Spatial modelling and decision analysis for sustainable aquaculture: the case of Nigeria

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By

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DECLARATION

I declare that this thesis in an original piece of work conducted independently by myself, and the work contained here has not been submitted for any other degree. All research material and sources of information have been duly acknowledged and cited.

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September 2022

ABSTRACT

Aquaculture sector planning takes two forms: expansion and intensification, both requiring context-specific tools to support decisions. This thesis is focused on expansion planning and aimed to help answer a key question about the future of aquaculture in developing countries like Nigeria: how much and where should aquaculture expand in response to global and local projections of future aquatic food demand?

First, Delphi technique was used to prioritize factors influencing the aquaculture sector in Nigeria: availability/cost of aquafeed, land use change, government policy and climate change. Through Scenario Analysis, four alternative but plausible pathways (scenarios) were generated for the sector's development to 2035, thus providing information to support government interventions. Second, a modelling approach was developed which combined the scenarios with Spatial Multi-Criteria Evaluation (SMCE) and GIS-based tools for aquaculture spatial decision support. The design was based on the low predictability of landscape change where legislations are weak, thus not all areas indicated by suitability models will remain suitable in the long-term. The approach was used to locate specific zones for aquaculture in Nigeria, to demonstrate how these vary with different development goals for aquaculture and to select the best zone respectively. Third, a survey of fish farmers in Nigeria was conducted to understand their perception of the concept, potential benefits, and limitations of aquaculture clusters. The questionnaire was divided into 4 sections: farm characteristics, farming practices, farmers' attributes and perception based on statements about aquaculture clusters. Majority of farmers have a positive perception. Using Random Forest method, the top 2 of 10 factors that influenced perception were farmers' source of advice and where they discharge farm effluents. Fourth, spatiotemporal changes in major land use: built-up area, vegetation and water surface were assessed in a previously identified potential zone for aquaculture. To identify possible indicators of sustainability, findings were compared with those at an established aquaculture area within the same region.

Overall, this thesis provides evidence and methods to support strategies for the sustainable expansion of aquaculture in Nigeria as well as other countries looking to develop spatial plans for existing or new areas for aquaculture.

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PEER REVIEWED PUBLICATIONS

- Yakubu, S.O., Falconer, L., and Telfer, T.C. (***under review***). A scenario-driven spatial multi-criteria evaluation to identify and rank potential zones for aquaculture at a national scale. Environmental Science & Policy, 136.

- Yakubu, S.O., Falconer, L., and Telfer, T.C. (2022). Scenario analysis and land use change modelling reveal opportunities and challenges for sustainable expansion of aquaculture in Nigeria. Aquaculture Reports 23, 101071. https://doi.org/10.1016/j.aqrep.2022.10107

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LIST OF ABBREVIATIONS

ADC	Aquaculturally Developed Country
AHP	Analytical Hierarchy Process
AIFP	Aquaculture and Inland Fisheries Project
ASCII	American Standard Code for Information Interchange
BGS	British Geological Survey
BMP	Better Management Practices
CART	Classification and Regression Trees
CCI	Climate Change Initiative
CCS	Closed Containment System
CGIAR	Consultative Group on International Agricultural Research
CI	Confidence Interval
CLABSHA	Clark Labs Hammer-Aitoff
CR	Consistency Ratio
CSC	Commonwealth Scholarship Commission
DA	Decision Analysis
DEFINITE	Decisions on a Finite set of alternatives
EAA	Ecosystem Approach to Aquaculture
EIA	Environmental Impact Assessment
EROS	Earth Resources Observation and Science
ESA	European Space Agency
FAO	Food and Agriculture Organisation
FCR	Food Conversion Ratio
FDF	Federal Department of Fisheries
FMARD	Federal Ministry of Agriculture and Rural Development
FO	Farmers' Organisations
GDP	Gross Domestic Product
GEE	Google Earth Engine
GIS	Geographic Information System
HWSD	Harmonised World Soil Database
ICES	International Council for the Exploration of the Sea
IFPRI	International Food Policy Research Institute
IIASA	International Institute for Applied Systems Analysis
IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade
IMTA	Integrated Multi-Trophic Aquaculture
IPCC	International Panel on Climate Change
ISPRS	International Society for Photogrammetry and Remote Sensing
ISRIC	International Soil Reference and Information Centre

ISSCAS	Institute of Soil Science, Chinese Academy of Sciences
IUCN	International Union on the Conservation of Nature
JRC	Joint Research Committee
LCA	Life Cycle Assessment
LCM	Land Change Modeller
LSMS	Living Standards Measurement Study
LUC	Land Use Change
LULC	Land Use and Land Cover
LUP	Land Use Planning
MA	Morphological Analysis
MCDA	Multi-Criteria Decision Analysis
MCE	Multi-Criteria Evaluation
MLP - NN	Multilayer perceptron - Neural Network
MNDWI	Modified Normalised Difference Water Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MPI	Multidimensional Poverty Index
MSI	Multispectral Instrument
NADP	National Aquaculture Development Plan
NALDA	National Agricultural Land Development Authority
NASA	National Aeronautics and Space Administration
NBS	National Bureau of Statistics
NDBI	Normalised Difference Built-up Index
NDVI	Normalised Difference Vegetation Index
NEPAD	New Partnership for Africa's Development
NGO	Non-governmental organisations
NIMET	Nigerian Meteorological Agency
NIR	Near-infrared
OECD	Organisation for Economic Co-operation and Development
OOB	Out-of-Bag
ORNL	Oak Ridge National Laboratory
OWA	Ordered Weighted Average
PS	Assessment Site
QGIS	Quantum Geographic Information System
RF	Random Forest
RMS	Root Mean Square
RS	Reference Site
SA	Scenario Analysis
SAS	Story and Simulation
SEA	Strategic Environmental Assessment
SMCE	Spatial Multicriteria Evaluation

SPSS	Statistical Package for the Social Sciences
SRTM	Shuttle Radar Topographic Mission
SWIR1	Short wave-infrared 1
SWOT	Strengths, Weaknesses, Opportunities and Threats
TPM	Transition Potential Map
UK	United Kingdom
UN	United Nations
UNDESA	United Nations Department of Economic and Social Affairs
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UNIDO	United Nations Industrial Development Organisation
USD	United States Dollar
UTM	Universal Transverse Mercator
WAPI	World Aquaculture Performance Indicators
WCMC	World Conservation Monitoring Centre
WDI	World Development Indicators
WDPA	World Database on Protected Areas
WGS84	World Geodetic System 1984
WLC	Weighted Linear Combination
WRI	World Resource Institute

CHAPTER 1 GENERAL INTRODUCTION

Global food production will continue to increase due to growing demand, driven by population and income (Falcon et al., 2022; FAO, 2018a; Naylor, Kishore, et al., 2021; OECD/FAO, 2020; Tilman & Clark, 2014). However, there are many questions on how to achieve sustainability in terms of technological, economic, environmental, and social acceptability within our food systems (Hunter et al., 2017; Springmann et al., 2018). For aquatic foods, the last three decades have seen a considerable increase in global production as shown in Table 1.1 (FAO, 2022). Aquatic foods are one of the cheapest sources of protein, mostly in developing countries and their role in food and nutrition security has been recognized (Belton et al., 2018; Béné et al., 2016; Beveridge et al., 2013). Like their terrestrial counterparts, i.e., crop and livestock production systems, the aquatic food system is therefore faced with the task of improving production to help meet the food demands of the world's growing population (Little et al., 2016). In Table 1.1, the increase in production is largely due to the rising contribution of aquaculture to the global supply of aquatic foods, compared to capture fisheries. The growth of aquaculture through expansion and intensification is expected to continue, and become the main source of future fish supply (Cai & Leung, 2017; Chan et al., 2019).

Table 1.1: Global aquaculture and fisheries production (average per year)

Production (Million tonnes)	1990-1999	2000-2009	2010-2019	2020
Capture fisheries				
Inland	7.1	9.3	11.3	11.9
Marine	81.9	81.6	79.8	81.1
Total	**88.9**	**90.9**	**91.0**	**93.0**
Aquaculture				
Inland	12.6	25.6	44.7	53.1
Marine	9.2	17.9	26.8	32.0
Total	**21.8**	**43.4**	**71.5**	**85.1**
Total	**110.7**	**134.3**	**162.6**	**178.1**

Data source: FAO (2022)

It is important that the expansion of aquaculture sector at different levels is planned and delivered in a sustainable manner. However, long-term planning is complex as there are many different considerations for land and water resources, and decision makers are often operating in challenging circumstances with no clear route to a particular decision. According to the United Nations Department of Economic and Social Affairs (UNDESA, 2019), human population will increase by about 26% from 2020 to reach 9.7 billion people by 2050. This increase is largely due to improved life expectancy/fertility rates accompanied by rapid urbanization and migration. At the same time, the climate is changing at an unprecedented rate (IPCC, 2021). Human activities have been the major cause of climate change since the early 19th century, and long-term impacts on weather pattern are likely to occur before 2050 even if action is taken now (Marchal et al., 2012); yet there are still many uncertainties about how climate change will affect aquatic food systems (Falconer et al., 2022; Naylor, Hardy, et al., 2021). The recent covid-19 pandemic was a sudden shock, and has subsequently changed many worldviews about the future (Falcon et al., 2022).

Along with all other food systems, there is emphasis on the need to build resilience into global aquaculture and capture fisheries, considering regional differences in geographic and economic situations (Béné, 2020; Love et al., 2021; Simmance et al., 2022). This means that, for developing countries like Nigeria, building resilience should focus particularly on improving data collection measures to help strengthen both farmers and institutional capacities to manage risks and develop appropriate adaptation strategies to local shocks/stressors (e.g., disease outbreak, flood, drought, conflict, insecurity, etc.). However, increasing globalization would often extend the impacts of local shocks/stressors from one region to another in the form of import or export deficits (Béné, 2020). In addition, economic and social impacts of geopolitical changes, including trade ban and territorial tension around the world affect fish supply and consumption within and between different countries (Barange et al., 2018; OECD/FAO, 2020). Such events together with the uncertainties of what the future might hold have made the decision-making environment increasingly complex to guide aquaculture development at different spatial scales. Interestingly, a future-focused thinking to address the challenges facing aquatic food systems has led to the ‘blue food revolution’ discourse. Although, the overarching goal is to boost aquatic foods production through sustainable aquaculture and fisheries, it is useful to consider their nuances in terms of sustainability issues, value chain actors, and required assessment tools for effective policymaking (Gephart et al., 2021; Naylor, Hardy, et al., 2021; Short et al., 2021).

Researchers have developed and used complex economic models e.g., IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade) (Robinson et al., 2015) and ‘Aglink-Cosimo’ (OECD/FAO, 2019) to generate various projections of future global food demand to inform policy action. For aquaculture and capture fisheries production, consumption and trade, these models have been adapted by authors such as Delgado et al. (2003), World Bank (2013), Lem et al. (2014) and Kobayashi et al. (2015) at global scale, while Chan et al. (2019) focused on Africa. However, since aquaculture is envisaged as the vehicle for increasing future global fish supply, projections of growth based on future demand is not in itself sufficient to develop strategies to drive the sector. Such projection is, at best, an emphasis on the need to develop and implement tools for better planning towards a sustainable future. Giller et al. (2021) suggested that the general assumptions that are often used for projecting global future demand for food need to be revisited for several reasons. Most importantly, the understanding that global projections unfold differently between continents, regions, and nations.

In contrast to global outlook of fish demand, Cai & Leung (2017) used an econometric model to generate a short-term projection (2015 – 2025) for nearly 200 countries and disaggregated into 5 fish species group. Their approach assumed that per capita income growth is the key driver of fish demand; provided other drivers such as price, dietary preference, consumer expectations, etc. remain stable. Furthermore, while the global models presented different possible scenarios of future fish supply, Cai & Leung (2017) calculated demand-supply gap per country as an indicator of aquaculture potential assuming that production trend is unconstrained. Although, the authors cautioned that the interpretation of the estimated potential must put a country in perspective, because countries may favour fish supply through imports or capture fisheries (inconsistent with global assumption). Also, that a country’s total aquaculture demand may be based on both domestic and export markets. Simple projections are a useful starting point, but for many decisions, there is a need for more detail that can support aquaculture planning and management. Consequently, there is a need to consider how future projections can be used within a decision-making context in a complex and changing world.

Scenario analysis (SA) is a common way to incorporate several drivers of change to reflect the uncertainties of long-term planning (Couture et al., 2021). The extrapolation of a single, short, or medium-term forecast to inform decision and long-term plans may suffer from over or under prediction; issues which SA helps to avoid (Schoemaker, 1995). SA is defined as a disciplined approach used to develop internally consistent and challenging set of narratives or scenarios that depict plausible futures (Schoemaker, 1991; Van Der Heijden, 1996). In other words, a scenario simply describes different but plausible ways in which the future might play out. SA is sometimes referred to as scenario planning or scenario thinking. Alcamo (2008) suggests that the term ‘analysis’ relates to scientists being inquiry-driven, while ‘planning’ is often used to address stakeholders such as policymakers who are relatively strategy-driven. Given the complexity of food systems, several studies have applied SA to better understand how these systems could respond to future socioeconomic and ecological changes based on outputs of different integrated assessment and foresight modelling (Reilly & Willenbockel, 2010). However, SA has just begun to attract attention in aquaculture research, with applications mostly at global and regional levels (Couture et al., 2021).

The success of an aquaculture development plan depends largely on how resource allocations are determined (Aguilar-Manjarrez et al., 2017; Cai & Leung, 2017; Miao et al., 2013). Decision-making on resource allocation should be consensus-oriented, achieved through detailed stakeholder consultation and not influenced by vested interests of powerful individuals or groups (FAO, 2017). Aquaculture spatial planning is strongly advocated as part of efforts to guide sustainable development of the sector worldwide (Brugère et al., 2019; FAO, 2013). Taylor (2010) defined spatial planning as the procedure employed by authorities at different levels to distribute people, infrastructure and activities in a manner that addresses their social, economic, and environmental concerns. Clearly, some criteria or evaluation procedure that are used to identify suitable aquaculture sites on land vary from those of water-based systems. For example, variables such as topography and soil quality are specific to pond aquaculture, while for cage site assessment, bathymetry and current are considered instead. Although, both pond and cage systems occur in coastal/marine or inland environments. In any case, the assessment tools for the different aquaculture systems can be categorized broadly into planning and management tools (Table 1.2). The paragraphs that follow will focus on tools for planning of inland pond aquaculture.

Table 1.2: Categories of aquaculture assessment tools

	Planning tools	**Management tools**
Application	Resource allocation for aquaculture development	Monitoring aquaculture operations
Examples	Site suitability assessment, Carrying capacity, Environmental Impact Assessment (EIA), Life Cycle Assessment (LCA)	Input quality assessment, Activity record, Resource use efficiency, Better Management Practice (BMP)

Whether for land or water-based aquaculture system, the process of site suitability assessment and allocation relative to other uses is a strategic problem (Aguilar-Manjarrez et al., 2017). Strategic decisions are context-specific; and this must reflect in the problem definition, to allow for appropriate techniques to be identified and used accordingly (Marttunen et al., 2017). The complexity in planning and managing aquaculture has increased due to the growing competition for space, impacts of climate change and consumer expectations (Falconer et al., 2022; Zander & Feucht, 2018). Recent technological advancements such as IoT (Internet of Things) have offered a paradigm shift, which is prompting more research into precision aquaculture (Antonucci & Costa, 2020; Føre et al., 2018). Precision aquaculture refers to the autonomous and continuous monitoring of farming practices and environment to improve fish welfare and productivity (Føre et al., 2018). However, strategic planning needs to consider possible changes in the priorities of farmers or regulatory authorities as well as uncertainties like climate change-induced storms, floods, and droughts.

Land can be used in various ways and for different priorities within the range of permitted uses in the land use plan of a specified area. As earlier noted, this is spatial planning that is particular to land. FAO (1993) pointed that land use planning (LUP) is often misinterpreted as a process where planners tell people what to do, instead of the systematic assessment of physical and socioeconomic factors to encourage and assist land users in selecting options that are sustainable and meet the needs of society. In other words, LUP is a logical decision-making process which is based on the premise that the characteristics of a land area set the boundaries for its possible uses (FAO and UNEP, 1999). Figure 1.1 shows the steps involved in land use planning. Across these steps, tools are required to guide the process up to the land use plan development and implementation. Such tools range from legal instruments, methods of stakeholder engagement, analytical procedure, to computer models (Aguilar-Manjarrez et al., 2017;

FAO and UNEP, 1999; Metternicht, 2017; Miao et al., 2013). LUP models are essentially models that are designed to explore the relationship between geographical locations to generate options for development (Riveira & Maseda, 2006). Geographic Information System (GIS) software has enjoyed a wide application in this regard. For example, in Mekong Delta, Trung et al. (2006) used GIS within three land use approaches under multiple scenarios of varying economic, social, and environmental significance. Harris & Elmes (1993) provide an account of its early usage in urban and rural planning in north America, while Davenhall & Kinabrew (2012) described how GIS has been used to achieve improved outcomes on health and human services. As a system for creating, managing, analyzing, and mapping various types of data, the GIS software can interact with other components: hardware, data repositories, network of user communities, web tools and other software (Longley et al., 2013).

