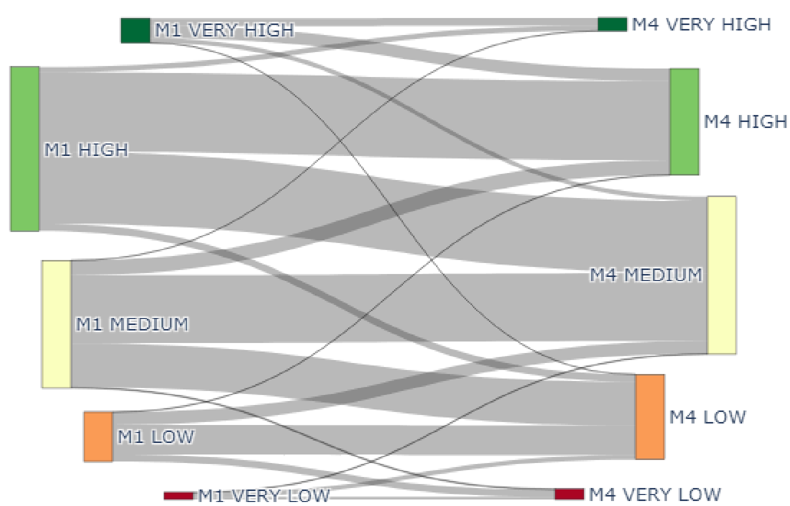


Figure 5.13 Sankey graph showing the direction of movement between classes from Model 1 to Model 4 for Vietnam.

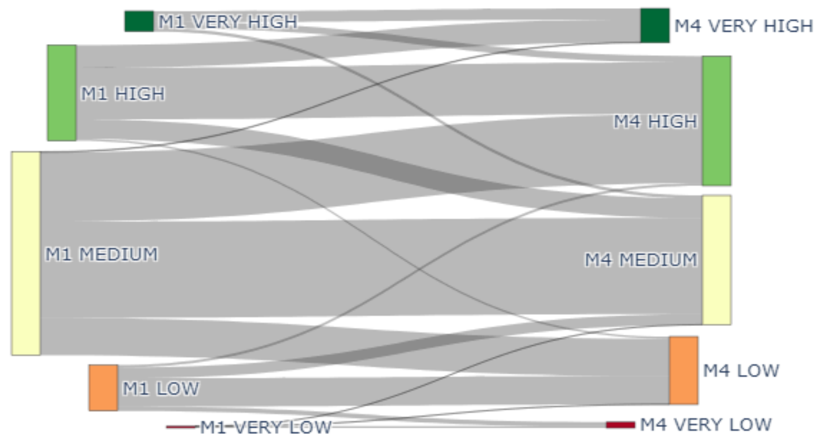


Figure 5.14 Sankey graph showing the direction of movement between classes from Model 1 to Model 4 for Kenya,

Model 4's results show a significant impact on class distributions for both case study countries when NDVI was removed, as illustrated in Figures 5.13 and 5.14. This outcome is not surprising, given that removing an indicator from a limited set of indicators can make the model more sensitive to the influence of individual indicators. However, what is interesting is the difference in impact between the two countries. About half of the observations for both Vietnam and Kenya shifted up or down at least one class, with 3.6% and 2.2%, respectively, shifting at least two classes. Nevertheless, the dominant direction of movement differed between the countries. Rural areas in Vietnam have an abundance of green vegetation and removing NDVI from the index resulted in 80% of the observations that changed class being downgraded to a lower class and for once the 'medium' class became the dominant class for the RDMI classes for Vietnam. Conversely, Kenya has vast areas with little vegetation, and removing NDVI from the RDMI led to an increase in suitability for these regions. As shown in Table 5.8 and Figure 5.14, Model 4 considers many more areas to have high or very high suitability than the base model. In fact, the number of observations in the 'medium' and 'high' categories is equal in the Model 4 output dataset, while in Model 1, the 'medium' class has more than twice as many observations as the 'high' class.

Model 1 vs. Model 4 - Maps of Vietnam

Vietnam - Model 1 **Vietnam - Model 4**

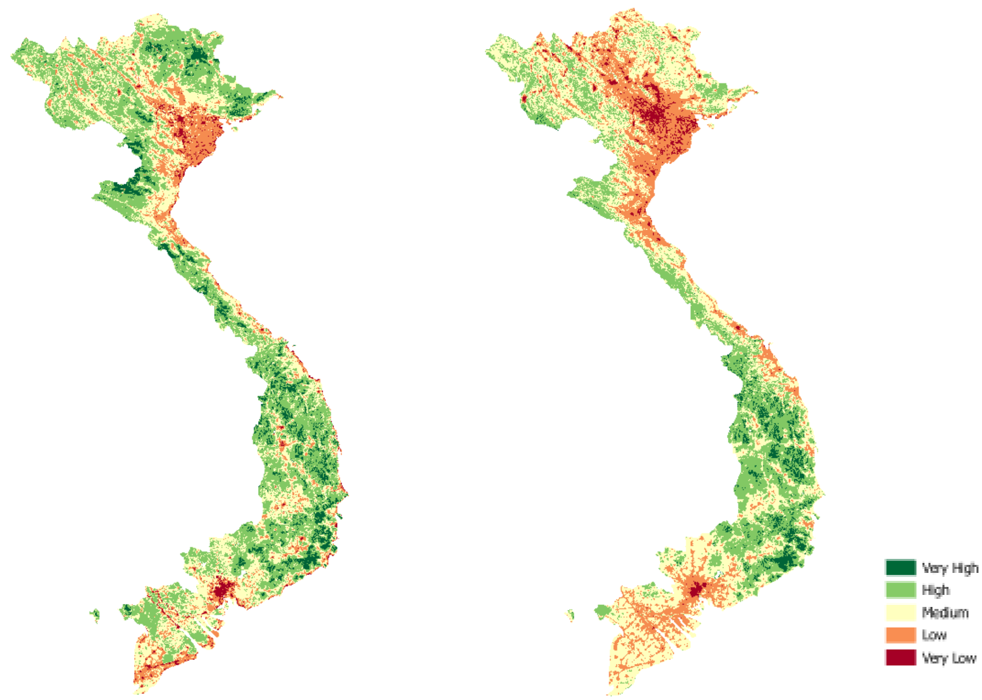


Figure 5.15 RDMI Maps of Vietnam - Model 1 (left) and Model 4 (right).

The map of Model 4 for Vietnam differs significantly from the map of Model 1, particularly in the northern half of the map and the southern part at the Mekong Delta, which appear to have dramatically decreased in suitability. As shown in Figure 5.16, the dark green patches in the north of the map, which indicated areas that were extremely suitable for the RDM programme according to Model 1, have disappeared. Instead, the northern part of the map is now dominated by yellow, orange, and red, indicating lower suitability. The city of Hanoi is now even more prominent on the Model 4 map (represented by the intense red section), and its surrounding areas are now more clearly marked as unsuitable for the RDM. The removal of NDVI has also significantly impacted the southern part of the map, with some of the most prominent changes visible around the city of Ho Chi Minh. However, the southernmost tip of the delta, which is a low-lying wetland area, has increased in suitability as it is no longer at a disadvantage for having a high amount of water (and therefore very low NDVI values).

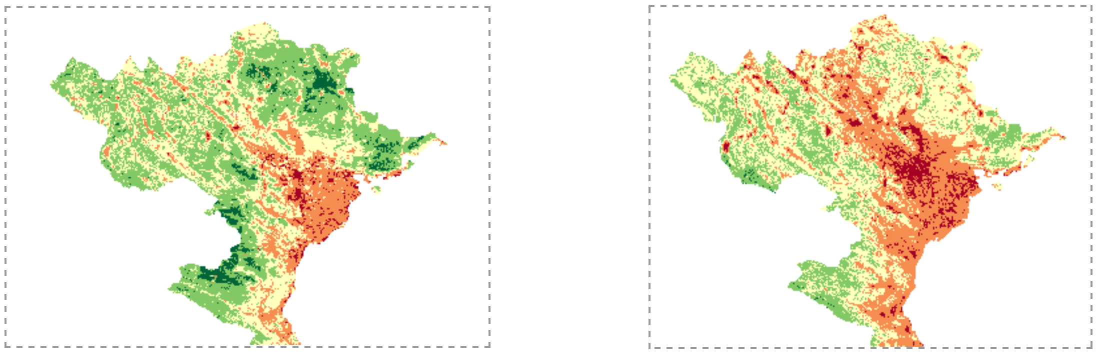


Figure 5.16 RDMI maps of Northern Vietnam - Model 1 (left) and Model 4 (right).