Figure 1.1: Framework for land use planning, modified from FAO (1993) and FAO and UNEP (1999). National planning is at high level with long-term objective of resource allocation and involves wider stakeholder composition than other levels. National plans guide LUP at state (subnational) or community (local) level in situations where these are meant to drive sustainable development rather than conflict resolution.

GIS and remote sensing technologies have been used in different fields to map land use changes over time. In aquaculture studies, application has been widely for site suitability assessments covering several species, systems, and study areas at different spatial scales (Falconer et al., 2020). The other common application is for the evaluation of land use change, particularly mangrove loss to shrimp aquaculture. Some examples of pond aquaculture studies in different countries, that applied GIS and remote sensing are as follows: 1) Land suitability modelling for shrimp farming in Indonesia (Andi et al., 2014), for microalgae farming in Australia (Boruff et al., 2015) and for Tilapia/Clarias species in Uganda (Ssegane et al., 2012). 2) Modelling land use change with aquaculture pond as a land use class in Thailand (Hossain et al., 2009), China (Huang et al., 2009) and Bangladesh (Islam et al., 2016). 3) Flood mapping to support aquaculture planning in Argentina (Handisyde et al., 2014) and Thailand (Seekao & Pharino, 2016). 4) Impacts of shrimp farming as a measure of mangrove loss in USA (Alatorre et al., 2016) and Vietnam (Bui et al., 2014) or as a measure of change in groundwater quality in India (Nila Rekha et al., 2015).

In areas where the enforcement of land use legislation is lacking, it is difficult to predict the pattern of land use change (Metternicht, 2017). Understanding land use dynamics and the ability to predict how patterns may change in the future is important to aquaculture planning. According to Heller (2017), the environmental sustainability of a proposed area for aquaculture should be assessed not only by its own potential impact on the environment but also by how much it could be impacted. Therefore, a comprehensive strategic planning exercise that seeks to establish an aquaculture zone (extensive area where aquaculture is a priority) should not only consider the present suitability of the area (Couture et al., 2021; Ellen et al., 2016). This is because incorporating knowledge of the past about the area could provide insights into possible future risks, including any additional steps that can be used to mitigate such risks at the planning stage (González Del Campo, 2017).

Complex decision problems need to be structured in a way that considers different perspectives and encourages the development of alternative action plans (Belton & Stewart, 2002; Keeney, 1982; Marttunen et al., 2017). This means that, unlike simple problems which have clearly defined alternatives from which the decision maker can choose based on instinct or rule of thumb, complex problems lack such clarity. Complex problems first need to be structured to provide context and flexibility for decision-making. For a comprehensive review of application of problem-structuring methods (including SA and SWOT analysis) in research, see Marttunen et al. (2017). As described by Keeney (1982) and Belton & Stewart (2002), the complexity of a problem could simply be because it is difficult for alternatives to be generated and/or compared due to various reasons. First, many stakeholders (with different disciplines) are involved. Second, multiple criteria may be required to satisfactorily evaluate each alternative. For example, an individual trying to decide what laptop to purchase may analyze their alternatives based on the following criteria: memory size, screen size and processor speed (quantitative criteria) and colour and touch screen (qualitative criteria), so that the best alternative is one that scored highest on these criteria. The expected value or utility of the laptop is thus proportional to the evaluated criteria. Moreover, the available budget and purpose of the laptop may be incorporated. Third, the impact of the decision can only be evaluated in the long-term. For example, rural or city redevelopment projects, breeding programme, educational reforms, etc. take several years before impacts can be measured in a meaningful way. Fourth, risks and uncertainties are high. Uncertainties could result from difficulty in measurements or data collection, e.g., number of people impacted by dust from a road project. What natural disaster is likely to impact decision or which competitor, or government action is likely to change are some examples of uncertainties. Fifth, decision involves value trade-off. It might be necessary to consider economic versus environmental costs and present versus future social implications of different actions.

Therefore, Decision Analysis (DA) captures all the methods, ranging from problem structuring to selection of best alternative when making decisions that are believed to be complex or with long-term impacts (Belton & Stewart, 2002; Cochran et al., 2011; Delen, 2019; Keeney, 1982). Drawing from the different technical definitions, DA is simply a process of evaluating the long- and short-term benefits and costs of alternative decisions. It provides a framework that allows the techniques of operations research, management science and systems thinking to be combined with expert judgements to support decision-making through four steps (Keeney, 1982):

i. Problem structuring aided by careful stakeholder engagement
ii. Highlighting potential impacts of each alternative
iii. Defining the values or preferences indicated by different stakeholders
iv. Evaluating and comparing the alternatives

In summary, considering the definition of spatial/land use planning, a well-informed land use plan for aquaculture (i.e., DA in practice) can help to address many aspects of its associated sustainability issues. Land suitability modelling is a core activity within the process, as it identifies potential areas for aquaculture zoning or site selection (Aguilar-Manjarrez et al., 2017). As mentioned earlier, substantial research has gone into the development of GIS-based spatial tools for aquaculture site suitability assessment. The focus has largely been on the present conditions of the suitability factors under consideration, with scenarios often presented as possible alternative uses of the identified area. However, very little work has been done so far, to incorporate impacts of potential future changes of different factors on the suitability of aquaculture sites. Particularly, in many developing regions where land use legislations are either not well-developed or properly enforced; there is high potential for conflict (UN, 2012). Also, worth considering is the growing pressure from climate change, rural-urban migration, and political instability on land use systems. DA has been underutilized in the field of decision support for aquaculture. To date, most studies have not gone beyond the development of a suitability map for aquaculture zoning to further provide support for allocation through the identification and strategic assessment of specific locations.

The overall aim of this thesis is to identify and compare alternative locations suitable for aquaculture zoning, including an evaluation against future uncertainties. This will improve modelling approaches that are used to support spatial decisions in aquaculture planning. The research questions were framed in the context of aquaculture in Nigeria, mostly at a national scale. Spatial relationships between aquaculture ponds and other land use/land cover were explored, with a view to informing future expansion across the different geographical regions in Nigeria. The specific objectives were:

1. To use scenario analysis to characterize the bottlenecks to aquaculture development in the study area and model different potential pathways to the future of the sector.
2. To develop and apply a modelling approach to locate specific areas as potential zones for aquaculture in the study area.
3. To identify from fish farmers' perspectives, what key factors to consider for effective planning of aquaculture clusters in the study area.
4. To detect and analyze spatiotemporal land use changes in a potential aquaculture zone using GIS and remote sensing.

Collectively, the findings in this thesis provide evidence and/or methods for developing national strategies towards sustainable expansion of aquaculture in Nigeria. Although the focus is on Nigeria, the modelling approaches can be applied to other countries to inform aquaculture spatial planning. The following chapters present the studies carried out to achieve the objectives outlined in this thesis. Chapter 2 describes the study area. Chapter 3 presents what aquaculture might look like in the study area by 2035 in terms of both expansion of farming area and resource use intensification. In Chapter 4, a flexible approach to GIS-based site suitability modelling was developed and applied to the study area to demonstrate usability of the approach for aquaculture planning at a national scale. Chapter 5 looks at fish farmers' perceptions of aquaculture clusters and the implications for interventions to expand existing or establish new clusters across the study area. Chapter 6 evaluates land use change in a suitable area for aquaculture (previously identified in Chapter 4) and compared with an existing aquaculture area. Finally, Chapter 7 gives a general discussion that summarizes the salient points from the preceding chapters, including the significance and limitations of the findings and recommendations for future research.

CHAPTER 2 STUDY AREA

2.1 General information

Nigeria is a west African country with a total area of approximately 923,770 km^2. It is divided into six geopolitical zones comprised of 36 states and Abuja, which is the federal capital (Figure 2.1). The country is highly diverse, which is evident in its large population and regional differences in natural resources and trade, as well as the many ethnolinguistic, religious and political groups (Metz, 1992). Nigeria is the most populous country in Africa with a population of approximately 200 million, which is projected to double by 2050 (UN, 2019).

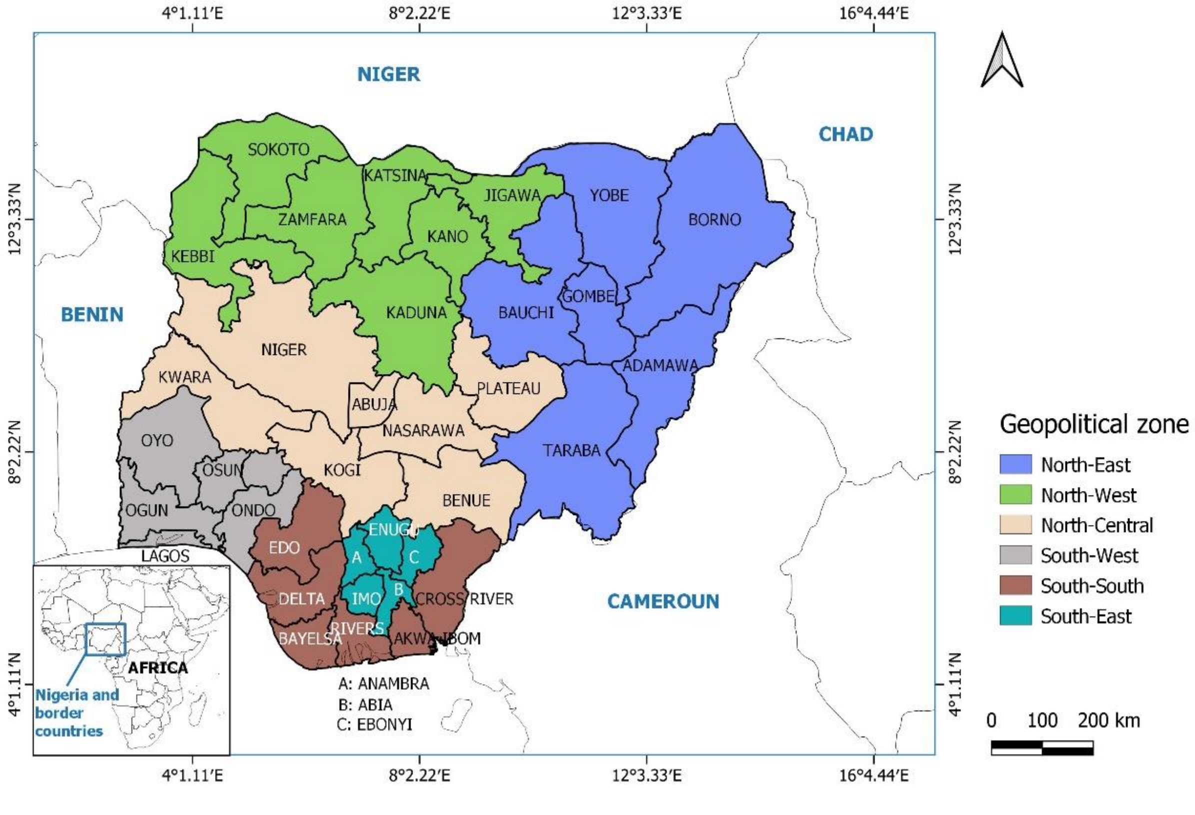

Figure 2.1: Map of Nigeria with indications of its border countries. The 6 geopolitical zones with their respective states are shown in different colours. Abuja in the North-Central is the federal capital of Nigeria and Lagos (South-West) is the commercial hub.

About half of the population lives in urban areas, with the growth pattern amplifying the pressure on the country’s diverse natural resources, from the tropical rainforests in the south to the Sahelian savannahs in the north (CILSS, 2016). A time series analyses of land use and land cover (LULC) change between 1975 and 2013 signify rapid transitions of landscapes, mainly to agricultural land (Figure 2.2). There is approximately 127,000 km^2 of protected land area (14% of Nigeria's total area), most of which is forest reserve (UNEP-WCMC, 2019).

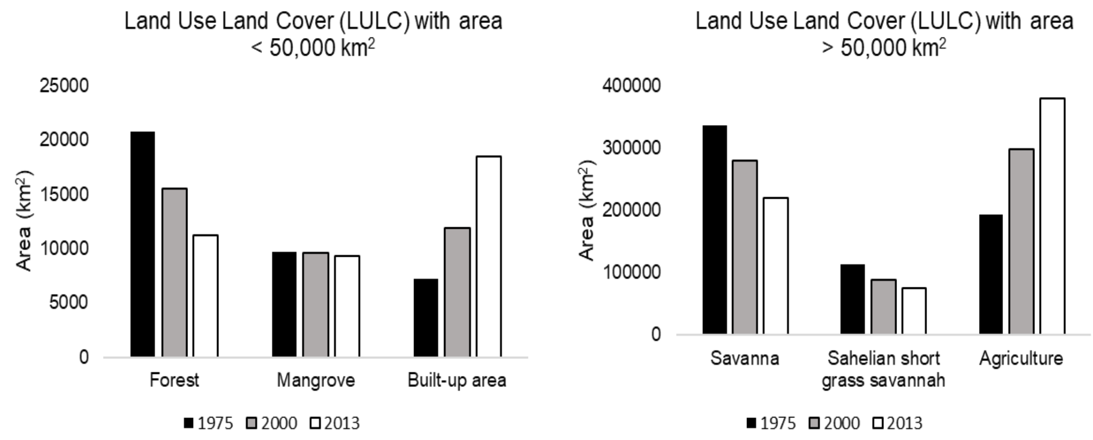

Figure 2.2: Some land use and land cover change in Nigeria from 1975 to 2013. Data source: CILSS (2016).

2.2 Climate, weather, and topography

Nigeria is a tropical region with the climate characterized by the interaction of moist southwest monsoon and dry north-easterly winds (NIMET, 2018). Gbode et al. (2019) observed a significantly increasing upward trend of average daily maximum and minimum temperatures across the country. This was based on temperature and rainfall data between 1971 and 2013 across 3 climatic divisions in Nigeria, namely Guinea coast, Savannah, and Sahel. There are two seasons in Nigeria, but the timings vary depending on the geographical location within the country. The wet season lasts from March to November in the south and from May to October in the north (NIMET, 2018). The day and night temperatures range between 30-38^oC and 19-25^oC respectively in the north, 30-32^oC and 20-23^oC in the central and 28-32^oC and 19-25^oC in the south. However, there are some notable high elevation areas (Figure 2.3) where daytime temperatures rarely exceed 25^oC. The mountain, Chappal Waddi in Taraba state is the highest elevation point in Nigeria, although most of Plateau state is on very high elevation in contrast to the rest of the country, making it the coldest state. The annual rainfall increases southward from 500 mm in the north to about 2,000 mm, with the Niger Delta region recording up to 3,500 mm (NIMET, 2018).