Model 1 vs. Model 4 - Maps of Kenya

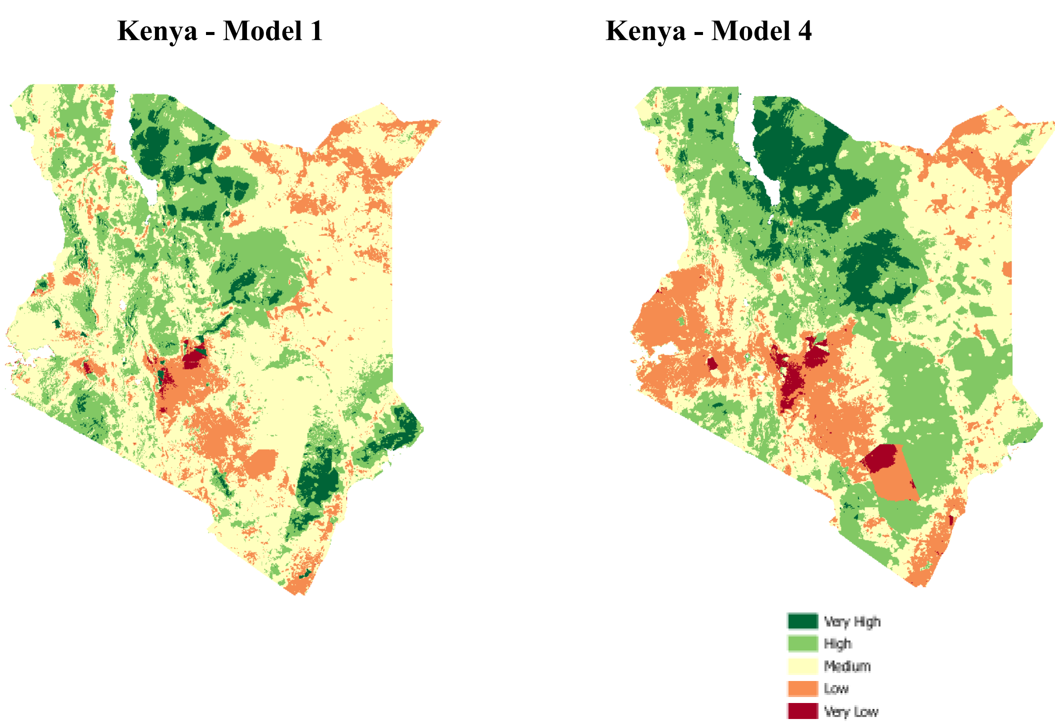


Figure 5.17 RDMI Maps of Kenya - Model 1 (left) and Model 4 (right).

The map of Model 4 for Kenya exhibits several significant differences from Model 1. In the northern regions of the country, which are arid and desolate but possess abundant renewable energy resources, there has been an increase in suitability due to the removal of NDVI, as evidenced by the appearance of more green and dark green areas on the map. While the overall map is greener, indicating an increase in suitability for most rural areas, there are some areas that have been downgraded to lower classes of suitability. These areas generally scored poorly on the social dimension, either because they have high population density or, in the case of national parks, have outlier data that has not been corrected in the pre-processing steps. Removing an indicator from a limited set of indicators makes the remaining indicators more influential, so areas with high renewable energy resources have seen a considerable increase in suitability while areas with low scores on the social dimension have experienced a decrease in suitability. Additionally, many of Kenya's inhabitants live in fertile regions that are more suitable for agriculture, such as the western areas near Lake Victoria. Therefore, the removal of NDVI has had an even greater impact on the suitability scores for these populous regions. However, given their already significant development and high populations compared to the rest of the country, it is reasonable to consider these areas unsuitable for the RDM programme.

5.1.4 Model 1 versus Model 5

Table 5.9 Summary of variations in class from Model 1 to Model 5.

Model 1 to Model 5	Moved 0 classes	Moved 1 class	Moved 2 classes	% of moved observations that increased class	% of moved observations that decreased class
Vietnam	80.2%	19.7%	0.1%	**76.9%**	23.1%
Kenya	76.1%	23.1%	0.8%	**59.7%**	40.3%

Table 5.10 Comparison of class distributions between Model 1 and Model 5 (values show % of total).

Vietnam	Very Low	Low	Medium	High	Very High
Model 1	1.9	13.3	34.2	**44.0**	6.6
Model 5	1.7	13.6	27.1	**47.4**	10.2
Difference	-0.2	+0.3	**-7.1**	+3.4	+3.6
Kenya	Very Low	Low	Medium	High	Very High
Model 1	0.5	12.5	**55.4**	26.1	5.5

Model 5	1.2	11.8	**50.1**	31.7	5.1
Difference	+0.7	-0.7	-5.3	**+5.6**	-0.4

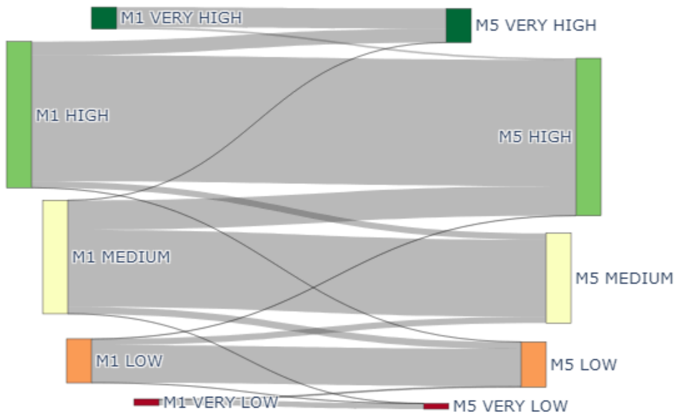


Figure 5.18 Sankey graph showing the direction of movement between classes from Model 1 to Model 5 for Vietnam.

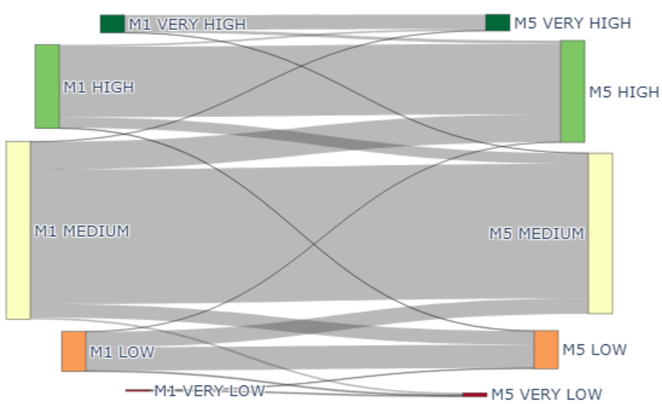


Figure 5.19 Sankey graph showing the direction of movement between classes from Model 1 to Model 5 for Kenya.

The sensitivity analysis included a final variation that incorporated NO_2 into the environmental dimension of Model 5. This variation, like the others, had a significant impact on the RDMI class distribution, however, it had the smallest effect on the two case study countries. Only 20% and 24% of observations in

Vietnam and Kenya, respectively, changed classes as a result. The majority of observations that changed classes in both countries shifted to a higher class. Figures 5.18 and 5.19 show that the largest shift occurred in observations previously classified as 'medium,' which moved up to the 'high' class. This pattern was consistent in both countries.

Model 1 vs. Model 5 - Maps of Vietnam

Vietnam - Model 1 **Vietnam - Model 5**

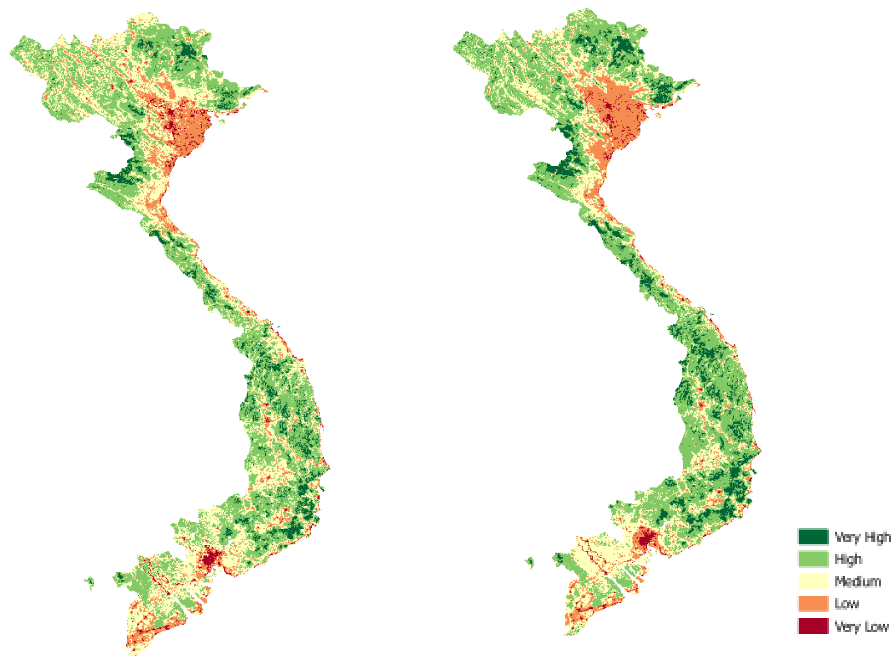


Figure 5.20 RDMI Maps of Vietnam - Model 1 (left) and Model 5 (right).

On first inspection, the maps for Model 5 and Model 1 in Vietnam may seem almost identical. However, as Table 5.9 reveals, the inclusion of NO_2 in the index led to a shift of 20% of observations to a different class. Upon closer examination of the maps, it becomes apparent that several rural areas have become more suitable for the RDM programme, as evidenced by an increase in green and dark green. Conversely, some areas around urban centres that were previously considered moderately suitable have seen a decrease in suitability, as shown in Figure 5.21 for the areas surrounding Hanoi.

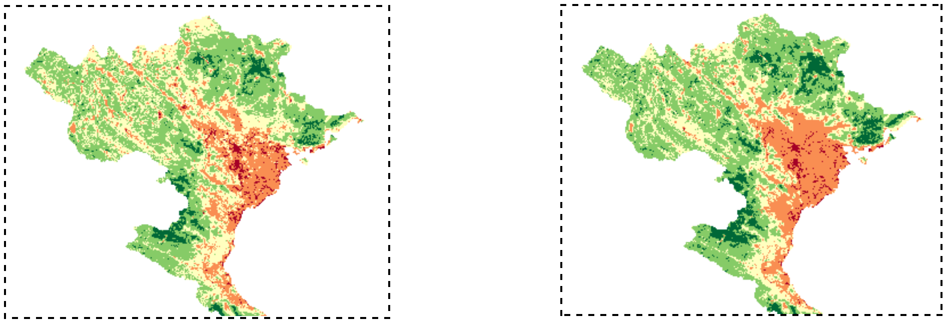


Figure 5.21 Maps showing that areas around Hanoi City in Northern Vietnam have lower levels of RDM suitability in Model 1 (left) compared to Model 5 (right).

Model 1 vs. Model 5 - Maps of Kenya

Kenya - Model 1 **Kenya - Model 5**

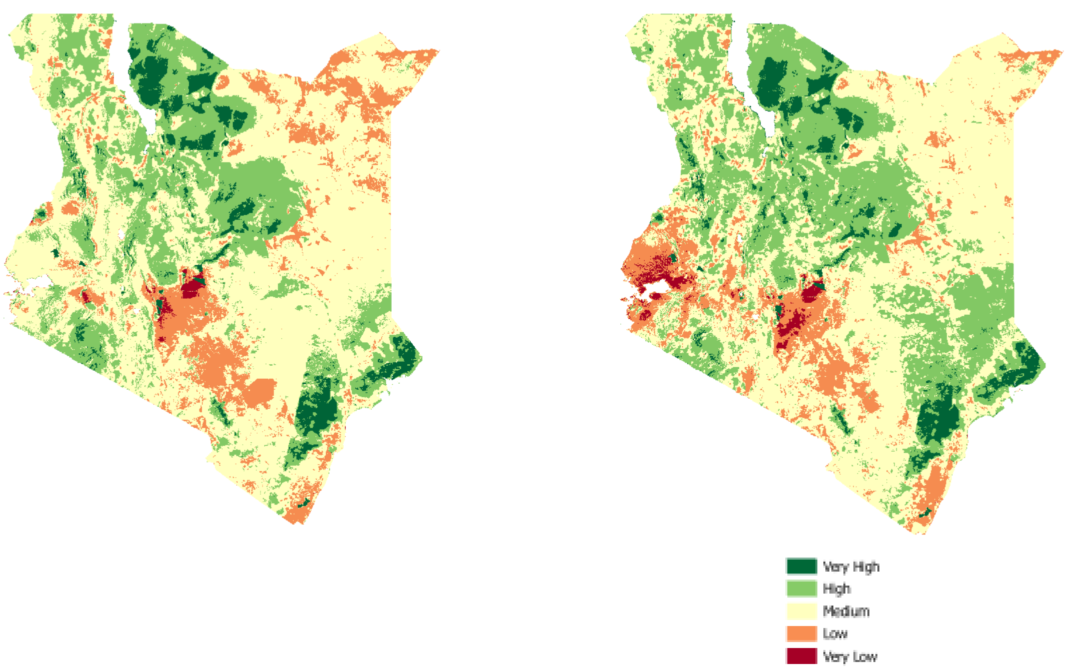


Figure 5.22 RDMI Maps of Kenya - Model 1 (left) and Model 5 (right).

Although the map for Model 5 is similar to the base model's map, there are noteworthy differences. One striking difference is the increased suitability of remote, rural areas with low populations and minimal wind presence. This change could be attributed to two reasons. First, as mentioned in the previous section, there is a positive correlation between population density and levels of NO_2. Therefore, areas with lower population density are more likely to have lower levels of NO_2 and, as a result, receive higher values for the environmental dimension when it is incorporated into the index. This also explains why areas in the central west part of the country have decreased in suitability, given their high population density and relatively high levels of NO_2. Second, the addition of another indicator to the environmental dimension reduces the influence of the other two indicators, namely, PV power potential and wind power density. As a result, rural areas with scarce clean energy resources will score higher than they did in the base model.

5.1.5 RDM Pilot Sites

As previously mentioned, Lotus Project is currently running two pilot projects for its RDM programme in Northern Vietnam, specifically in two remote mountainous villages: Chi Lang and Van Quan. In the final step of the sensitivity analysis, the RDMI scores for each village were retrieved by filtering the datasets using their coordinates, which are geocoded in the GIS data. The table below shows the RDMI outputs for each village.

Table 5.11 Comparison of RDMI scores and levels of suitability for the different models for the two RDM pilot sites.

		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Chi Lang	Score	0.690	0.643	0.750	0.587	0.690
	Class	High	High	**Very High**	High	**Very High**
Van Quan	Score	0.552	0.584	0.662	0.501	0.552
	Class	High	High	High	**Medium**	High

Since these villages are in an area that has been sensitive to changes in the RDMI model, as explained in previous subsections, it is not surprising to see variations in the RDMI scores and classifications between different models. Chi Lang generally has higher scores than Van Quan, with a score of 0.690 for the original RDMI model, making it highly suitable for the RDM programme according to the base model and its thresholds of suitability. Van Quan is also considered highly suitable for the programme, with a base score of 0.552.

The scores for Chi Lang vary up to 0.1 points on the RDMI scale, which is from 0 to 1. A difference of 0.1 points equates to a ten percent increase on this scale. Chi Lang increases classes for Model 3, where the maximum is used as the sub-dimension aggregation, and for Model 5, where NO_2 is integrated into the index. However, its RDMI score for Model 1 remains the same for Model 5, with no difference when the scores are rounded to three decimal places. Despite the scores being similar, it is classified as having 'very high' suitability for Model 5, due to the use of different thresholds for the quantiles. Both datasets have the same minimum value, but as seen in Table 5.1, the maximum value decreases from 0.874 for Model 1 to 0.841 for Model 5, and thus the thresholds of suitability are also lowered.

Van Quan's RDMI scores varied by up to 0.11 points, but it only changed classes once, when its score dropped to 0.501, and it decreased to medium suitability for Model 4, which excludes NDVI.

Readers may notice that the RDMI scores for both pilot sites are the same for Model 1 and Model 5. This is due to the use of the median as the aggregation method for the dimensions. Despite adding a new indicator to the index for Model 5, the environmental dimension was not the middle value for either of these observations; instead, the values for the social dimension were chosen, so the influence of introducing NO_2 was not observed.

In conclusion, the RDMI scores and classifications for the pilot sites in Chi Lang and Van Quan were found to vary depending on the model used, with changes in scores leading to changes in classes in some cases (Model 3 and 5 for Chi Lang and Model 4 for Van Quan). These findings highlight the sensitivity of the RDM index to changes in parameters and variables, emphasising the need for careful consideration of the RDMI methodology and its indicators. Furthermore, the use of the median as the aggregation method at the dimension level can cause changes to go unnoticed, as seen with the inclusion of the new indicator NO_2 which had no impact on the sites' scores.