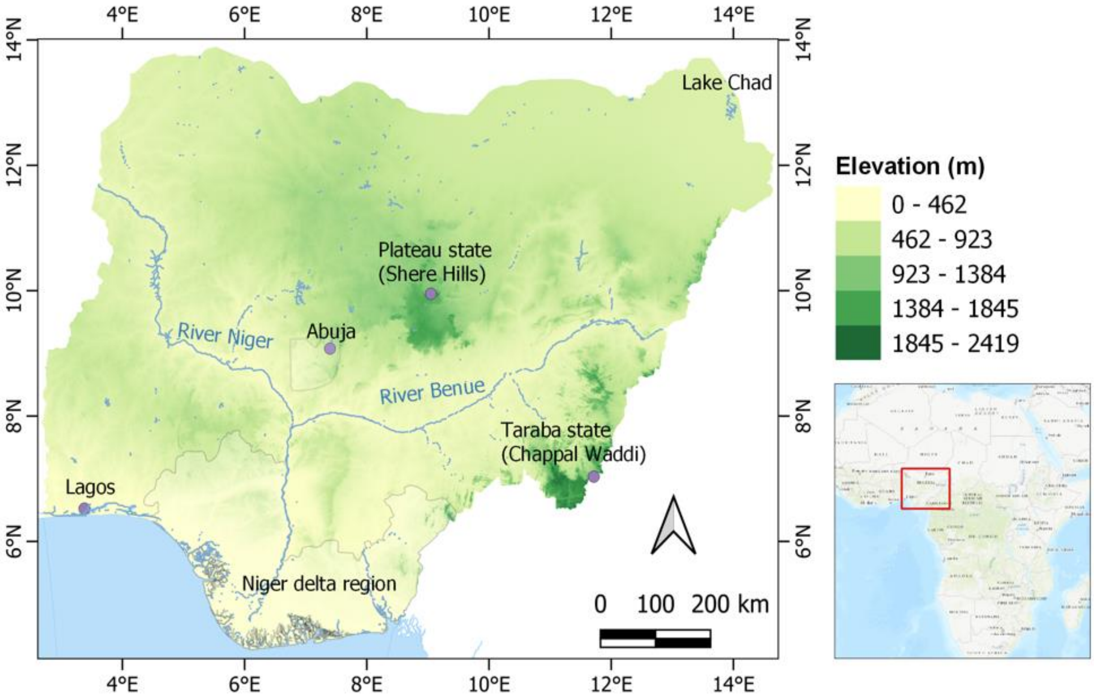

Figure 2.3: Relief map of Nigeria (Data source: Jarvis et al., 2008) with two very high elevation points in Taraba and Plateau states. Abuja is the federal capital, while Lagos is the commercial hub of Nigeria

2.3 The Nigerian aquaculture sector

Aquaculture is an important sector in Nigeria, providing a vital source of nutrition, income, and employment. Nigeria is a focal point for aquaculture in sub-Sharan Africa, being the second largest aquaculture producer in Africa after Egypt. As illustrated in Figure 2.4, aquaculture in Nigeria grew rapidly from around the year 2000 and peaked at about 317,000 metric tonnes (USD 905 million) in 2015. Production is largely private sector-led, in response to growing fish demand, although the government and various NGOs have been promoting aquaculture as a means for poverty alleviation (Anetekhai, 2013; Jamu et al., 2012). The devaluation of Nigeria's currency in 2014 and economic recessions in 2016 and 2020, may be linked to the recent downward trend in aquaculture production (Subasinghe et al., 2021; World Bank, 2020). Over 80% of production comes from small-scale farms, with facilities located mostly within urban areas (Miller & Atanda, 2011; Wuyep & Rampedi, 2018), and no mechanism for collecting statistical information required for planning and management. For example, a national water resources bill was recently proposed to regulate water use in Nigeria. Clearly, it is not a question of whether this will impact the industry but how; and robust data on farm locations and management practices would be key to understanding such issue.

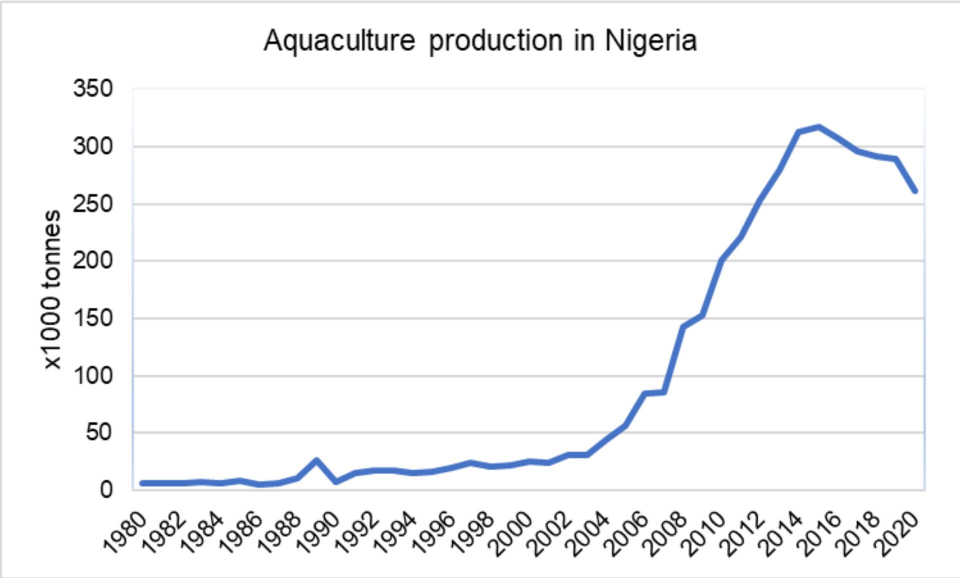

Figure 2.4: Status and trend of aquaculture production in Nigeria. Data source: FAO (2022)

Along with the rural-urban dynamics in Nigeria, there is variation between the northern and southern regions in terms of demographics and food security, including fish demand and supply (Liverpool-Tasie et al., 2021). Although prices of fish are higher in southern Nigeria, consumption per capita for all fish forms in the region more than double that in the north and while the percentage of households consuming fish in the south increased between 2010 and 2015, the percentage remained unchanged in the north (FDF, 2017; NBS and World Bank, 2019). There are several reasons for this disparity. First, over 40% of fish supply in Nigeria come from imports as frozen products arriving at seaports, all of which are in the southern area. While frozen fish are a common fish form in the south, the north is more inclined to smoked and dried fish, with the fresh fish form seen as a luxury option across the country (Liverpool-Tasie et al., 2021). Second, population density, which is one of the determinants of household consumption (Liu & Yamauchi, 2014), is higher in the south than north (Figure 2.5). The northern region is relatively higher in total population and poverty, with lower educational attainment. Third, artisanal fishing and fish farming are higher in the southern region, with a declining artisanal fishing and less fish farming activities in the north. The Lake Chad area in northeast Nigeria is well known for its artisanal fisheries and contribution to dried fish supply across the country, however, this area is also under threat due to political conflict which is severely affecting fishing activities and trade in the area. These are clearly useful considerations for national aquaculture planning.

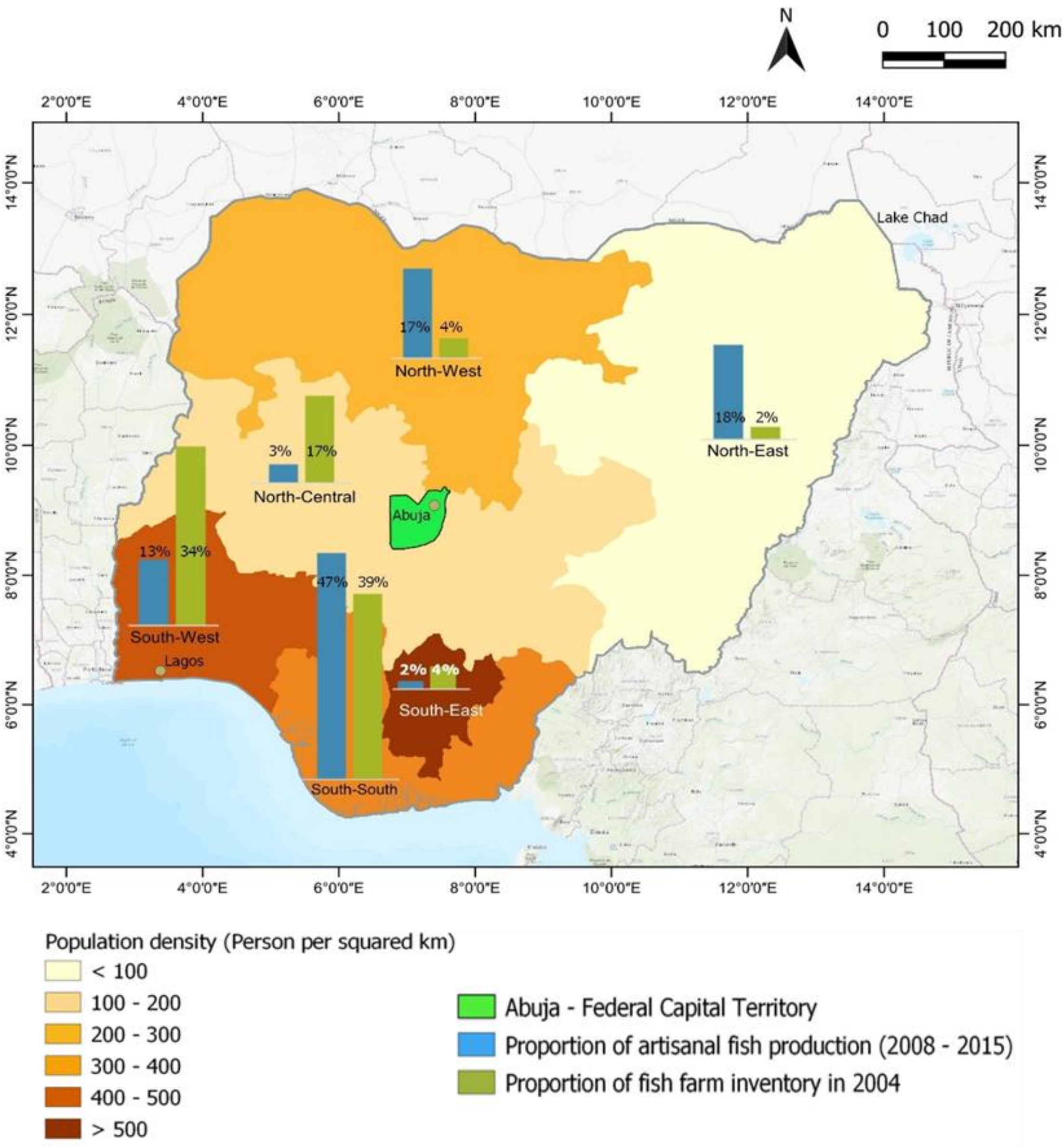

Figure 2.5: Map of Nigeria showing population density and proportions of artisanal fish production (653,852 t) and fish farms (2658) by the six geopolitical regions. For each region, population density is 2015 estimate (NBS, 2021); Artisanal fish production is annual average (2008-2015) (FDF, 2017) and fish farm is sum of reported numbers (FAO, 2007).

The production of African catfish species constitutes more than 70% of aquaculture in Nigeria (Anetekhai, 2013; Subasinghe et al., 2021). In an assessment of the catfish industry, Anetekhai (2013) categorized aquaculture into two major groups. 1) The homestead or backyard farming as it is commonly called, encourages families to set up farms in their residences for subsistence and small business. This system mostly involves the use of small culture facilities such as locally constructed wooden frames lined with tarpaulin. 2) Commercial farming, which is entirely for business purpose, mainly takes place in larger and dedicated space outside homes. Table 2.1 describes some common characteristics of farming practices in Nigeria

Table 2.1: Description of common farming practices* in Nigeria

Characteristic	**Description**
Culture facility	The culture facilities used in Nigeria for producing fish includes earthen pond, concrete pond, plastic and fiberglass tanks, and tarpaulin troughs. The earthen ponds are wholly or partially dug into the ground. Similarly, concrete ponds built using concrete/bricks may be cast below ground level, although most concrete ponds extend above ground level (Figure 2.6). Earthen and concrete ponds are the two most common grow-out fish culture facilities, with depth ranging between 1.2 to 2 meters. In some cases, the earthen pond walls are reinforced with stones, sandbags, or sand-filled tyres.
Stocking density	The common stocking practice is monoculture of African catfish, with stocking density varying from one to ten catfish/m^2 in earthen ponds. Juvenile fish (15-30g) are often used for stocking earthen ponds, because of their relatively better capacity to withstand stress than fingerlings (<15g). In concrete pond and others, the stocking density is usually higher, ranging from 10 to 40 catfish/m^2. Whereas functioning flow-through and recirculating systems stock up to 300 catfish/m^2. Only a few farms engage in the culture of other species, such as tilapia, *Oreochromis niloticus* and African bonytongue, *Heterotis niloticus*.
Feed management	Fish farmers use sinking or floating pellets, which are either imported or locally produced with FCRs ranging from 1.5 to 3:1, depending on management level. For many farmers, the ration fed to fish assumes ad libitum feeding, and for some, daily feed is split based on the amount of feed in stock, rather than prescriptive feeding using charts or other technical means. Broadcasting method of feed supply is more popular among fish farmers in Nigeria compared to the spot or point method.
Water management	It is common practice in Nigerian aquaculture to use personal experience of foul smell or colour of the culture water to determine when to manage culture water. The configuration of the water inlet and outlet largely depend on the farm surrounding and water source. A fenced farm that is built within residential areas and having a borehole as water source, is more likely to have an overhead water inlet pipe with an outlet made up of stand/elbow pipes. However, there are two categories of water management methods widely practiced, namely manual exchange and semi-flow through. For manual exchange, culture water is completely or partly drained through an outlet structure (monk, elbow pipe, etc) or using a pumping machine fitted with hose. For the semi-flow through method, a common practice for concrete and other fish culture tanks is that fresh water is let into the culture facility while the screened outlet is open for an extended period to allow for significant amount of culture water to be replaced. In the case of earthen pond, water supply usually from a waterbody passes through inlet canals into ponds until an overflow level is reached, at which water flows back through outlet canals to the waterbody. This system of water exchange is popular in southern Nigeria.

* (Adeogun et al., 2007; Alfred et al., 2020; Anetekhai, 2013; Ayinla, 2007; Dauda et al., 2017; Offem et al., 2010; Omofunmi et al., 2017).

Figure 2.6: Examples of aquaculture facilities commonly used in Nigeria. Concrete pond sitting on ground level (a), layout of indoor plastic tanks (b), improvised facility using tarpaulin and wooden frames (c), Fishpond wall reinforced with sand-filled tyres (d) and a cluster of earthen ponds with water canals (e).

The national aquaculture development plan for Nigeria (Abdullahi, 2011) suggested areas of attention including, the need to establish a good environment (through funding, research, security, and regulations) for investment to facilitate access to government's support. However, the first and only regulation that included aquaculture to date, was the Fisheries Act (2014) which repealed those only focused on artisanal/industrial fishing (the Sea and Inland Fisheries Acts of 1992). More information on policies and regulatory frameworks relevant to aquaculture in Nigeria can be found in Subasinghe et al. (2021).

CHAPTER 3 OPPORTUNITIES AND CHALLENGES FOR SUSTAINABLE AQUACULTURE DEVELOPMENT IN NIGERIA: A SCENARIO ANALYSIS

3.1 Introduction

The sustainable development of aquaculture needs a long term and comprehensive plan, which is often difficult to formulate due to uncertainties of the future (Gephart et al., 2020). Scenario analysis is one of the common methods for problem structuring (Marttunen et al., 2017) and strategic planning (Schoemaker, 1995). Scientists and planners use scenario analysis as a tool to generate plausible futures based on trends of events and uncertainties that support stakeholders in strategic decision-making (Vervoort et al., 2014). The definition of scenario varies with its purpose (Biggs et al., 2007). Popular proponents of scenario analysis in the 1990s such as Schoemaker (1991) and Van Der Heijden (1996) view scenarios as internally consistent and challenging set of narratives used to describe fundamentally different but possible futures. Scenario narratives may sometimes have a quantitative underpinning to help check the consistency of the narratives (Alcamo, 2008; Godet, 2000). In any case, scenario narratives or storylines that are relevant and credible help to stimulate creative thinking among stakeholders and decision makers on strategic issues (Bohensky et al., 2011; Malinga et al., 2013; Schoemaker, 1995).

Scenarios can take three forms — what-if (projection), what should (normative) or what could (exploratory) — happen in the future (Börjeson et al., 2006). In building scenarios, various flexible techniques are being used, such as matrices, Delphi, system dynamics and morphological analysis. Due to the wide range of methods available for conducting a scenario exercise, it is often difficult to decide what methodology to adopt (Bradfield et al., 2005). For this reason, it is suggested that a good understanding of the purpose which the intended scenario would serve, should be the topmost of the considerations for adopting a methodology (Biggs et al., 2007; Bradfield et al., 2005). Alcamo (2008) noted that scenarios tend to be qualitative when used in planning and quantitative for research. Adding that these can however be combined to achieve robustness.

Scenario analysis is sometimes referred to as scenario planning. According to Alcamo (2008), the term ‘analysis’ associates more with scientists being inquiry-driven, while ‘planning’ is often used to address stakeholders such as policymakers who are relatively strategy-driven. Robinson et al. (2015) emphasize that a scenario-based approach is often required for *ex ante* analysis of systems that are dynamic, including trends and nonlinear relationships that may deviate significantly in the future. This explains why several studies that explore how food systems could respond to future social and ecological changes have employed scenario analysis (Reilly & Willenbockel, 2010). However, in aquaculture planning, interest is just beginning to grow in the use of scenario analysis (Couture et al., 2021).