5.1.6 Summary of Sensitivity Analysis Results

The results of the sensitivity analysis demonstrate that the RDMI outputs, both scores and classes, are significantly influenced by each of the variations in the model's parameters and variables. For example, the quantitative results show that up to 50% of pixels moved to a different class when the arithmetic average was used as the dimension level aggregation instead of the median. The use of Sankey diagrams and the visual comparison of the RDMI maps for different models allowed for a better understanding of the effects each of the model variations had on the RDMI classes. Furthermore, by obtaining the RDMI results for each of the models for the two RDM programme pilot sites and comparing these results, it emerged that these examples were also affected by the changes, and three of the four alternative models caused one of the pilot sites to either increase or decrease a level of suitability.

5.2 Uncertainty Analysis

The results of the uncertainty analysis are summarized in Table 5.12 and Table 5.13, and they will be discussed in the following subsections.

Table 5.12 Table showing percentage of observations that are within the 90% confidence intervals, and the results of the correlation analysis between Model 1, Model 2, and the Monte Carlo simulations.

	% of observations within the 90% CI of the MC simulations		Pearson's Correlation Coefficient		
	Model 1	Model 2	Model 1 & median of MC simulations	Model 2 & median of MC simulations	Model 1 & Model 2
Vietnam	41%	100%	0.91697	0.99998	0.91689
Kenya	37%	100%	0.80369	0.99959	0.80680

Table 5.13 Table showing distance between the Model 1 scores and the median of the Monte Carlo simulations, and the size of the 90% confidence intervals.

	Distance between M1 score & median of MC simulations			Size of 90% CIs for MC simulations		
	Mean	Min	Max	Mean	Min	Max
Vietnam	0.044	0.000	0.190	0.068	0.006	0.165
Kenya	0.059	0.000	0.245	0.087	0.003	0.221

5.2.1 Monte Carlo Results

After the 1,000 Monte Carlo simulations were run using the weighted average and random weights, the median and 90% confidence intervals (CIs) of the RDMI scores for each row of the sample data frame were calculated. The sample data frame was then ranked in order of the median values for the simulations, and the median scores were plotted on a scatter plot with the bounds of the 90% CI shaded in grey, as shown in Figure 5.23 and Figure 5.24. The y-axis shows the RDMI score, while the x-axis shows the RDMI ranking for the median value.

Upon comparing the graphs of the RDMI scores for Vietnam and Kenya, it was observed that the shaded grey areas indicating the 90% CIs were wider for Kenya than for Vietnam. To determine if this difference was significant, an independent samples t-test was performed, and the results revealed that the sample data frame for Kenya had a significantly larger confidence interval on average compared to Vietnam (0.087 versus 0.068, respectively). Additionally, Table 5.13 shows that the largest difference between the upper and lower bounds of the 90% CIs for Kenya was 0.221, compared to 0.165 for Vietnam. These findings suggest that the RDMI model is sensitive to weight selection when the weighted average is used, which can result in greater uncertainty in certain countries, as evidenced by the wider confidence intervals observed for Kenya compared to Vietnam. Therefore, if Lotus Project decided to use the weighted average as the main aggregation method in the future, they should be aware of these limitations, and it should be used with caution.

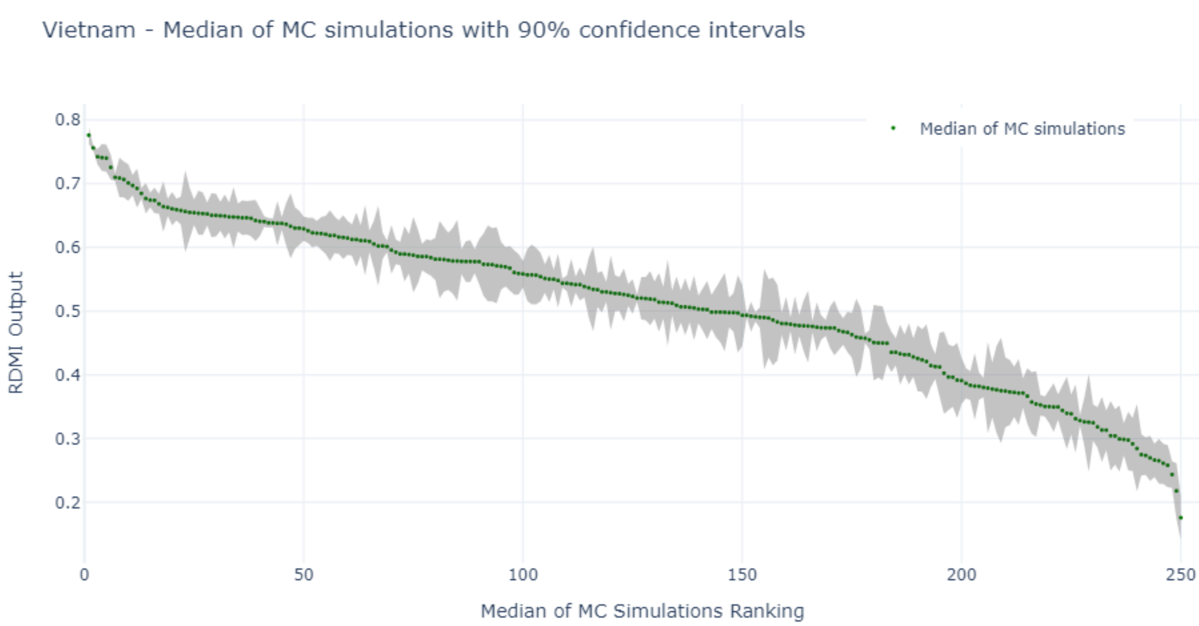


Figure 5.23 Scatter plot showing the median of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Vietnam's sample dataset.

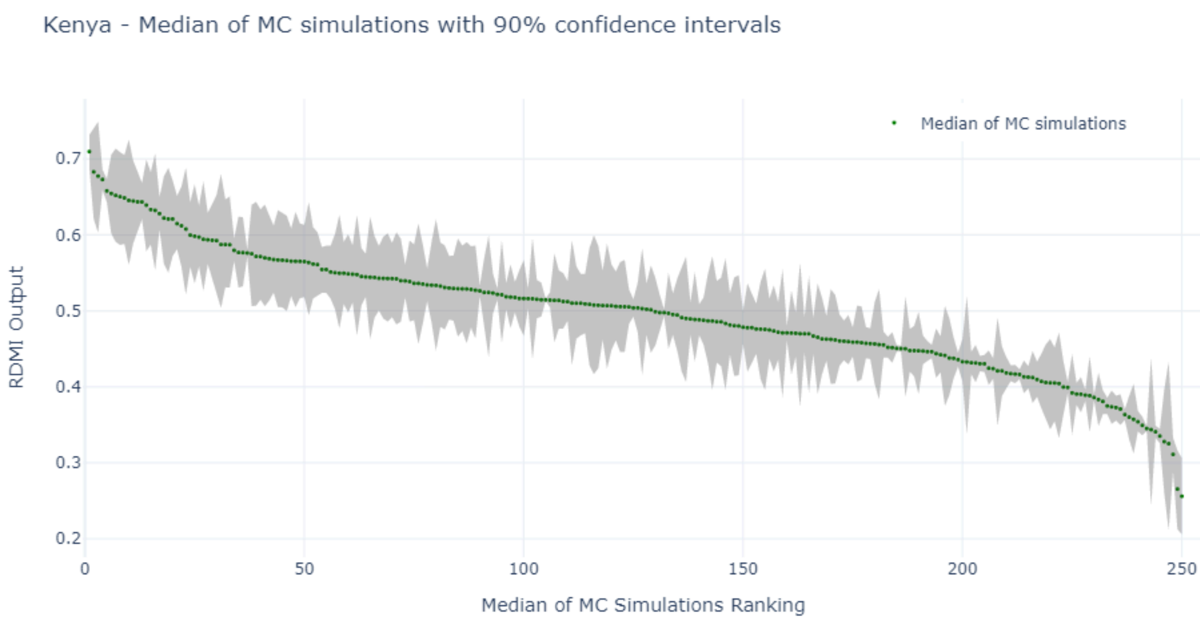


Figure 5.24 Scatter plot showing the median of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Kenya's sample dataset.

5.2.2 Model 1 versus Monte Carlo Results

To compare the RDMI scores obtained from Model 1 with those from the weighted average, a scatter plot was created using the sample RDMI scores for Model 1 (displayed in blue) against the median scores (shown in green) and 90% CIs (shaded in grey) for the MC simulations (see Figure 5.25 and Figure 5.26). The sample data frame was this time ranked according to the Model 1 score, and this ranking was used as the x-axis for these graphs. In both countries' graphs, there is a substantial difference between the scores for Model 1 and the MC simulations for the same sample, with the median score fluctuating a great deal when it is ordered by the Model 1 ranking. This suggests that the scores obtained from Model 1 are not well-aligned with those obtained using the weighted average. Furthermore, only 37% of the sample Model 1 scores for Kenya and 41% of the scores for Vietnam were within the 90% CI for the weighted average simulations (see Table 5.12). The average distance between the Model 1 scores and the median of the MC simulations for the samples were also calculated for each country (see Table 5.13), and again this distance on average was statistically greater for Kenya (0.059) compared to Vietnam (0.044). And there was less correlation between the Model 1 scores and the median of the MC simulations for the Kenya sample (0.80) compared to Vietnam's sample (0.96). These findings suggest that the RDMI scores for

Kenya may be more sensitive to the choice of aggregation method than for Vietnam, and caution should be exercised when using the Model 1 method for countries with similar characteristics to Kenya.

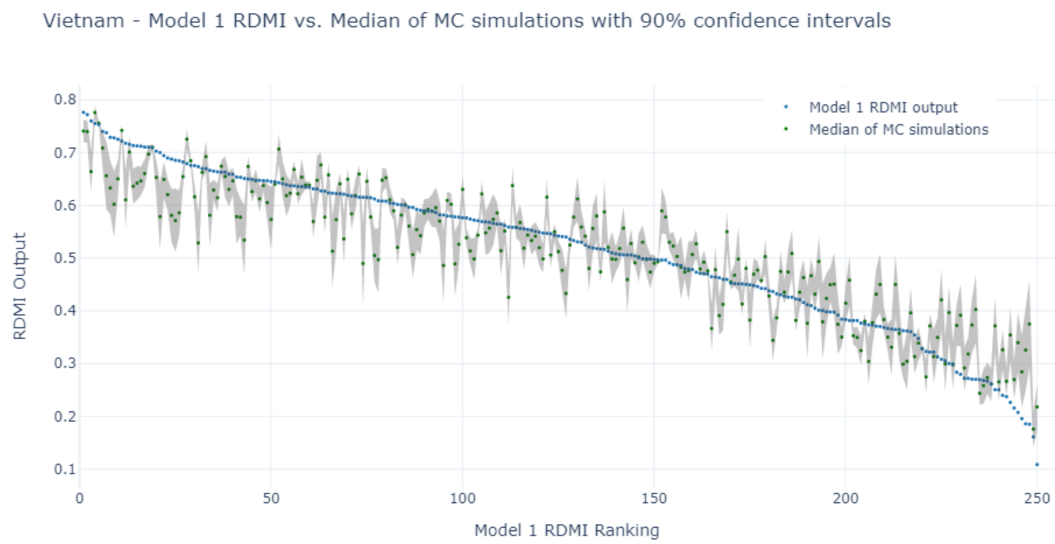


Figure 5.25 Scatter plot showing the RDMI scores for Model 1 (blue) and the median scores of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Vietnam's sample dataset.

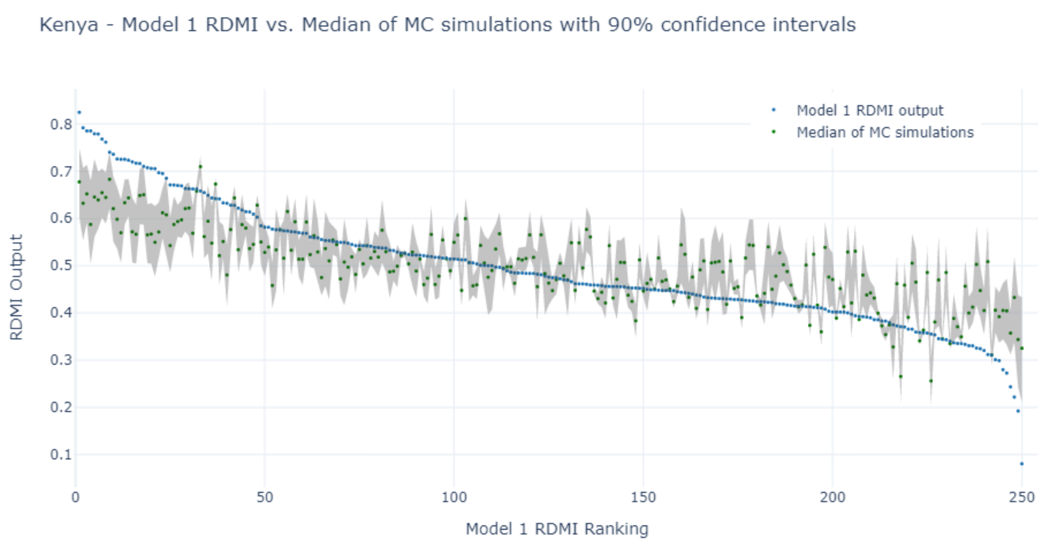


Figure 5.26 Scatter plot showing the RDMI scores for Model 1 (blue) and the median scores of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Kenya's sample dataset.

5.2.3 Model 2 versus Monte Carlo Results

Finally, the study conducted an analysis of the agreement between scores obtained from weighted average simulations and those from Model 2, which employs arithmetic average as the dimension-level aggregation. A scatter plot was created to display the results, with scores for Model 2 shown in red, median of the MC simulations in green, and the 90% CI shaded in grey (see Figure 5.27 and Figure 5.28). The Model 2 RDMI ranking was used as the x-axis indicator. This time, the plots revealed a clear alignment between the Model 2 scores and the results from the MC simulations, with the Model 2 scores falling in the middle of the shaded areas and in most cases overlapping with the median scores. The Model 2 scores fell within the 90% CI for 100% of the samples for both countries, while the Model 2 scores were highly correlated with the median of the MC simulations (0.99998 for Vietnam and 0.99959 for Kenya). To further examine the agreement between Model 2 and the MC simulations, the study calculated the difference between the Model 2 scores and the median of the MC simulations for each sample. The average absolute difference was found to be miniscule for both countries, indicating that the Model 2 scores are highly consistent with the results obtained from the MC simulations. These findings support the use of arithmetic average as a more stable method of aggregation for the RDMI and suggest that it may be more aligned with different possible weighting schemes than the median. However, it is important to note that while arithmetic average may produce more robust results, it can be more influenced by outliers or extreme values in the data compared to the median.

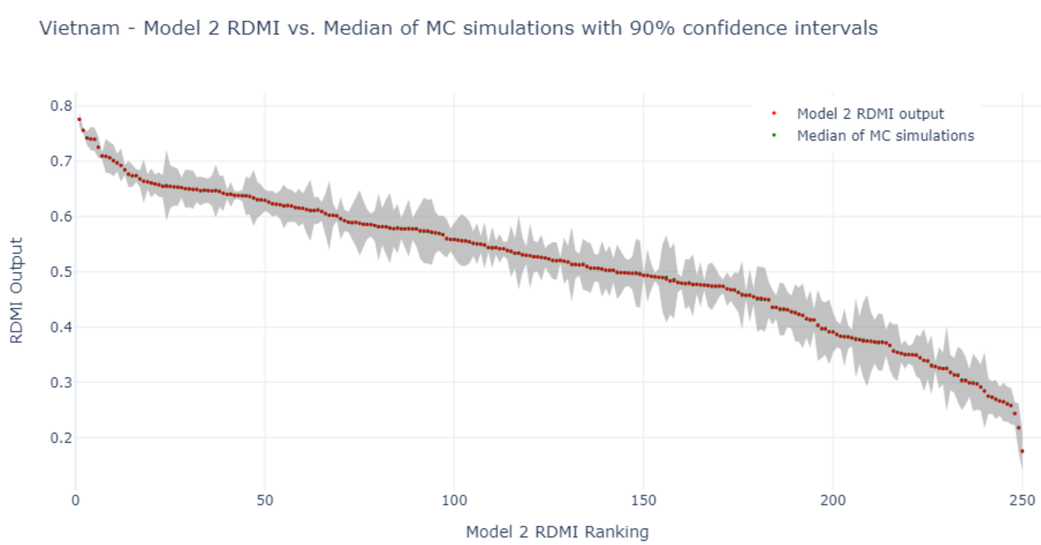


Figure 5.27 Scatter plot showing the RDMI scores for Model 2 (red) and the median scores of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Vietnam's sample dataset.