Scenarios of aquaculture development in relation to food security at global (Gephart et al., 2020) and regional (Chan et al., 2019) levels have been published. Using exploratory scenario narratives, Gephart *et al.* (2020) suggest that a globalised world in which economic policies are aligned with social equity and environmental concerns are necessary for the development of a nutrition-sensitive industry between 2030 and 2050. Chan *et al.* (2019) used the IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade) to generate a “business-as-usual” and three alternative scenarios of fish production, consumption, and trade in Africa by 2050. The alternative scenarios show how these outcome variables may respond if the trends in aquaculture investment and GDP per capita deviate from the current trends. However, it will be difficult to translate the insights of these larger scales directly to country-level applications to inform aquaculture policy and planning (Couture et al., 2021). The perspective of such top-down approach of assessing aquaculture development is different from that of bottom-up in that the former is broad, while the latter is more specific, as a result, the findings and recommendations are very likely to vary between global, regional, and national scales. For example, global aquaculture production and per capita fish consumption are expected to increase between 2018 and 2030 due to urbanization and income growth, but average consumption in Africa is expected to decrease by 0.2 percent per year, signifying different priorities for the African continent (FAO, 2020b). An optimistic scenario by Chan et al (2019), which assumes a largely improved growth rate of aquaculture and GDP across the continent, portrays increasing per capita fish consumption up to 2050, yet it remains an open question as to how much effort and in what direction, different governments or agencies might invest to drive such development. Hence, the role of country-specific drivers of aquaculture development, including ‘political will’ needs to be considered (Stead, 2019).

Although the African continent is recognized as a region with high potential for aquaculture development (Aguilar-Manjarrez & Nath, 1998; Brummett et al., 2008), the absence of proper governance of the sector has been a critical factor in this potential remaining untapped (Chan et al., 2019; FAO, 2017). Nigeria is currently one of the top producers of farmed fish in Africa and is pivotal to supply and trade of the product in the sub-Saharan region (Adeleke et al., 2020; FAO, 2018b). The country's aquaculture industry is characterised by African catfish (*Clarias gariepinus)*, providing a vital source of nutrition, income, and employment (Anetekhai, 2013). Production grew impressively from 25,000 metric tonnes (t) in the early 2000s and peaked in 2015 at 317,000 t (FAO, 2020a). However, the goal of reaching self-sufficiency in fish supply in the mid-term according to the national aquaculture strategy (Abdullahi, 2011; FMARD, 2008) could not be met. Meanwhile, the Federal Department of Fisheries (FDF) estimates the national aquaculture potential at some 2.5 million t annual production (FDF, 2017). Hence, there is need for a better understanding of the constraints to aquaculture development in Nigeria, including options for addressing these.

Freshwater pond aquaculture is the most popular production system in Nigeria (Miller & Atanda, 2011; Subasinghe et al., 2021) and its potential to expand in terms of availability of suitable land has long been established (Aguilar-Manjarrez & Nath, 1998). Poor access to land by smallholder farmers is highlighted as one of the factors affecting aquaculture expansion in the country (Adedeji & Okocha, 2011; Subasinghe et al., 2021). Worldbank (2020) show that arable land (ha per person) in Nigeria is on a downward trend, dropping from 3.0 to 1.7 between 1990 and 2018. The magnitude of impact of this trend on aquaculture across the country has not been studied. Although, the peri urban nature of aquaculture expansion (Miller & Atanda, 2011) suggests that any deliberate attempt to move towards rural areas may be met with challenges. One of such challenges is the rapid urbanization. The growth rate of urban population in Nigeria increased from 30% of the total population in 1990 to 50% in 2018 (UN, 2015, 2019). Given the poor knowledge on how much the accessibility to land, among other factors, is influencing the aquaculture industry in the country, an assessment of land use and land cover (LULC) change could offer some insights.

This study aims to use scenario analysis to develop and assess potential futures of freshwater pond aquaculture in Nigeria. Specifically, the assessment considers whether the Nigerian aquaculture sector could produce 2.5 million t of fish annually (FDF, 2017) by 2035. The objectives are: i) To identify via a stakeholder consultation, the key factors that may affect the future of aquaculture in the country, ii) To generate scenarios of Nigerian aquaculture development in 2035, iii) To assess the trends in land use change and potential trajectories under the scenarios, and iv) Evaluate the potential aquaculture production under each scenario and compare to the FDF (2017) estimate. The findings of this study will provide better understanding of the key issues affecting aquaculture production in Nigeria. More broadly, the study demonstrates an approach to support the development of national aquaculture strategies using scenario planning and LULC change assessment.

3.2 Methodology

3.2.1 Identifying critical uncertainties and trends for aquaculture

In scenario analysis, critical uncertainties refer to factors that drive something of interest (in this case aquaculture development) and for which prediction of change is complex both in terms of magnitude and direction (Schoemaker, 1995). Accordingly, critical uncertainties in the present study were identified as factors that score very high in both importance and uncertainty.

To populate these factors and assign scores, the Delphi method described by Okoli & Pawlowski (2004) was employed. The Delphi process involves establishing a structured group communication process where the opinions of individuals are elicited through a series of iterative questionnaires, to reach consensus. The advantages of this method over the face-to-face consultation include convenience, anonymity and ease of achieving agreement (Okoli & Pawlowski, 2004). In the present study, the process began with an overview of the literature (Table 3.1) to generate factors thought to be affecting aquaculture development in Nigeria. The summary as shown in Table 3.1 was also used to design the questionnaires (Appendix A). The literature highlighted a lack of collaboration between research institutions and the aquaculture industry, which led to the decision to establish two groups of experts: academics (in aquaculture science) and practitioners (fish farmers, fish feed producers and extension officers). The groups each had nine individual experts, who had at least five years' experience in aquaculture.

Table 3.1: A summary of factors identified in the literature[8], as important for aquaculture development in Nigeria

Factor	Description
Government policy	The inconsistency between governments results in unstable economic policies. A key aspect being the lack of coherent sector policy for aquaculture that can help to improve production. For example, the national aquaculture strategy and plan were stimulated by the agricultural transformation agenda (ATA), but the policy (growth enhancement scheme within the ATA) meant to facilitate smallholder farmers access to inputs, made little or no mention of aquaculture.
Land	Land rights and land use regulation are very important considerations for aquaculture development. This is because, the type of ownership or tenure security determines what aquaculture system and practices are adopted. Therefore, land administration is affecting aquaculture expansion, particularly for smallholder famers.
Input supply	The low expertise and technology for fish seed and feed production creates excessive reliance on imported materials in Nigeria. This implies poor distribution and high cost of inputs, with subsidies left as a window (just as in crop production) to sustain increase in farmed fish production.
Disease	Despite the role of good disease management in sustainable production, there is less attention in this direction for aquaculture in Nigeria. This is because major outbreaks are rare, making such measures to be considered by farmers as additional cost.
State of the economy	Macroeconomic factors such as interest rate, unemployment, international trade, GDP affect businesses including aquaculture. These factors are big issues interacting with the fast population growth in Nigeria to influence the demand and supply of farmed fish.
Geopolitical change	In addition to geopolitics, the differences across the so-called geopolitical regions of Nigeria affects the outcomes of aquaculture development projects. The geography, infrastructural development, economic and cultural landscapes, known to influence aquaculture investments vary with region. However, it is not clear how aquaculture expansion/intensification across the country is changing over time.
Research and development	There is weak linkage between research institutions and the aquaculture industry in Nigeria. This affects the drive for innovation, which in turn stagnates productivity.
Climate change	The understanding of the effects of changing climate on different livelihood activities including aquaculture is largely based on theoretical/qualitative data in Nigeria. Despite the evidence from changing weather pattern, flood and drought occurrence, the impacts of their interaction on aquaculture production across space and time is unknown.

[8]References: (Adedeji & Okocha, 2011; Adeleke et al., 2020; Anetekhai, 2013; Atanda, 2007; Atanda & Fagbenro, 2017; FMARD, 2016; Magawata & Ipinjolu, 2014)

The questionnaires were administered online to the two groups of experts. The first round of exercise treated all participants the same, regardless of their group. Each expert was asked to score the initial list of factors between 0 (not important) and 5 (highly important) based on their perceived importance of each factor to pond aquaculture development in Nigeria. The experts were also able to add more factors that they thought were important. The responses were collated, and a list of the top-ten factors was generated in order of descending average score.

In the second round, the list of top-ten factors from round one was used. Participants were asked to score each factor based on perceived importance (where 0 was not important and 10 was highly important) and level of uncertainty (where 0 was low uncertainty and 10 was high uncertainty) and suggest trends that may continue in the long-term. For each group, the Kendall's W (coefficient of concordance) was computed to measure the level of agreement in factor scorings using SPSS version 26 (IBM, 2019). The value of 'W' ranges from 0 to 1, indicating no agreement to perfect agreement respectively within groups. According to Okoli & Pawlowski (2004), a value of W ≥ 0.7 signifies strong agreement, meaning no further iteration of questionnaire is required. In the present study, W was less than 0.7 for the academic group, hence a third iteration of questionnaire was resent to the said group. Descriptive statistics of scores as well as notes on suggested trends from the previous round was enclosed to help revise their scoring, for participants who decide to do so. The Kendall's W was considered satisfactory after the third round. This produced a scored list of factors by each group in terms of importance and uncertainty and the mean scores of both groups were used to plot the chart of critical uncertainties (the factors that scored high in importance and uncertainty).

3.2.2 Scenario construction

Four scenario themes that depict alternative developments of aquaculture were created using a morphological analysis (MA). MA is a technique used to create a scenario space in which alternative outcomes or perspectives can be explored by a team during problem structuring (Ritchey, 2006). Accordingly, the MA technique was used to form the scenario themes by combining the critical uncertainties that emerged from the previous section, based on a gradient of possible outcomes: low to high (Table 3.2). Every alternative combination represents one scenario theme. The internal consistency and plausibility of each combination was assessed considering the interdependence between the critical uncertainties, along with their current trends as described by Schoemaker (1995). Each theme was given a title and its narrative developed taking into account other factors and information that were gathered from the Delphi exercise.

Table 3.2: Critical uncertainties and boundaries of possible outcome used in the Morphological Analysis (MA)

Scenario theme	**Critical uncertainty I**	**Critical uncertainty II**	**Critical uncertainty III**	**Critical uncertainty IV**
1	medium/high	medium	medium	low
2	medium/medium	medium	medium	medium
3	high/low	high	high	medium
4	low/high	low	low	low

3.2.3 Scenario simulation

Aquaculture development is dependent on the availability of suitable areas to establish farms, since areas with low suitability may require more investment, therefore less room for expansion and/or intensification. Thus, Land Use and Land Cover (LULC) change was used to estimate the potential expansion of pond area under each scenario. The potential pond area was then used to calculate the aquaculture production potential. Such quantitative projection is useful for better understanding of the scenario narratives and assessment of strategic options (Alcamo, 2008).

3.2.3.1 Land change data and modelling

Global land cover maps for 2000, 2010 and 2015 available at 300m resolution were downloaded from the ESA-CCI (European Space Agency Climate Change Initiative) database version 2.07 (ESA, 2017). From these maps, the spatial extent of Nigeria was extracted using TerrSet geospatial software system version 18.31 [Clark Labs, Massachusetts, USA] to create the land cover data layers. These were projected onto the Clark Labs Hammer-Aitoff Grid for Africa (CLABSHA), since Nigeria spans across three UTM zones (30N, 31N and 32N) and does not have a harmonized national grid for projection. The original land use classes were then reclassified into 12 thematic land use categories (Table 3.3) for use in the change analysis and projection. The land cover data layers for 2000 and 2010 were used to model LULC change and transition potential, and the layer for 2015 was used for validation.

Table 3.3: Reclassified LULC values with their new label for the study area

Original value	Original label	New value	New label
0	No data	1	No data
10, 11	Cropland, rainfed	2	Rainfed cropland
20	Cropland, irrigated or post-flooding	3	Irrigated cropland
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	4	Mosaic vegetation
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland	4	
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	5	Forest
60, 62	Tree cover, broadleaved, deciduous, closed to open (>15%)	5	
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	6	Mosaic forest
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	6	
120	Shrubland	7	Shrubland
130	Grassland	8	Grassland
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	8	
170	Tree cover, flooded, saline water	9	Marshy areas
180	Shrub or herbaceous cover, flooded, fresh/saline/brackish water	9	
190	Urban areas	10	Urban areas
200	Bare areas	11	Bare areas
210	Water bodies	12	Water bodies

The Land Change Modeler (LCM) in TerrSet was used to analyse LULC change. The LCM enables the user to model an empirical relationship of LULC change based on some explanatory variables to create transition potential maps (TPMs) for every specified transition sub-model. Two transition sub-models (all transitions to urban and to rainfed cropland categories) were considered in this study because aquaculture mostly associates with these two land use categories in the study area. Explanatory variables are drivers that would influence or contribute to a change in land use (e.g., distance to an urban area could be an explanatory variable for urbanisation). The explanatory variables used in the present study are given in Table 3.4. Given the large study area, common physical explanatory variables of land use change (e.g., slope) (Linard et al., 2013) was selected along with a key socioeconomic variable (population/wealth indicator) (Stehfest et al., 2019) for each sub-model. The TPMs indicate the potential of each pixel to transition from one LULC class to another, thereby helping to project future changes (Eastman, 2016a).

Table 3.4: Explanatory variables for modelling transitions to urban areas (sub-model I) and to rainfed cropland (sub-model II) LULC

Sub-model I	Sub-model II	Operation§
Distance* from urban areas	Distance* from rainfed cropland	Dynamic
Population density by state	Poverty index by state	Static
Elevation	Elevation	Static
Slope	Slope	Static
Empirical likelihood of change‡ to urban area	Empirical likelihood of change‡ to rainfed cropland	Static

** Distance refers to Euclidean distance between each pixel of urban areas/rainfed cropland to the nearest pixel of other LULC.*
‡Empirical likelihood of change is the quantitative representation of a LULC based on its vulnerability to change to either of the two LULC classes being modelled.
§Operation: Dynamic means that the distance will be recalculated at the end of every interval during the land change prediction, whereas Static operation remains constant.

The spatial layers of the distance variables were created from the ESA-CCI extracted LULC map of the study area for year 2000. The elevation layer, resampled (bilinear) to 300m, was derived from the 90-m hole-filled SRTM for the globe Version 4 (Jarvis et al., 2008). Slope was derived from the elevation layer. A map of state boundaries was obtained from DIVA-GIS (https://www.diva-gis.org/gdata), and used to create the poverty index data layer using data obtained from UNDP (2018) and the population density layer using data from NBS (2021). The population density layer was normalised to values between 0 and 1. The empirical likelihood variables were created using the variable transformation utility tool in the LCM. All the data layers were projected onto CLABSHA.

3.2.3.2 Land use change quantification and transition potential modelling

For the LULC change analysis, the reclassified LULC layer for year 2000 was used as the start date and LULC layer for year 2010 was used as the later date (Figure 3.1). The loss and gain in area (hectares) were computed for each LULC class, with every change representing a transition. Focusing on the two transition sub-models specified above (all transitions to urban areas and to rainfed cropland categories), only transitions that were greater than five percent of the highest in each sub-model were considered in this study. The rationale was that those transitions less than the threshold may not be worth modelling relative to the highest transition that occurred between 2000 and 2010.