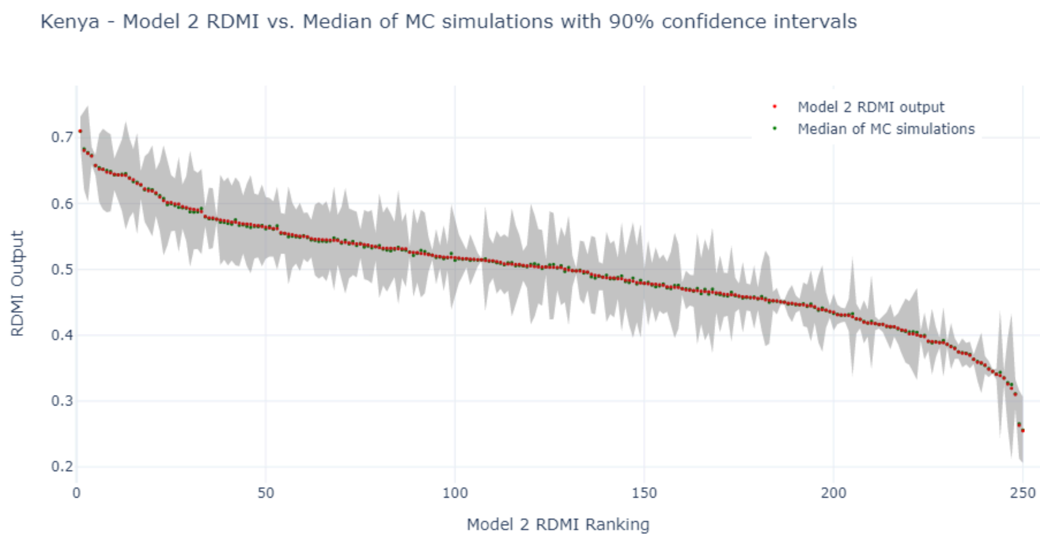


Figure 5.28 Scatter plot showing the RDMI scores for Model 2 (red) and the median scores of the Monte Carlo simulations (green) with the 90% confidence intervals (grey) for Kenya's sample dataset.

5.2.3 Summary of Uncertainty Analysis Results

In conclusion, the Monte Carlo simulations using random weights have shown that if the weighted average was used as an alternative aggregation method the RDMI scores would be subject to significant uncertainty, with wider confidence intervals observed for Kenya compared to Vietnam. These results indicate that the RDMI is highly sensitive to weight selection, and alternative weighting schemes could yield different outcomes.

Moreover, the comparison of Model 1 and Model 2 scores with the MC simulations highlights the criticality of careful method selection. The results show that the scores for Model 1 are poorly aligned with the results of the MC simulations with approximately 60% of both countries' sample scores for Model 1 falling outside of the 90% CIs, and this indicates that is even greater uncertainty associated with the use of the median, with slightly more uncertainty present for Kenya. On the other hand, the findings show that the use of arithmetic average as an aggregation method may offer more consistent and reliable results, as its scores were highly correlated with the scores from the MC simulations.

Overall, the study emphasises the need for the Lotus Project team to consider uncertainty and sensitivity as they continue to develop the RDMI to ensure the robustness and reliability of their findings. The results summarised in Tables 5.12 and 5.13 underscore the importance of carefully considering the method of aggregation and weight selection, if applicable, when constructing the RDMI. The findings highlight the need for further research and exploration of alternative weighting schemes to improve the accuracy and reliability of the RDMI scores.

Chapter 6 Discussion and Recommendations

The evaluation of the RDMI through various steps, such as expert interviews, indicator-criteria mapping, exploratory data analysis, and uncertainty and sensitivity analyses, has generated valuable results and insights into the research questions. Consequently, this section aims to address the two main research questions that were introduced in section 1.4 and discuss the results in the context of sub-questions within each of the research questions. Finally, this section will conclude with a summary of the recommendations and potential for future work.

6.1 RDMI as a Reflection of RDM Suitability

Research Question 1: To what extent does the RDMI reflect the key criteria for an optimal area for the RDM programme?

How suitable are the indicators and data sources?

The RDM Index determines the suitability of areas for sustainable rural development using publicly available, high-resolution, and globally accessible data sources that are free for non-commercial use. This approach enables Lotus Project to access data from around the world without compromising on quality or availability, in line with their mission to promote sustainability and equitable development.

Based on the review of the RDM programme framework, it was found that three of the four indicators currently used in the RDMI are highly relevant to the programme's criteria, while a new indicator is being considered to measure another desirable quality of an area.

Population density data from WorldPop is an appropriate way to determine if an area is sparsely populated and thus likely to be a rural area, which is vital for the programme. Likewise, another key criterion of the programme is the availability of renewable energy resources, and two of these types of resources are measured through PV power potential and wind power density. NO_2 levels are also a suitable way to measure the rate of air pollution in an area, which should be considered to avoid targeting areas that have already experienced detrimental effects of development.

The role of Normalised Difference Vegetation Index (NDVI) as an indicator in the geographical dimension of the RDMI is less clear. It was originally incorporated into the index as a measure of rurality and potential for agriculture, but agricultural productivity is not one of the criteria for the RDM programme. Moreover, the correlation analysis for the case study countries revealed a negative correlation between population and NDVI in Vietnam, indicating that higher NDVI indicates more ‘ruralness’, whereas in Kenya, a positive relationship exists between these two indicators, with people tending to live in areas with more green vegetation. In addition, including NDVI in a sub-Saharan context is problematic, as studies show that areas with low NDVI may have higher poverty levels and poorer health outcomes. These are the areas that are most in need of rural development programmes but including NDVI as an indicator may result in prioritising less disadvantaged areas over the most vulnerable.

This issue with NDVI highlights one of the biggest challenges in creating a geospatial index for global use. Assumptions made about an indicator in one country may not hold true in another context or may even have the opposite meaning in another region. Geographic diversity must be taken into account when creating the index to ensure that it accurately reflects the needs and conditions of each region.

Are there any criteria in the RDM framework that are not measured?

Creating the RDMI has been a challenging task for Lotus Project, mainly due to the limited availability of global, high-quality geospatial data. The use of publicly available data has allowed Lotus Project to reduce costs and increase accessibility for non-profits and governments interested in identifying areas for sustainable rural development. However, this approach has also posed some limitations, including the lack of measurement of certain criteria that are important for the RDM programme.

One of the key criteria that is not currently reflected in the index is access to electricity. The success of the initial phases of the RDM programme relies heavily on the establishment of microgrid systems, making it crucial to identify areas with limited, unreliable or no access to electricity. While geospatial datasets that show the main grid for electricity would be extremely helpful in order to estimate a community's access to electricity, these types of datasets have only been available on a country-by-country basis. However, the work of initiatives such as the Global Electrification Platform suggests that it may soon be possible to obtain this type of data globally and incorporate it into the index.

Another criterion that is challenging to measure is poverty. High levels of poverty are a core criterion of the RDM programme, but data on poverty levels at a sub-national level is mostly limited to household surveys such as MICS and DHS which are only undertaken by some countries and the results are usually only released at an administrative level. While many studies have used geospatial data and machine learning techniques to estimate poverty for some areas, the studies are often limited to small areas within a country.

However, during the literature review, several datasets with poverty-related, sub-national data for most countries worldwide were identified. These include the World Bank's Global Subnational Atlas of Poverty and the Global Gridded Relative Deprivation Index developed by the Center for International Earth Science Information Network at Columbia University. Incorporating one of these datasets into the RDMI would bridge current data gaps, providing a more accurate representation of areas most in need of rural development interventions.

And so, it is recommended to include additional data related to data gaps for a specific country, even if it is not available for all countries, as it would be valuable for better targeting interventions to communities experiencing the highest levels of poverty and most in need of electrification. Moreover, incorporating sub-national poverty data in the RDMI would provide a more nuanced understanding of the factors contributing to poverty at the local level, enabling more effective programmatic interventions.

How do the data differ between the case study countries?

The two case study countries are in different regions of the world, and so unsurprisingly there are some noticeable differences between the country datasets. One of the most striking differences is the level of vegetation in each country as measured by NDVI. Vietnam appears to be much greener than Kenya, with higher levels of vegetation throughout the country. This could be due to a variety of factors, including differences in climate, land use, and agricultural practices.

Another notable difference between the two countries is that Kenya has much higher levels of PV power potential than Vietnam. While in both countries there are regions with high wind power potential, and their mean values for wind power density are comparable. Additionally, they both appear to have higher wind power density in areas at higher elevations.

Population density is another area where the two countries differ. While both countries have the highest population density in their main cities, Vietnam is generally more populous than Kenya. Additionally, Kenya has large areas of land with no or very low population density due to the presence of large national parks, whereas Vietnam does not have any zero population density pixels according to its GeoTIFF file for population density. This difference has implications for the pre-processing and transformation of the population density data, which will be discussed further in the next subsection.

Finally, both countries exhibit high levels of NO_2 pollution around their most populated areas. This suggests that air pollution is a common problem in both countries and that interventions to address this issue could be a valuable component of rural development programmes.

While the RDMI provides a useful framework for evaluating rural development potential, it is important to recognize that the data used to develop the index can vary significantly between countries and regions. This is particularly evident in the case study countries of Vietnam and Kenya, where there were notable differences in key indicators such as NDVI, population density, and PV power potential. Therefore, the Lotus Project team needs to be aware of these differences in data and how they can affect the results of the RDMI when applying it to a new country or region.

How do the data for different indicators relate to each other, and do these relationships differ between the case study countries?

The relationships between the different indicators in the RDMI were found to be complex and context-specific, with different correlations observed for different dimensions and sub-dimensions of the index in the case study countries. The correlation analysis using Pearson's correlation coefficient revealed strong positive correlations between the overall RDMI and the social and geographical dimensions for Vietnam, but a weak correlation between the environment and the index. For Kenya, a strong positive correlation was found between the environmental dimension and the overall index, while there was no significant relationship between the geographical dimension and RDMI. The correlation between the social (population) and geographical (NDVI) dimensions was positive for Vietnam, but negative for Kenya. This confirms that greener areas in Vietnam tend to be more rural and less populated, whereas the opposite is true for Kenya.

Furthermore, the integration of a new air pollution indicator into the RDMI revealed positive correlations between NO_2 and the social dimension for both Vietnam and Kenya, indicating that areas with higher population density tend to have higher levels of air pollution. For Vietnam, there was also a slight positive correlation between NO_2 and the geographical dimension, while for Kenya, there was a negative relationship between NO_2 and the geographical dimension. This suggests that greener areas in Kenya tend to have higher air pollution levels, likely due to higher population density in these areas.

Overall, these findings highlight the need to consider how indicators relate to different concepts in different regions and contexts when using the RDMI in a new area.

How does the pre-processing of the data affect the output of the index?

The pre-processing of data is a crucial step in the calculation of the RDMI, as it determines how each indicator is normalised to a scale of 0-1. However, the treatment of zero values for certain indicators, such as NDVI and population density, has shown to have a significant impact on the output of the index. For example, the masking of zero values for NDVI in Kenya led to the exclusion of areas with very low levels of vegetation from the RDMI map, whereas this was not an issue for Vietnam. Likewise, the team had not considered that countries might have areas with zero values for population density as this does not occur in the population density dataset for Vietnam. However, Kenya has large areas with zero values for population density due to national parks, and the current pre-processing steps have not taken this into account. Consequently, after the population density data has been transformed and multiplied by -1 (as this indicator has decreasing polarity), these areas end up receiving low scores for the social dimension, despite the fact that lower population density should indicate higher suitability for the RDM programme. And yet this is still an oversimplification, as areas need to have at least a small number of people living there for the programme to be successful. Furthermore, while these areas of zero population are easy to identify when the social dimension is visualised separately, they are no longer noticeable when the RDMI map is visualised as the median is not very sensitive to these types of outlier data.

To improve the accuracy of the RDMI, it would be beneficial to reconsider how zero values are treated for all indicators and set thresholds for each indicator. This would ensure that areas with extremely low or high values for a particular indicator are assigned appropriate RDMI values, regardless of the values of other indicators (i.e., if an area has zero population it should be automatically classed as very low suitability, even if it may also have very high scores in the other dimensions). Furthermore, setting population thresholds for suitability could help to ensure that areas with very low population are not falsely identified as suitable for rural development interventions. Overall, careful consideration of data pre-processing is essential for accurate and reliable application of the RDMI to different countries and regions.

How can the visualization of the RDM Index be improved?

The visualization of the RDMI is a critical aspect of communicating the index's results, and improvements could increase its effectiveness. High-resolution maps are a useful way to present the RDMI results, and interactive maps that allow users to see specific values when hovering over areas can be even more accessible. However, the GIS experts' feedback revealed that the RDMI maps could be more effective if additional layers of information were added. These data layers do not need to be limited to raster data, and they can include vector data such as roads or point data for locations of social amenities. Customizing these layers based on data availability and context could enhance the RDMI's effectiveness, such as including a layer for national parks in Kenya or clearly marking water bodies in countries with many of them. By adding this additional information, the RDMI could become a more comprehensive tool for identifying areas suitable for sustainable development. Additionally, visualizing the RDMI outputs through classes (as was done in the sensitivity analysis) rather than continuous data could make the results even clearer and more understandable for users. These improvements could enhance the RDMI's effectiveness in communicating its results and reflecting the key criteria for an optimal area for the RDM programme.

6.2 RDMI Sensitivity and Uncertainties

Research Question 2: How do variations in the index affect the RDMI outputs?

What is the effect of adding the proposed new indicator (nitrogen dioxide)?

While adding NO_2 had a significant impact on the RDMI class distribution, of all the model variations it had the smallest effect on the two case study countries. Only 20% and 24% of observations in Vietnam and Kenya, respectively, changed classes as a result. Nevertheless, there were still some observable changes in the maps, which showed that areas surrounding towns and cities decreased in suitability. However, the majority of observations that changed classes in both countries shifted to a higher class. This could in part be caused by rural areas which do not have a high availability of renewable energy resources scoring more highly when the impact of these indicators is lessened by adding another indicator into the environmental dimension.

What is the effect of removing one of the indicators (NDVI)?

Removing NDVI produced the biggest change in the RDMI outputs for both countries, with approximately half of the observations in both countries' datasets moving up or down a class after its removal. This could be partly due to the fact that removing NDVI led to there only being three indicators left in the index, and thus the output is based on just population density and renewable energy resources. However, as already discussed there are many reasons why it is problematic to continue having NDVI in the index, and it appears from the results that it has played a significant role in determining the output of the RDMI and therefore the suitability of an area. These results also highlight the strong need for the inclusion of more indicators into the model, provided that they are appropriate ways of measuring the criteria for the RDMI, to produce more robust results that do not depend so heavily on a couple of factors.

What is the effect of using a different form of aggregation at the dimension and sub-dimension level?

The sensitivity analysis conducted in this study suggests that the choice of aggregation method used at the dimension and sub-dimension level has a significant impact on the index results. The use of the arithmetic average as an alternative to the median as an aggregation method led to approximately one third of the samples in both countries shifting to a different class of suitability. Most of these observations were downgraded to a lower class of suitability, with the 'medium' class becoming the dominant one in Vietnam, and the 'very high' class experiencing the most significant change in Kenya. This suggests that using the arithmetic average decreased the coverage of areas in the countries that are considered very highly or highly suitable for the RDM programme. Moreover, the maps generated using the RDMI outputs for Model 2 displayed the zero population areas more clearly as the arithmetic average is more sensitive to these types of extreme values, which can be helpful for identifying unsuitable areas but could also misidentify some areas as being highly suitable.

The study also found that the choice of aggregation method at the sub-dimension level can have a significant impact on the index results, particularly when there are few dimensions, as evidenced by the use of the maximum value of PV power potential and wind power density for the environmental dimension resulting in a quarter of the observations for Kenya and one fifth of the observations for Vietnam shifting to another class.

How much uncertainty is related to the aggregation method used for the index?

The current RDMI model used by Lotus Project employs the median without assigning weights to different dimensions or sub-dimensions. However, this approach can give undue weight to certain dimensions, potentially leading to biases in the overall index. To assess the uncertainty associated with this issue, the study compared the median to two alternative aggregation methods: weighted average and arithmetic average. Monte Carlo simulations were conducted with 1,000 randomly assigned weights drawn from a range of 0.18-0.48, and the resulting weighted average was calculated. The study found that the 90% confidence intervals for the simulations were significantly larger for Kenya compared to Vietnam, with a mean size of 0.09 for Kenya and 0.07 for Vietnam, and a maximum size of 0.22 for Kenya and 0.17 for Vietnam. These results suggest that using the weighted average as the primary aggregation method could introduce greater uncertainty for countries like Kenya that are more sensitive to weight selection.

The study also compared the results of the MC simulations with the outputs of Model 1 and Model 2. Although there was some overlap between the 90% confidence intervals of these simulations and the RDMI scores generated by Model 1, the study found that for 59% and 63% of the observations for Vietnam and Kenya respectively, the Model 1 score fell outside the 90% confidence interval. This indicates that even with a wide range of weights assigned to the individual dimensions in the weighted average simulations, there was still greater variability when the median was used in Model 1. This is because the median of three dimensions results in one dimension having a weight of 1 and the other dimensions having zero weight or influence on the score for that observation.