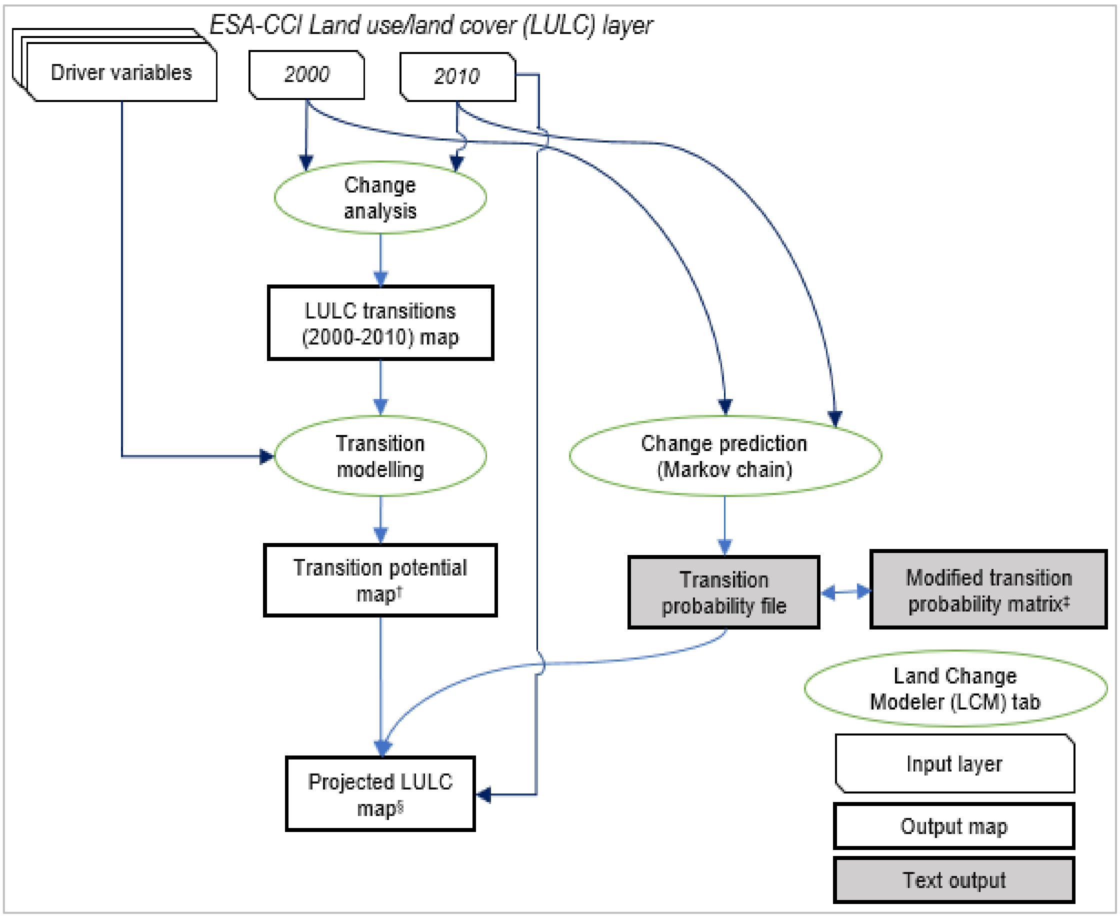

Figure 3.1: Flowchart of the land change modelling procedure. Note: †Transition potential maps are regenerated at every interval of prediction (5 intervals from 2010 to 2035) as the distance variables are recalculated. ‡Four different transition probability files, each representing one scenario projection. §One LULC map produced at the end of each stage of prediction per scenario.

In creating the TPMs, the Multi-Layer Perceptron Neural Network (MLP-NN) option in the LCM was used since there was more than one transition in a sub-model. The MLP utilizes a back-propagation algorithm to train and test for each transition sub-model. The process starts from random selection of samples of the pixels that transitioned and those that did not (persisted). Thereafter, the MLP selects 50% of these sample pixels for training and keeps the remaining 50% to test the predictive power of a transition sub-model. The training/testing is then allowed to run on default parameters or modified. In the present study, some parameters were modified as shown in Table 3.5, following recommendations in Eastman (2016a).

Table 3.5: Values of the parameters, default (***modified***) for running the MLP neural network

Parameter	**Value**
Sample size per LULC class	Sub-model I = 849
	Sub-model II = 10000
Training	
Learning rate	0.01 (***0.00238***)
Momentum factor	0.5
Sigmoid constant	1.0 (***3.0***)
Hidden layer node	3 (***9***)
Stopping criteria	
RMS error	0.01
Iteration	10000
Accuracy rate	100%

The MLP trained on the sample pixels and developed a multivariate function for predicting the potential for transition (to urban areas and to rainfed cropland) based on the values at any location for the five explanatory variables provided for each sub-model. This means that the five variables specified for each of the two sub-models were used to explain their respective transitions which occurred between 2000 and 2010.

The transition potential maps (TPMs) were then created for each sub-model following a satisfactory accuracy and skill measures output from the MLP training/testing. The skill measure (Equation 3.1) of the sub-model increases with increase in its accuracy rate as the MLP continued to run (see Eastman (2016a) for further information on the MLP-NN process). The skill measure varies from -1 (worse than chance) to +1 (Perfect prediction) with a skill of 0 indicating random chance.

Skill measure = (A – E(A)) / (1 – E(A)) (Equation 3.1)

where A = measured accuracy

E(A) = expected accuracy. E(A) = 1/(T+P)

T = the number of transitions in the sub-model

P = the number of persistent classes

3.2.3.3 Model validation

The final model is made up of the two transition sub-models, each containing a set of TPMs. To validate the model, LULC map of 2015 was predicted and compared with the actual 2015 LULC map.

In predicting change, the LCM used the Markov module to quantify the pixels or area that would change by the specified prediction date. The module then outputs a transition probability matrix, calculated as the ratio of the number of pixels that are expected to change or persist per LULC class to the total number of pixels across rows. The probability matrix can be modified to portray different scenarios of future land change (Eastman, 2016b). Finally, the LCM spatially allocates the expected change according to the TPM of each transition. The allocation starts from the pixels with the highest potential to change and continues in that order until the change demand was met for each transition. The predictive power of the model was tested using Equation 3.2 (Eastman, 2016b).

$S_r = [h/\Sigma (h, f)] \times 100$ (Equation 3.2)

Where S_r is success rate (%); h (number of hits) = areas correctly predicted to change and f (number of false alarms) = areas predicted to change but did not.

3.2.3.4 Land use change and aquaculture projection under each scenario

Quantitative simulation of pond aquaculture production under each scenario was achieved using Equation 3.3. This was based on adaptation of the original concept of FAO (1984) which determines how a country could be designated as aquaculturally developed. The FAO (1984) concept involve setting a target production, indicated as per unit (of current population and areas of rainfed and irrigated croplands), then comparing these values with the situation in a designated aquaculturally developed country (ADC) to assess feasibility. In the present study, projected population and land use change were used rather than a comparison with supposed ADC. The change in pond area was modelled relative to change in the areas of urban and rainfed cropland LULC following the narrative of each scenario. This assumption was necessary because land use maps containing fishpond as a land use class was unavailable for the study area.

$$A_p = P_t \times Y_t \qquad \text{(Equation 3.3)}$$

Where A_p is aquaculture production in pond (kg); P_t is pond area (ha) and Y_t potential yield (kg/ha) each year.

LULC change to urban areas and rainfed cropland from 2010 to 2035 was projected under each scenario at 5-year intervals. For the baseline scenario in which past to present trend of events is expected to continue, simulation was achieved as follows: (1) The LCM was allowed to use the Markov projected quantities of change (transition probability) per modelled LULC to 2035. (2) The TPMs changed automatically after every 5-year interval because they were recalculated by the MLP at the end of each period, based on the dynamic operation specified for the distance to urban areas/rainfed cropland variables.

For the alternative scenarios, the projected quantities of change originally determined by the Markov module was modified (Table 3.6) by altering the probability matrix. Based on the detected change in LULC (between 2000 and 2010 & 2010 and 2015), a plausible range of deviation from a baseline projection up to 2035 was assumed to be 1 to 5%. However, 1% deviation was used here because not all transitions were modelled. Whereas the signs show the direction of deviation considering each scenario narrative. The LCM then allocated the projected quantities according to the recalculated TPMs in each scenario. On the other hand, change in fishpond yield was assumed to be a function of the relevant factors described by each scenario narrative. Hence, a plausible percent change in yield was specified for each scenario (Table 3.6).

Table 3.6: Values[8] used to modify the transition probability matrix and pond yield for each scenario

Scenario	Transitions to		Potential yield (%)
	urban areas (%)	rainfed cropland (%)	
1 (Baseline)	0	0	0
2	+1	-1	0
3	-1	+1	+30
4	+0.5	+0.5	+15

[8]Values show cumulative change within the projection period (i.e., between 2010 and 2035). A change of -1% means a loss of 0.01 in the probabilities of expected transitions (indicated in the original matrix) to urban areas or rainfed cropland and a gain of 0.01 by the other LULC. Every row must equate to 1 (i.e., the sum of probabilities of expected transitions and persistence). In scenario 4, the +0.5% change for the two LULC refers to a gain of 0.005 each from the probabilities of expected persistence. Change in potential yield was assumed to start from 2025.

Each scenario simulation produced five maps (5-year interval), from which the areas in hectares of urban and rainfed cropland LULC were computed. The proportion of urban and rainfed cropland area in the actual LULC map 2015 that equated to 150,000ha (available data on existing pond area as at 2015 according to FDF (2017)) was used to model past and future change in pond area.

The average annual yield from fishponds in the baseline scenario was 1,500 kg/ha, i.e. the lower limit for commercial pond yield (1500 – 3500 kg/ha) as reported by FDF (2017). The results of pond aquaculture production were then generated by applying Equation 3.3 under each scenario. Production per capita were also computed using the UN (2015) projected population of Nigeria.

3.3 Results

3.3.1 Critical uncertainties and trends

From the Delphi exercise, the Kendall's 'W' for the scores of factor importance was 0.771 (Chi -Square = 62.564) in the 'academic' group and 0.834 (Chi-Square = 67.564) in the 'practitioner' group. For the scores of factor uncertainty, 'W' was 0.775 (Chi -Square = 62.735) in the 'academic' group and 0.824 (Chi-Square = 66.728) in the 'practitioner' group. A value of W ≥ 0.7 signifies strong agreement. Figure 3.2 shows the critical uncertainties (factors with high score in importance and uncertainty) of aquaculture development in Nigeria identified in this study. Availability/cost of input was the highest scoring critical uncertainty. However, LULC, climate change and government policy appeared in the same quadrant of the plot, hence, were all considered as critical uncertainties.

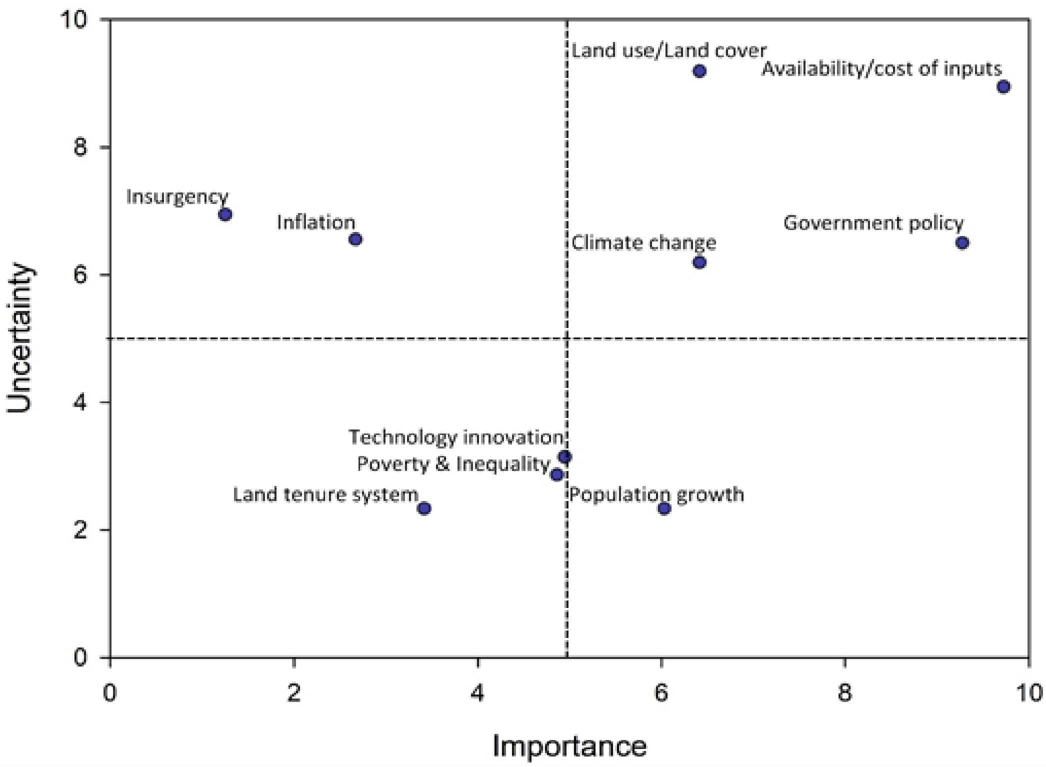

Figure 3.2: Two-dimensional plot of factors with all four critical uncertainties in the top-right quadrant.

3.3.2 Scenario themes

The themes of the four scenarios are given in Table 3.7. Scenario S1 portrays a baseline situation in which past to present trends of aquaculture-related events are thought to continue up to 2035. As Availability/cost of inputs was the highest scoring critical uncertainty, it was a key focus and differentiator in the themes. In S1, there is a medium availability and high cost of inputs like fish feeds and fingerlings which is a somewhat preferred outcome. In S2, the medium availability and cost of inputs also portray a somewhat preferred outcome, while in S3, high availability of low-cost inputs show the most preferred (positive) outcome. S4 is the least preferred (negative) outcome with low availability of high-cost inputs. Also, evidence-based government policies, effective regulation of land use and fair understanding of climate change impact on aquaculture as in S3, are favourable outcomes for aquaculture development, which contrasts with the situation in S4 scenario.

Table 3.7: Possible outcomes defining the critical uncertainties under each scenario

Scenario	**Availability/cost of inputs**	**Government policies**	**Land use & land cover**	**Climate change**
			Regulation:	Understanding of impact/adaptation:
S1: A familiar route	Medium/high	Politically motivated	Ineffective	Poor
S2: Vicious cycle	Medium/medium	Politically motivated	Ineffective	Fair
S3: Nipped in the bud	High/low	Evidence-based	Effective	Fair
S4: Autopilot	Low/high	Largely absent	None	Poor

3.3.3 Scenario narratives

The four scenario narratives are presented as follows.

A familiar route (S1): This is the baseline scenario. Nigeria follows a path in which past-to-present social and economic trends remain largely unchanged. Aquaculture is receiving the same kind of attention by the relevant authorities as it used to since the activity became popular in the early 2000s. Fisheries supply is almost flattened across the country. The costs of animal feed, raw materials and energy are rising without a corresponding rise in farmed fish price. The effects are seen in small to medium scale fish farmers gradually crashing out of business. Support schemes by relevant government agencies and NGOs providing soft loans and incentivized training, are increasingly available to existing and prospective fish farmers. Wealthy individuals and companies are taking advantage of the schemes to establish farms with arrays of water recirculating fish tanks with few earthen ponds. Land use regulation and tax regimes are weak, such that extensive land around peri urban areas is easily converted from one use to another. It is not clear how much progress has been achieved in the use of local feed materials and brood stock development due to lack of reliable data for evaluation. The impacts of changes in temperature, rainfall pattern and desertification on pond farms across geographical regions are not understood.

Vicious cycle (S2): Human population in Nigeria grows as expected with significant rise in urbanization than baseline projection. Alleviating poverty and inequality remain a big challenge. The government is offering subsidies on imported animal feed including raw materials, causing significant rise in imports. More erratic rainfall and reduced stream flow is being experienced, even in the southern region. The water use legislation is in force, so measures are becoming stricter for conserving ground & surface waters along with aquatic resources. The expected decrease in the rate of expansion of fish farms, is however counteracted by the low-interest loan packages available for prospective and existing fish farmers. Other challenges include the growing competition for land between large-scale pond and rice farmers in some states. Allocation decision requires local knowledge, but there is insufficient data on both resource use efficiency and household economies. Since urban dwellers have better access to the government incentives, many are establishing fish farms in rural areas which are managed mostly by rural inhabitants.

Nipped in the bud (S3): Following a strategy road map to implementing a comprehensive long-term aquaculture development plan, Nigeria sees light at the end of the tunnel. The country's urban population is growing at a significantly lower rate than expected. This may have resulted from the increasing number of manufacturing industries being established around rural areas. Road networks are rapidly improving with rail lines increasingly functional. In a bid for protectionism, the government aggressively regulates import and cost of inputs, while recording some progress in the development of local feed resources. Food systems research is being strategized, helping to create links with industries. The effort to develop tilapia and shellfish production is being intensified, while major private and government owned fish hatcheries are setting up promising breeding programmes for *Clarias gariepinus*. The federal department of fisheries (FDF) have identified highly suitable land areas away from urban areas for large scale catfish production. Although, the process for obtaining license and the requirements to meet regulatory standards are yet to be established. Short-term droughts are more frequent in the Sudan-Sahel agroecological zone resulting in reduced water availability for fish farming.

Autopilot (S4): Because the contribution of aquaculture to Nigeria's GDP is deemed negligeable, no deliberate plan targets its development at the national level since the short-term national plan of 2011. Urban population and GDP growth rates are slightly more than the baseline projections. Only few states are attempting to provide guidelines for increasing cage fish farming to boost production. Built-up areas are more compact in the supposed peri urban areas as population density increases. Due to widening inequality, the proportion of the population living in extreme poverty increases proportionally to changes in population size. Many local authorities do not have legal restrictions on land conversion, and aquaculture widely remains a peri urban affair. Prices of most commodities including fish are unregulated. To stay in business, many small-scale fish farmers are cutting down on production cost by using waste food materials, including from slaughterhouses to feed their fish. Some have resorted to seasonal farming following the availability of these materials. Others do so in response to seasonal variation in temperature and rainfall.

3.3.4 Quantitative projection

3.3.4.1 Land use change

The results of LULC change analysis is shown in Figure 3.3. Every LULC class lost land to others between 2000 and 2010; only the urban area did not. In year 2000, urban area was approximately 284,000 ha and rainfed cropland was 41,110,000 ha. From 2000 to 2010, a total of 233,000 ha was gained by urban area from the other ten LULC classes, while rainfed cropland gained 1,680,000 ha from eight classes (Figure 3.3. a and b respectively). However, the transitions to urban area between 2000 and 2010 that were above the set threshold (5% of highest transition or 4,600 ha) were from marshy area, forest, grassland, shrubland, mosaic vegetation, and rainfed cropland. In the case of transition to rainfed cropland, only forest, grassland, shrubland met the 5% or 64,000 ha threshold.

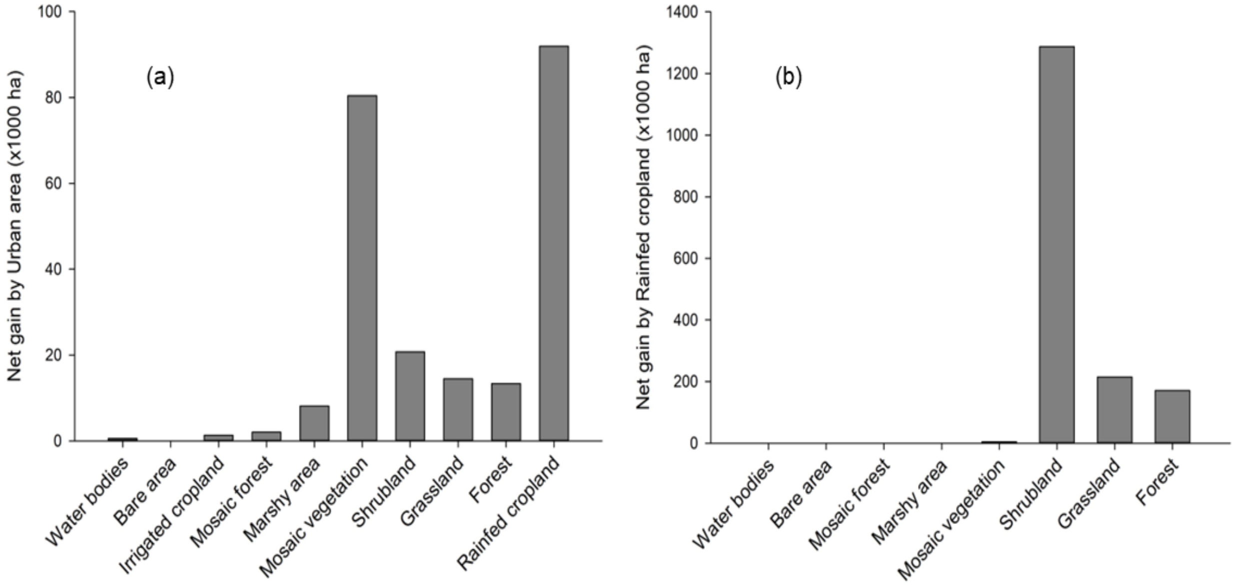

Figure 3.3: Contributions to net gain experienced by Urban areas and Rainfed cropland between 2000 and 2010.

3.3.4.2 Transition model and validation

The model comprises a set of transition potential maps for each of the selected transitions to urban areas and rainfed cropland LULC (sub-model I and II respectively). The skill measure of urban sub-model is 0.69, and 0.65 for the rainfed cropland sub-model. This suggests that the transitions to urban areas and rainfed cropland LULC in the training dataset (2000 - 2010) were adequately predicted. For predicted transitions between 2010 and 2015, the overall model shows a success rate of 24.3% (Figure 3.4). The success rate refers to the percent of transition areas correctly predicted as illustrated by the portions A and B, while C and D show the spatial characteristics of the predicted transitions. Furthermore, the difference in quantity of change between actual and predicted LULC in 2015 (S1, baseline) is shown in Figure 3.5. The model underestimates urban areas in 2015 by 2.52% and overestimates rainfed cropland by 0.95%, when the actual quantities were 0.647 million ha and 42.881 million ha, respectively.

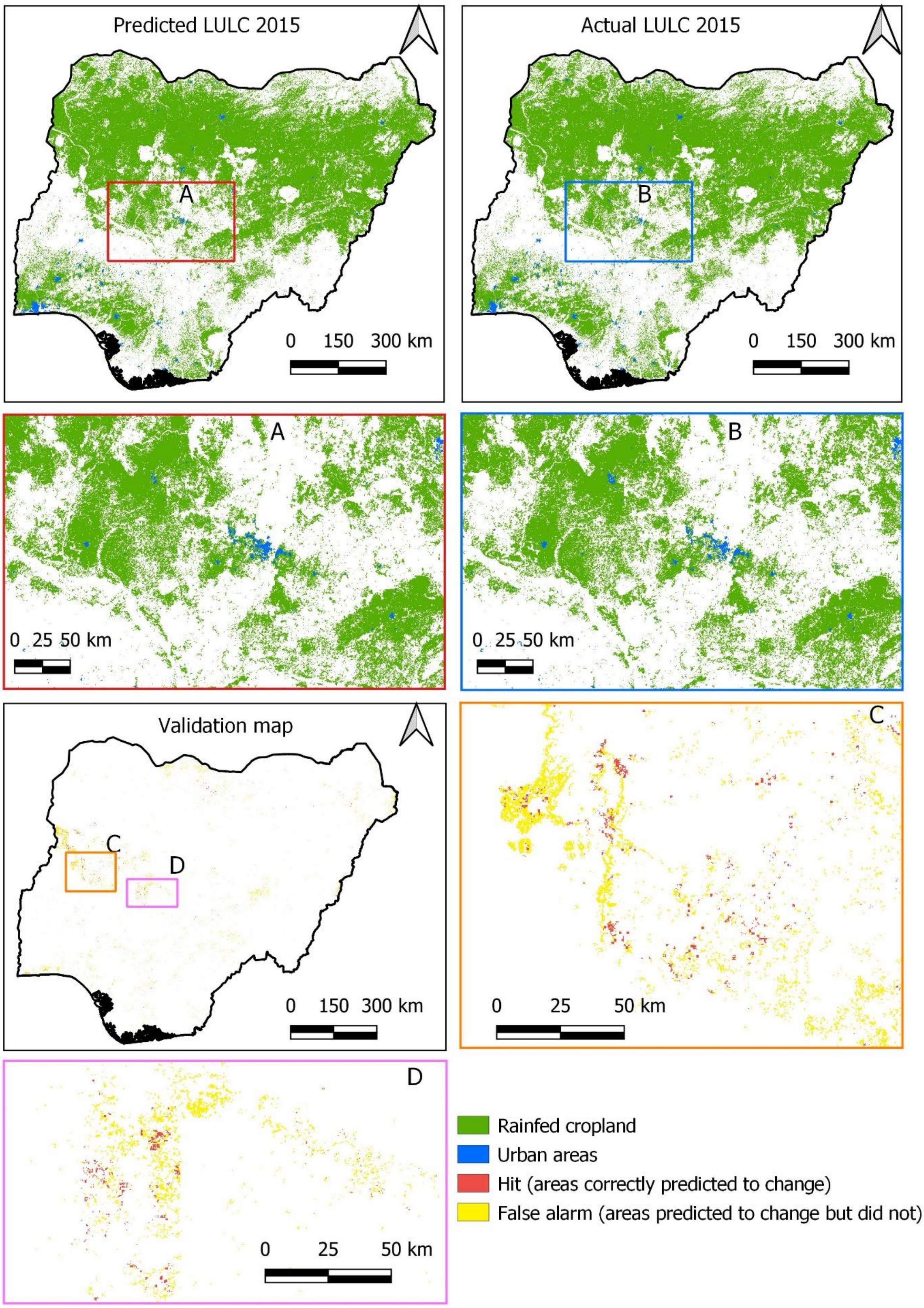

Figure 3.4: Predicted, actual and validation maps for Urban areas and Rainfed cropland LULC (Land use/land cover) between 2010 and 2015.

3.3.4.3 Projection of land use change under the four scenarios

The change projected for urban and rainfed cropland areas under each scenario are given in Figure 3.5. Between 2010 and 2035, the baseline projection (S1) shows a 110% increase in urban areas. In the same period, rainfed cropland experienced an increase of only 6.9%. The three alternative scenario projections show the effects of at least 1% change respectively, in LULC transitions to urban areas (a) and rainfed cropland (b). In S2 (Vicious cycle), urban areas increase significantly, while rainfed cropland experiences slow growth rate as describe in the scenario narrative. In the S3 scenario (Nipped in the bud), where a greater control of urban sprawl is portrayed, urban area is projected to increase by 90% between 2010 and 2035, while rainfed cropland increased by 7.2%. The S4 (Autopilot) projections show higher increase for urban areas than those of S1 and S3 but less than S2 projection. For rainfed cropland, S2 projection is least and shows a marked deviation from others.

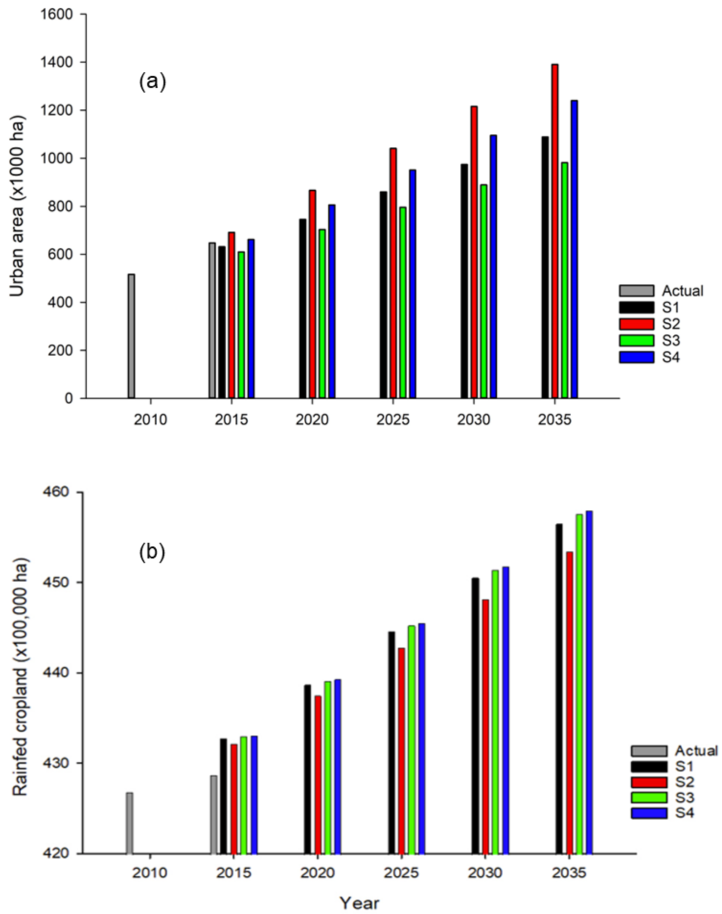

Figure 3.5: Projected change in Urban areas (a) and Rainfed cropland (b) across the different scenarios.

3.3.4.4 Projection of pond aquaculture production under the four scenarios

Based on the actual LULC map and the estimated area of aquaculture pond in Nigeria as of 2015, this study shows that aquaculture pond area was only 0.35% of the area of rainfed cropland and 23% of urban area. As seen in the land use change results in Figure 3.6, the rate of increase in urban areas (a) is significantly higher than rainfed cropland (b). Therefore, the estimate of pond area projected by 2035 relative to change in urban area almost double the projections based on rainfed cropland in all scenarios. As a result, in Figure 3.6, the projected aquaculture pond production across scenarios varies more in (a) than (b). In the baseline (S1) scenario, the estimate is 376,000 t and 240,000 t respectively by 2035. On a per capita basis, the projections of aquaculture production show a steadily increasing upward trend in the S3 scenario in (a) compared to others. Also, the trajectory of S3 in (b) is less steep than others. Thus, signifying the role of improved yield per hectare of pond area. However, the results show the range of possible per capita production to be between 0.7 and 2 kg/person/year by 2035.

3.4 Discussion

This study evaluates the potential future of aquaculture development in Nigeria using a scenario approach. Scenarios are useful to help stimulate creative thinking among stakeholders in designing interventions for development. The four scenarios described in this study represent four alternative, but plausible trajectories of aquaculture development based mostly on the four critical uncertainties identified in this study. The S1 scenario (a familiar route) considers the past and present situation of the Nigerian aquaculture sector and projects this to 2035. By so doing, it presents a comprehensive picture of the nature of opportunities and threats, to inform development planning. For example, as the availability/cost of fish feed is the priority constraint found in this study, stakeholders could use the scenario narratives around this constraint to develop interventions. Because aquaculture production cost has been increasing across the country without reasonable returns, the chances to make change also increase. Fish prices vary from one state to another, as middlemen have a significant impact on prices, although, the major constraint to increased farmed fish price is affordability. Majority of the urban population are in the low-income category who would easily go for substitutes (e.g., imported frozen/smoked herring) where they are cheaper (Liverpool-Tasie et al., 2021).

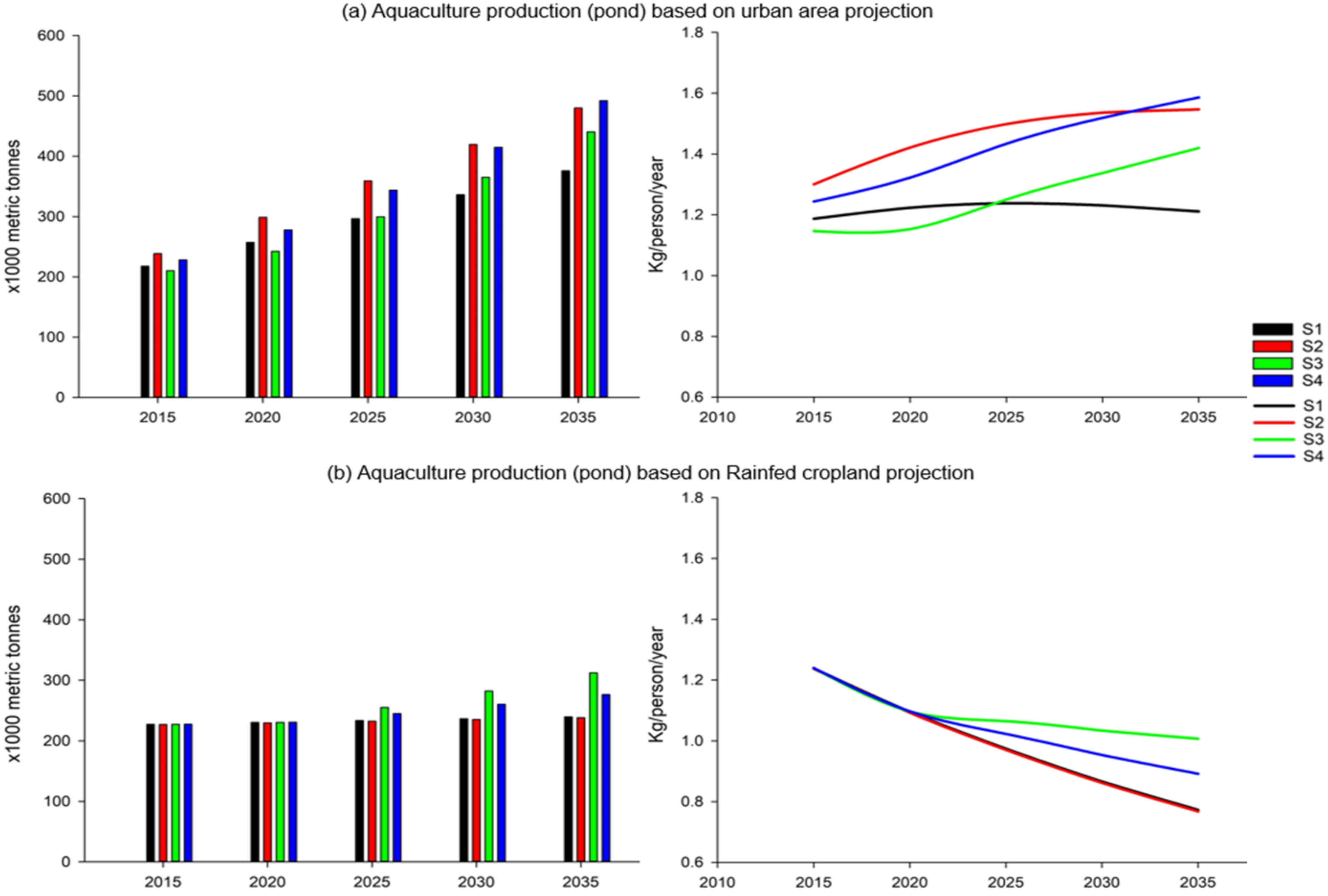

Figure 3.6: Projected aquaculture production (t) in pond, as total and per capita, across the different scenarios

However, if intervention(s) fail to consider options for aggressively developing local feed and seed resources and improve yield through better practices in the existing ponds and tanks, their benefits may be short-lived. As noted by Chan et al. (2019), the African continent is likely to remain a huge net importer of fish up to 2050, and this indicates opportunities for businesses to develop if the needed policies are put in place. These suggestions reiterate the fact that scenarios are not meant as forecasts or predictions, but plausible descriptions of how the future might play out, based on a coherent and internally consistent set of assumptions about driving forces (Badjeck et al., 2011).