In contrast, the arithmetic average in Model 2 fell within the confidence intervals for 100% of the observations for both countries and was highly correlated with the median of the weighted average simulations. In fact, it mostly overlapped the median of the MC simulations on the graph. This suggests that, in the absence of a weighting scheme, the arithmetic average is a more stable choice than the median used in Model 1 as it is more aligned with the possible outcomes that a weighting scheme could produce.

Do the case study countries exhibit the same level of sensitivity to changes and uncertainties in the RDMI?

In general, the case study countries do not exhibit equal sensitivity to changes and uncertainties in the RDMI. For example, while the removal of NDVI caused approximately 50% of the observations in each country's dataset to move to another class, the dominant direction of movement differed. Around 80% of the observations that moved classes in the Vietnam dataset moved to a lower class, whereas in the Kenya dataset, more observations increased class compared to those that decreased. The decrease in suitability in Vietnam may be due to the negative correlation between NDVI and population density in Vietnam. Areas with higher levels of green vegetation tend to be more sparsely populated, resulting in these areas being classed quite highly in the original index. In contrast, in Kenya, vast areas of the country with low levels of green vegetation scored higher when NDVI was removed, and the greener, more developed areas scored lower due to the high levels of vegetation no longer compensating for the high populations in those areas.

Although both countries were equally sensitive to the effects of adding NO_2 to the index, Kenya was slightly more sensitive to changes in the aggregation methods, with more values moving one or more classes than in Vietnam when the aggregation was changed at the dimension and sub-dimension level.

Additionally, the uncertainty analysis revealed greater variability in the results of the Monte Carlo simulations for Kenya, with significantly larger confidence intervals. This indicates that Kenya is more sensitive to weight selection when using the weighted average. Furthermore, the scores of Model 1 were more poorly aligned with the results of the weighted average simulations for Kenya, suggesting that countries with a similar profile to Kenya may be even more sensitive to the type of aggregation method used in the index. Therefore, it is essential to consider the unique characteristics and context of each country when testing any new aggregation method or weighting scheme.

How did variations in the RDMI affect the scoring of the RDM pilot project sites?

Both pilot sites were classed as highly suitable for the RDM programme according to Model 1, but the sensitivity analysis revealed that three of the four alternative models resulted in a shift in these levels of suitability, with Chi Lang being classed as 'very high' suitability for Models 2 and 4, while Van Quan dropped to a lower class for Model 3. These examples further demonstrate that the RDMI is highly sensitive to variations in its parameters and variables.

6.3 Final Recommendations for Future Work

Below are the key recommendations for future work that have arisen from this research:

- The organisation should reconsider including NDVI in the RDMI as it is not suitable to be used to identify rural areas in all parts of the world (some rural areas are very arid and lack vegetation). However, as sustainability is key to the RDM programme, Lotus Project should also consider the effect of any development project on the local environment, geography, and society, and NDVI may be a suitable metric to monitor the land cover change due to development, and so it may have a purpose outside of the index.

- Lotus Project should also do further research into the effect of adding NO_2 to the RDMI as it is correlated with population density and adding it to the environmental dimension also lessens the importance of the other two indicators in this dimension. These indicators are related to the availability of renewable energy resources which is essential for the success of the RDM programme, and so it is vital that they are not overshadowed by NO_2, especially as the median is currently used as the sub-dimension aggregation, meaning there might be bias towards a certain indicator when there are only three in the dimension.

- The pre-processing methodology needs to be updated to account for valid zero values in certain datasets, and it is recommended for thresholds to be set for certain indicators (such as population density), as having much too high or low values should automatically class these areas as not being feasible or suitable for the RDM programme.

- The RDMI is not currently measuring all the key criteria for the RDM programme, in particular it is lacking indicators that measure access to electricity or poverty levels in an area. In order for the RDMI to be a comprehensive estimate of an area's suitability for sustainable development, it is crucial that more factors are considered in the index. While to date there has been limited global availability of the type of high-resolution raster datasets that are needed for the RDMI, there are new datasets being published every year. Thus, the Lotus Project team should continue to research and review new datasets as they become available, particularly datasets that are related to the data gaps in the index. As a starting point, future work could start with further reviewing the potential new datasets that were proposed in section 4.4, such as the GRDI which has subnational poverty data for 133 economies.

- The RDMI map could be further enhanced by adding additional data as optional layers that can be switched on and off. These layers could include vector data such as road networks to give users a better understanding of road access (which is a factor to be considered when identifying areas for the RDM programme but hasn't been incorporated in the index yet) and point data, such as the location of social amenities which should also be considered when planning for rural development. Furthermore, the RDMI map could be even more effective at communicating the results by classifying the data into levels of suitability, rather than displaying the continuous data for the RDMI outputs.

- While there are such limited indicators used in the index, further consideration should go into the aggregation methods used in the index. The study showed that the RDMI outputs are highly sensitive to the variations in the aggregation methods. At the dimension level, the median may be the most suitable option when there are a greater number of dimensions, but while there are only three dimensions, it leads to some dimensions having too much influence. Moreover, there is currently more uncertainty associated with the median than the arithmetic average.

- The use of the median as the method for aggregating values for the renewable energy resources should also be reconsidered as it may not be necessary to have high values for both, and the sensitivity analysis showed that changing this sub-dimension aggregation to the maximum has significant effects on both countries' RDMI scores, therefore it warrants further consideration.

Chapter 7 Conclusion

Throughout the course of this study, it has become apparent that the RDMI has huge potential as a tool for identifying areas suitable for sustainable rural development. Moreover, the Lotus Project team has ambitious plans to make it available for all countries, however, in its current form it has some limitations. While the use of publicly available, high-resolution datasets that have global spatial coverage enables its potential for use by other non-profits and governmental agencies around the world, it is clear that it still does not capture all of the factors that should be considered when planning for development. Thus, there is a need for the index to be further developed, and future work should aim to continue to explore how changing the variables and parameters of the index will affect its outputs in different contexts and regions, especially when the team is proposing to include a new indicator.

One important aspect of this study was the analysis of the effects of variations in the model parameters and variables on the RDM Index scores and classes through quantitative measures. It was also crucial to visually explore in maps how these changes affected the index outputs, as this provided a better understanding of why these changes were happening. The study has shown that the use of the median as the dimension level aggregation method is not advisable due to there being only three dimensions, resulting in the middle value always being chosen. Instead, the arithmetic average or weighted average may be better alternatives, but they also have issues such as being more susceptible to extreme values and some countries may be more sensitive to weight selection. Although, the findings also revealed that indicator thresholds could be helpful in dealing with extreme data values and outliers in some of the indicators. It is also advised to consider aggregating the renewable energy resources by their maximum, as long as only one of these resources will ultimately be used to power a microgrid system.

The study recommends removing NDVI as a variable as it may lead to wrongly targeting more developed areas for the RDM programme in countries where the most marginalized communities may live in arid areas. The effect of including NO_2 should be further researched, and it is not advised to aggregate it with renewable energy resources as this would lessen their importance.

Overall, this study contributes to understanding how the RDM Index can identify suitable areas for sustainable rural development, while also highlighting the need for further development and exploration. It is hoped that this work will inspire further research and development of the RDM Index and similar tools, ultimately contributing to the goal of sustainable rural development worldwide.

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Appendices

Appendix A – Questions for Semi-Structured Interviews

1. In your opinion, how effective is the RDM Index map at highlighting areas that are most suitable for sustainable rural development in Kenya, and please give reasons for your answer? (Rating scale: 1 - Not at all effective, 2 - Slightly effective, 3 - Moderately effective, 4 - Very effective, 5 - Extremely effective)

2. In your opinion, how could the RDM Index be improved upon?

3. Are there any specific indicators or variables that you believe are missing or should be included in the index or map to provide a more comprehensive understanding of rural development in Kenya?

4. Can you suggest any additional layers or contextual information that could be integrated with the map to provide more insights into the rural development landscape of Kenya?

5. In your opinion, how important are each of the indicators in estimating how suitable an area would be for sustainable rural development, and please give reasons for your answers? (Rating scale: 1 - Not at all important, 2 - Slightly important, 3 - Moderately important, 4 - Very important, 5 - Extremely important)

6. From a GIS perspective, are there any technical improvements or enhancements that you would recommend for the map to enhance its functionality or visual clarity?

7. Based on your expertise, what are your general recommendations for improving the RDM Index and/or map to make it more informative, accessible, and impactful for policymakers and development practitioners in Kenya?

8. Finally, do you have any other comments or concerns about the index or map?

Appendix B – Link to GitHub Repository

The Python code for the data analysis, the raw data in the form of GeoTIFF files, and the maps and graphs used in this thesis paper are stored in this GitHub repository: https://github.com/lotus-project/RDMI_Evaluation