Land use change is another important factor identified for aquaculture development. The S1 scenario describes a situation where the pattern of land use change continues for most of the categories including inland fishpond expansion. If the average yield from pond is maintained at the same rate of 1500 kg/ha, then production (according to Figure 3.6) will range between 240,000 t in (b) and 376,000 t (a) by 2035. This means that, on a per person basis, total production in ponds will not exceed 1.2 kg. However, If the 2.5 million t potential annual production were to be realised by 2035, this would mean a per capita production of 8kg/person/year based on the UN projection of Nigeria's population. Using the FAO (1984) ADC concept would imply that the 8 kg/person/year is feasible considering ponds alone, just by China's achievement for example, as a reference ADC. In China, pond area had reached 2 million hectares with average yield of over 7500 kg/ha even in polyculture systems since 2010 (Wang et al., 2015). This gives about 15 kg of pond aquaculture production per capita (given a population of 1 billion). Although, considering recent reports (e.g., Subasinghe et al., 2021) on catfish pond yield reaching 14.27t/ha/cycle for smallholder farmers in Nigeria means that, the average yield could be significantly more than 1500 kg/ha (FDF, 2017) which was adopted in the present study. However, this allowed the estimated aquaculture production between 2015 and 2020 to fall within the FAO's estimations for Nigeria. Therefore, consistency in the collection of data is required to allow for a better understanding of how changes in both aquaculture area and yield from different production systems across the country can be used for projections and decision making.

The S2 (Vicious cycle) is a slightly different pathway from that of S1. It shows some positive results but unsustainable. S2 describes some policy actions that may be politically motivated rather than based on evidence. For example, subsidizing the cost of imports at the detriment of local feed resource development for animal production will rarely do the aquaculture sector any good. The importance of regulating the aquaculture value chain in a manner that encourages both smallholder farmers as well as low-income consumers have been discussed by Chan *et al.* (2019) and Kaminski et al. (2020). Providing loan packages to farmers where the business environment is hostile, especially to resource poor farmers will not yield expected outcome. Inequality will continue to spread across communities, along with rural-urban migration.

Scenario S3 (nipped in the bud) highlights an alternative future development that offers better prospect for aquaculture growth. The scenario indicates a potential for the aquaculture sector to achieve a significant and sustainable transformation, resulting from the implementation of evidence-based policies. This includes aquaculture not being treated in isolation, such that exogenous aspects to the industry are considered alongside the internal ones. For example, while improving farming practices and development of less popular aquaculture species, land use zoning and international trade for aquaculture must consider the sector as part of a whole. The ecosystem approach to aquaculture (FAO, 2008) is a framework that links the internal and external parts of aquaculture development.

The knowledge of climate change impact on aquaculture is important for planning. In scenario S2 and S3, the situation was termed 'fair' to portray a sector which has begun to benefit from a robust research investment. In scenarios for fisheries and aquaculture development in west Africa by 2050, Badjeck et al. (2011) described the role of climate change. It is also important to note that some plans like establishing breeding programme and developing raw materials for feed are a long-term investment. Hence, the trajectory of aquaculture production in S3 would be less steep if pond yield were assumed to improve later than 2025. Gephart *et al.* (2020) suggests the possibility of reduced production efficiency and protein intake across middle and low-income countries, if nationalism is upheld as global aquaculture evolves. Some reasons being that technology transfer will be limited, regulatory systems will be underdeveloped and import barriers will affect feed prices. National authorities must however uphold the role of governance (FAO, 2017a) during interventions for sustainable aquaculture development.

On the other hand, scenario S4 describes a situation in which the national government trivializes the role of aquaculture in its food security and economic plans. Farmers and other actors along the value chain are then forced to take absolute responsibility for aquaculture activities around the country. In this case, production may continue to rise with increasing urbanization and average income. But increasing average income does not translate proportionally into betterment of the livelihoods of more numbers of poor farmers or consumers due to widening inequality. Market forces could favour fish prices, hence sustaining the upward trend in production in the mid to long-term, given a steady consumer preference. However, public health concern may result from an excessive improvision of farming methods by smallholders, thereby harming the industry's food safety reputation. Resorting to uncontrolled usage of slaughterhouse wastes for instance, to feed pond fish directly, may increase disease risks (Anh et al., 2010; Glencross et al., 2020).

The methodology adopted in the present study combined recommendations from both business and environmental scenario literatures. Nowack et al. (2011) suggested the integration of Delphi technique in scenario building process when expert knowledge is required to boost credibility and objectivity. The Delphi method was used here to support the ideas generated previously from the literature. Qualitative and quantitative scenarios were combined to promote transparency and reproducibility of the narratives and complement model assumptions. Ideally, scenarios should be interrogated by a guidance team through which iterations are necessitated (Alcamo, 2008). But the supposed users in the study area were assumed not to be familiar with the scenario approach, as its application has only just begun in aquaculture. Hence, the present study used expert opinions from the Delphi exercise instead, as well as the literature regarding aquaculture in Nigeria, to shape the narratives and simulation. While acknowledging that certain assumptions may be limited by the availability and quality of data, they are sometimes necessary. For example, modelling rainfed cropland and urban area as proxies for cultivated pond area was thought reasonable, since estimates of change in pond area can better inform strategic options for aquaculture development compared to the use of common indicators like fish demand.

Importantly, models such as the land use model used here, are inherently sources of uncertainty since they attempt to simplify complex systems. Although, the scenario narratives often serve to manage such uncertainties (Reilly & Willenbockel, 2010), different combinations of the driver variables and/or incorporation of the error maps from the validation results may help improve the simulation outputs. Also, future studies may reflect on the nuances of aquaculture. Firstly, aquaculture can be characterised by species, system, production scale, geographic scale, etc. and each of these can uniquely define the topic of a scenario analysis. Secondly, the interdependence of aquaculture and fisheries is considerable (Kristofersson & Anderson, 2006) yet, it seems difficult to associate them with the same set of drivers (Ravagnan et al., 2016). Despite these, global food models used for simulating aquaculture production treat aquaculture products as commodities often from an econometric point of view. Therefore, more specialised tools that includes environmental and technological interactions for foresight modelling in fisheries and aquaculture will be useful. For Nigeria in particular, improved regulatory and data collection protocols are required and further studies should address options for improving farming practices, sustainable land use and potential impacts of change in consumer preference.

3.5 Conclusion

The Nigerian aquaculture sector is unlikely to realize its estimated potential of 2.5 million tonnes annual production (FDF, 2017) by 2035, if the current trend of change in price of fish feed, land use change and research investment continue. For this estimate to be reached, aquaculture must grow by at least 21% from 2025 to 2035. This requires interventions to both expand aquaculture production areas including pond, tank, cage, etc. and improve yield through efficient resource use. In terms of expansion, the findings in this study point to the need to integrate aquaculture areas in land use plans. This will help to identify and establish highly suitable sites for the sustainable development of aquaculture and encourage clustering of farms. Cluster farming may be a way to improve farmers access to financial and technical supports as well as strengthen aquaculture value chain in Nigeria. Scenario planning shows the potential effects of action and inaction on a long-term basis. With the rapid growth of total and urban population in Nigeria, fish demand will increase, and land use pattern may change across geographic locations. The country's aquaculture development strategy and plans must respond accordingly to ensure a sustainable future for the sector.

CHAPTER 4 A SCENARIO-DRIVEN SPATIAL MULTI-CRITERIA EVALUATION TO IDENTIFY AND RANK POTENTIAL ZONES FOR AQUACULTURE AT A NATIONAL SCALE

4.1 Introduction

Spatial planning is the procedure employed by authorities at different levels to distribute people, infrastructure and activities in a manner that addresses their social, economic, and environmental concerns (Taylor, 2010). In aquaculture, spatial planning is an essential part of promoting sustainable aquaculture development (Brugère et al., 2019; FAO, 2013). Research efforts focused on developing tools for aquaculture siting are usually location-specific, primarily based on Geographic Information System (GIS) and spatial models (Falconer et al., 2018). Also, there is strong interaction between aquaculture and the environment (Boyd et al., 2007), so a good understanding of both spatial and temporal changes in an environment is critical for sustainable aquaculture. Some negative environmental impacts such as habitat loss and nutrient pollution that are associated with aquaculture have resulted from inappropriate spatial planning and site selection (De Silva, 2012; Falconer et al., 2018; Martinez-Porchas & Martinez-Cordova, 2012). Given the increasing competition for space and resources, as well as new challenges due to climate change, it is becoming increasingly important to improve on existing tools for aquaculture spatial planning, in terms of scope and usability (Falconer et al., 2020). Moreover, the implication of different value judgements by stakeholders on the outcome of spatial tools needs to be addressed (Gonzalez & Enríquez-De-Salamanca, 2018).

The process of assessing spatial suitability for aquaculture and consequent allocation of sites relative to other uses is a strategic problem as there are often conflicting objectives and interacting uncertainties (Couture et al., 2021). The effectiveness of strategic planning is based on five principles: should be participatory, transparent, comprehensive, rigorous, and scenario-driven (Ellen et al., 2016). This means that stakeholders should be properly identified and engaged; decision criteria should be wide-ranging; the planning exercise should involve consistent data and analysis; and the initiatives under consideration should be assessed against future uncertainties. Decision support tools must be capable of capturing these issues to enable informed judgement.

Site suitability assessment and modelling constitute about a third of GIS applications in aquaculture, with wide variations in the suitability factors considered and level of importance these are assigned (Falconer et al., 2020). It is important to note that a set of factors and weightings used for modelling site suitability at a small-scale, e.g., district level or portion of waterbody may not be directly applicable at a larger scale. This is because the spatial issues, amount and resolution of available data vary with space and time (Aguilar-Manjarrez et al., 2017). It is no surprise, therefore that aquaculture site suitability models at global and national scales are mainly useful for general assessment of aquaculture potential. Where many locations are found to be suitable for aquaculture, it is necessary that more specific spatial assessments or information are sought to reach a planning decision for development (Falconer et al., 2018). Some studies have used alternative models of aquaculture site suitability, based on modifications of one or more components, to provide decision options. For example, Salam et al. (2003) used site suitability models for shrimp, crab, carp, tilapia, and prawn respectively to calculate and compare their potential economic benefits and employment generation in Khulna region of Bangladesh and Díaz et al. (2017) developed five suitability models for aquaculture siting in Uruguay, each model for a different production system. The authors compared the sum of suitability for the five production systems between the 50 administrative divisions in the study area. Most of the differences between suitability models in the literature have been in one or more of the following: the set of factors used, suitability thresholds of factors, weightings, and spatial multi-criteria evaluation (SMCE) procedures. However, as recommended by Ellen et al. (2016), a scenario-driven approach can improve decision support.

In strategic planning, scenarios are defined as plausible and simplified descriptions of how the future may develop (Alcamo, 2008; Schoemaker, 1995). In other words, scenarios are simple and effective narratives that are used for defining the goals and intended use of a model (Alcamo et al., 2011; Delen, 2019). The capability of scenarios to serve multiple purposes during planning, explains the considerable attention it has received from many users, particularly in changing the worldview of decision makers (Malinga et al., 2013; Ram & Montibeller, 2013; Trutnevyte et al., 2012). So, for aquaculture spatial planning, a scenario-driven approach should be able to identify and compare specific locations suitable for aquaculture under alternative but plausible conditions.

Land can be used in many ways, for a range of environmental, social, and economic purposes, and there will be different priorities depending on the stakeholders involved. However, in areas where land use regulation is weak, it is difficult to predict the pattern of land use change. Since aquaculture development does not occur in isolation from land use challenges, use of aquaculture site suitability models alone will not provide sufficient information for decision makers. Scenario planning can overcome some of these uncertainties and provide narratives that can support land use planning. The integration of GIS with scenarios has already been described for urban planning (Chakraborty & McMillan, 2018). Alternative futures are created, mostly through alterations in current land use, employing GIS coupled with specialist urban and regional planning tools, to enable visualization of impacts on strategic issues. This is then used to elicit stakeholders' opinion before arriving at a course of action (Chakraborty & McMillan, 2018).

The aim of this study was to develop an approach that combined scenario analysis and SMCE to identify potential zones suitable for aquaculture, based on scenarios previously developed for Nigerian aquaculture. The use of scenarios to inform GIS-based aquaculture site suitability analysis is a cost-effective approach that could improve decision support, facilitating more strategic development through the identification of appropriate aquaculture zones for specific goals. Therefore, this study had three objectives: 1) To use scenarios to define the strategic priorities for which aquaculture site suitability models are developed, 2) From the suitability models, identify suitable areas as potential aquaculture zones for each strategic priority, 3) To rank the zones and assess the sensitivity of the rankings.

4.2 Methodology

The proposed scenario-driven approach to identify and compare suitable zones for aquaculture in this study followed Simon's model for decision making (Figure 4.1). According to Simon (1977) cited in Delen (2019), every decision-making task can be classified into three broad phases: intelligence, design, and choice. In the intelligence phase, the aim is to structure the problem, set goals or strategic priorities and identify data requirements. The design phase involves developing suitable alternatives towards the goals. Also, criteria can be set in this phase for evaluating the performance of the alternatives. The choice phase involves the evaluation of the alternatives with a view to selecting the best performing one.

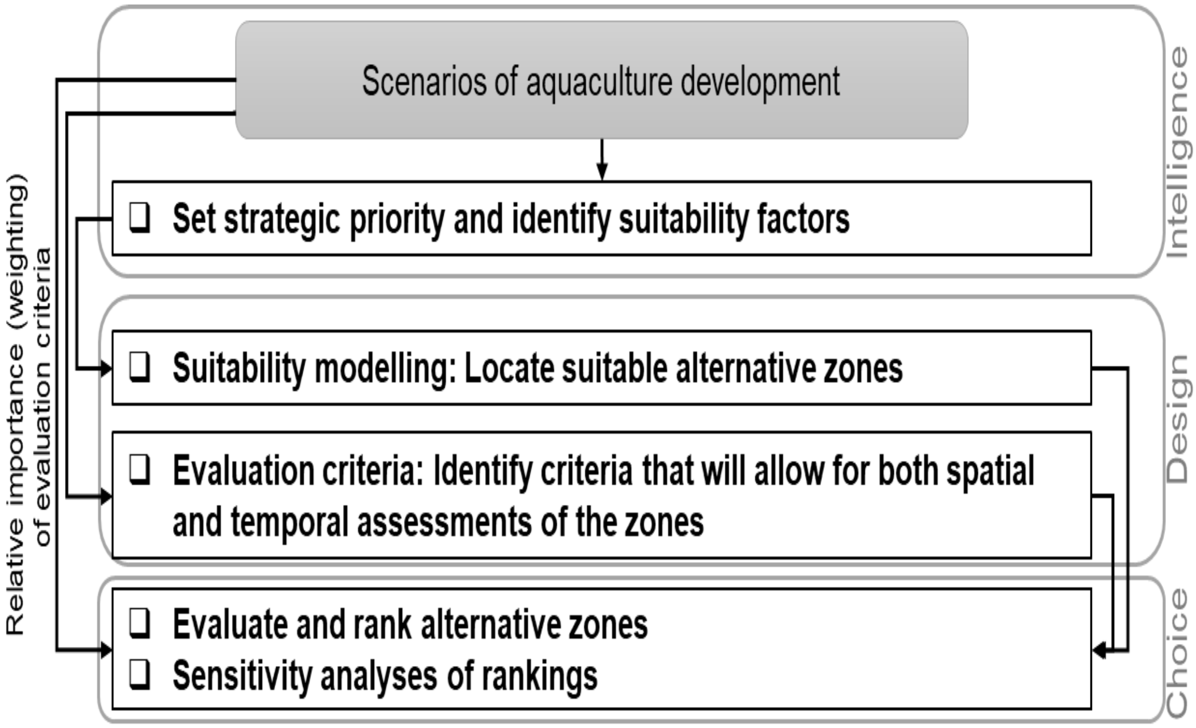

Figure 4.1: Conceptual diagram of the proposed scenario-driven approach based on Simon (1977) model for decision making.

4.2.1 Intelligence phase

4.2.1.1 Problem definition

Considering the scenarios of Nigeria's aquaculture development in Chapter 3, which describes how different factors may interact to shape the future of the sector, potential intervention strategies can be identified for sustainable expansion. Such strategies may be to establish aquaculture zones for different goals, for example to: (i) reduce the rate of overfishing (ii) help address poverty (iii) minimize rural-urban migration (iv) boost aquaculture's contribution to GDP (v) improve interaction with research institutions. These can be planned at different spatial scales: national, subnational, and local. To demonstrate the proposed approach, two potential goals (establish zones for poverty alleviation and economic growth) at a national scale were defined as the strategic priorities to inform the design and choice phases.

4.2.1.2 Identification of site suitability factors

Five themes of suitability were outlined to cover all elements of the scenarios S1-S4, including water requirement, pond construction, land cover, social environment, and economic environment (Table 4.1). ‘Water requirement’ could express the potential impacts of climate change on aquaculture, whereas ‘Pond construction’ and ‘Land cover’ were linked to land use regulation. The social and economic environment categories were associated to the role of government policies in shaping the aquaculture business environment. Various factors were identified for each theme and their selection was based on a balance between relevance and data availability. Constraints were areas where aquaculture could not or should not take place, and included protected areas, urban areas, waterbodies, and areas with very steep slopes. Accordingly, the site suitability models focused on pond aquaculture systems, were developed in the Design phase, and used to identify five alternative zones suitable for each strategic priority (Priority I and II).

Table 4.1: Factors, constraints and data used for modelling aquaculture site suitability

Category	**Factor**	**Data (unit)**	**Format (original resolution)**	**Data source**
Water requirement	Rainfall	Precipitation (mm/month)	Raster (30 arcseconds)	WorldClim 2.0 (Fick & Hijmans, 2017)
	Water temperature	Air temperature (°C/month)	Raster (30 arcseconds)	
	Groundwater	Groundwater productivity (l/s)	xyzASCII text file (3 arcminutes)	British Geological Survey digital groundwater maps for Africa (MacDonald et al., 2012)
	Drought risk	Drought frequency based on historic data	Polygon vector	Aqueduct Global Maps 2.0 (Gassert et al., 2013)
Pond construction	Percent soil clay	Soil clay content (%)	Polygon vector (30 arcseconds)	HWSD 1.2 (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
	Slope	Elevation (m)	Raster (3 arcseconds)	Hole-filled SRTM for the globe Version 4. (Jarvis et al., 2008)
	Flood risk	Flood frequency based on historic data	Polygon vector	Aqueduct Global Maps 2.0 (Gassert et al., 2013)
Land cover	Land use/land cover	Land use/land cover	Raster (10 arcseconds)	ESA CCI Land Cover time-series v2.0.7 (1992 - 2015) (ESA, 2017)
Social environment	Distance to major road	Road	Line vector	Digitized major roads in Nigeria 2019 (Google Earth, 2019) Major roads in Nigeria 2009 (World Bank, 2009)

	Distance to major airport	Major international and domestic airports	Text	Global airports (Karakostis, 2019)
	Population density	Population density (persons/km^2)	Raster (30 arcseconds)	Landscan 2000 & 2018 datasets (ORNL, 2019, 2020)
	Share of local fish market	Artisanal fish production by state. Area of Nigeria by states (Km^2)	Data table	Fishery statistics 2008-2015 (FDF, 2017) (NBS, 2020)
Economic environment	Multidimensional poverty index	Multidimensional poverty index (MPI) by state	Data table	Multidimensional poverty peer network (UNDP, 2018)
	Change in fish price	Fish price by state (₦/Kg)	Data table	Fishery statistics 2008-2015 (FDF, 2017)
Constraint	Protected areas	Protected areas	Polygon vector (30 arcseconds)	World database of protected areas (UNEP-WCMC, 2019)
	Waterbodies	Land use/land cover	Raster (10 arcseconds)	ESA CCI Land Cover time-series v2.0.7 (1992 - 2015) (ESA, 2017)
	Urban areas			
	Slope	Elevation (m)	Raster (3 arcseconds)	Hole-filled SRTM for the globe Version 4. (Jarvis et al., 2008)

4.2.2 Design phase

4.2.2.1 Site suitability modelling

Figure 4.2 shows the aquaculture site suitability modelling framework. The Intelligence phase was described in Section 4.2.1, the Design phase is outlined here, and the Choice phase is detailed later in Section 4.2.3. The model was designed so that factors in each suitability theme are combined to form a sub-model, which can be assessed separately, allowing users to understand its effect on the overall suitability model. The spatial resolution adopted for the study was 300 meters. This resolution enabled a balance between the availability of data and quality, given the large study area.

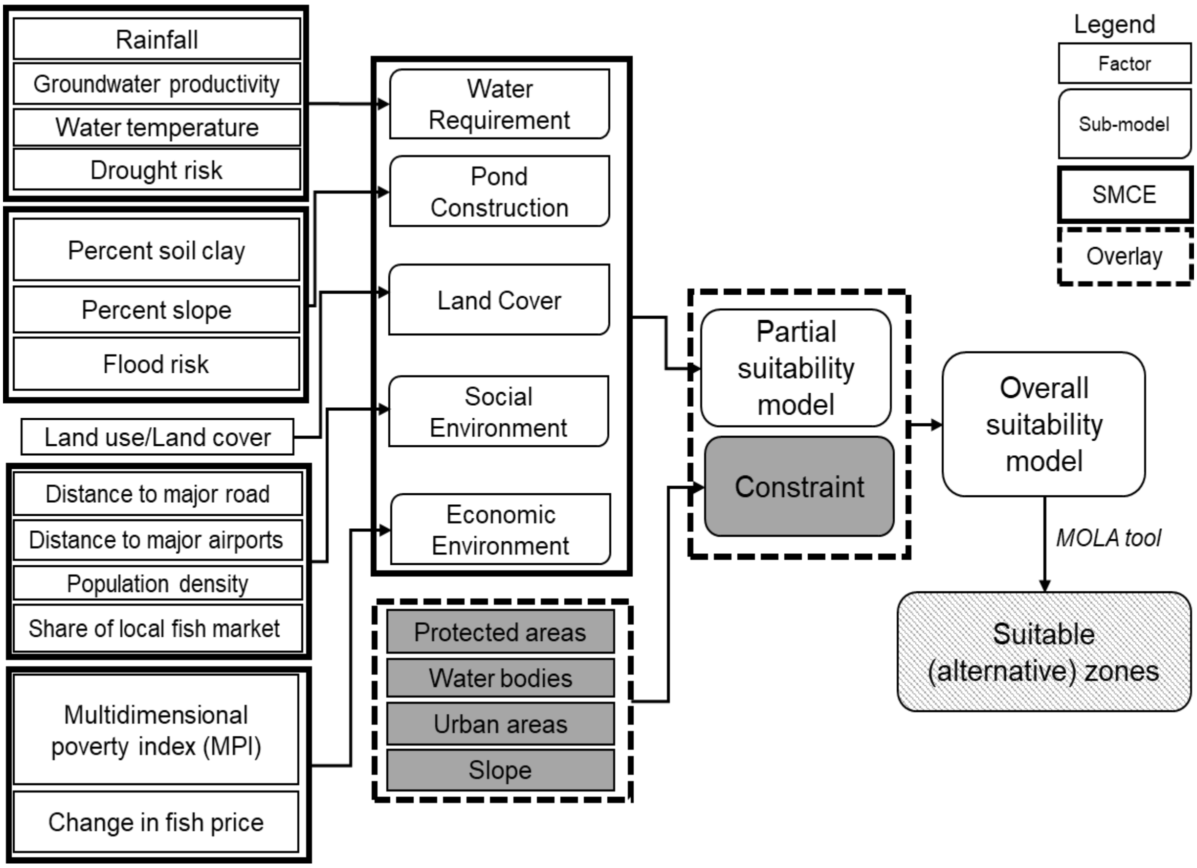

Figure 4.2: Framework of the aquaculture site suitability model.

4.2.2.2 Data processing

Modelling was carried out using TerrSet [Clark Labs, MA, USA] and the output images were displayed using QGIS v3.16.11 (QGIS Development Team, 2020). It is important that all input layers have a common spatial property to allow for compatibility during analysis and modelling. This was achieved by georeferencing — the process of assigning location to data using a reference system (Longley et al., 2013). The spatial property of the study area as used in the present study is given in Table 4.2. The data layer for each factor was projected using the CLABSHA (Clark Labs Hammer-Aitoff) reference system with a resolution of 300 m. CLABSHA is the regional reference system parameter file for Africa provided in TerrSet, which was necessary in this study because the study area spans three UTM zones (30N, 31N and 32N) and does not have a harmonized national grid for projection. After pre-processing, the data layers in each of the five suitability categories were reclassified and weighted before they were combined into sub-models respectively.

Table 4.2: Parameter values of window and projection of the study area

Parameters	Value	
	Window	Projection
Number of columns	4517	4518
Number of rows	3562	3563
Minimum X	2.2611111	3365.6272799
Maximum X	14.808333	4762.0736065
Minimum Y	4.1277778	5347.6891408
Maximum Y	14.022222	6448.9384997
Ref. system	Latlong	CLABSHA
Ref. unit	Degrees	Meters

Reclassification

To allow the different input data layers to be combined meaningfully, their values were reclassified to a common scoring system. There are different methods that can be employed. The simplest method is the Boolean reclassification which is binary, and values are scored 1 (favourable) or 0 (unfavourable). Other popular methods of reclassification are the use of discrete classes (e.g., suitability scores of 1 - 4) or fuzzy membership function. In this study, fuzzy reclassification was used to assign suitability scores from 0 to 1 (real numbers) as a set of continuous values, where 0 represents non membership and 1, complete membership (Eastman, 2016b). The sigmoidal fuzzy function was used as most appropriate based on knowledge of the fishpond systems and literature of the suitability factors.

Fuzzy reclassification is different from the Boolean or discrete method in that the former relaxes the definition of a boundary by admitting intermediate values of class membership, hence helps to accommodate uncertainties when interpreting the suitability map (Eastman, 2016b; Falconer et al., 2018). The 'Fuzzy' module in TerrSet provides four options for the membership function: sigmoidal, J-shaped, linear, and user-defined. The reclassification process is determined by the position of four control points, a, b, c, and d on the curve as well as the shape of the curve (Figure 4.3). In this study, the control points and choice of fuzzy (Sigmoidal) function were determined based on both knowledge of the study area and literature on the suitability factors being considered. The sigmoidal function is the most used option in fuzzy set theory (Eastman, 2016b).

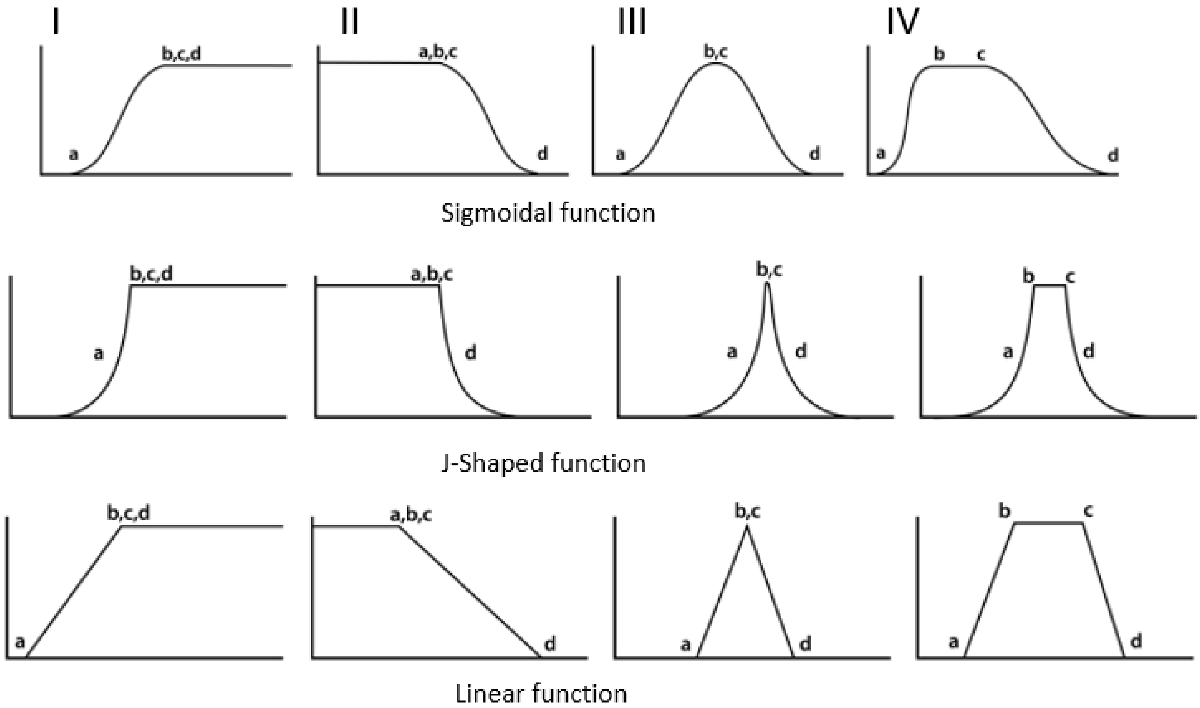

Figure 4.3: Fuzzy membership functions. **I** = monotonically increasing; **II** = monotonically decreasing; **III** = symmetric (b = c) and **IV** = symmetric (b ≠ c). Modified from Eastman (2016).

<u>Weighting and SMCE</u>

The factors were assigned weights based on experts' opinion. Weighting is necessary to enable a SMCE. The weight of a factor or criterion is an expression of its importance relative to others (Perez, 2002). The 'Weight' module in TerrSet uses the pairwise comparison method, which is an application of the analytical hierarchy process (AHP) developed by Saaty (1987). Firstly, the factors are arranged in a matrix, then each factor in a row is compared to each column factor across the same row on a scale of 1 to 9. Once the weights have been computed, a consistency ratio (CR) is generated alongside.

According to Saaty (1987), CR value less than 0.10 indicates consistency in the pairwise comparison, while a value greater than 0.10 suggests a departure from consistency. An unsatisfactory CR implies that the decision-makers should reconsider their ratings.

SMCE is the evaluation and combination of multiple criteria to achieve a single or set of objectives. TerrSet offers three options for conducting a SMCE: Boolean Intersection, Ordered Weighted Average (OWA) and Weighted Linear Combination (WLC), each with its benefits and limitations. The WLC method was used in this study, because unlike the other two procedures, it allows factors to be combined in a compensatory manner (tradeoff) according to their respective weighting (Eastman, 2016b). SMCE can be expressed as Equation 4.1.

$s = \sum WiXi$ (Equation 4.1)

Where s = Suitability, Wi = Weight of factor i and Xi = Score of factor i

4.2.2.3 Sub-models

Water requirement

Aquaculture operations largely depend on water availability and quality (Boyd et al., 2007). In Nigeria, the major source of water for farms is borehole (Anetekhai, 2013), so, rainfall was used to represent groundwater availability rather than direct source of pond water in this sub-model. This meant that where rainfall is high, the potential for groundwater availability is high and vice versa. Other important factors considered were temperature, groundwater productivity (rate at which water can be abstracted) and drought risk. The weights and fuzzy reclassification function used in developing the sub-model are given in Table 4.3.

Temperature influences fish growth performance and most tropical warmwater fish species have been found to grow at temperature ranging between 20 and 35^{o}C, with optimum for African catfish at 28^{o}C (Conceição et al., 1998). Water temperature was estimated using Equation 4.2 (Kapetsky, 1994).

$MMWT = -6.35 + 1.3\ (MMDT)$ (Equation 4.2)

Where, $MMWT$ is mean monthly water temperature and $MMDT$, mean monthly daytime air temperature.

Global datasets of average monthly rainfall and air temperature (1970-2000) were obtained from WorldClim version 2.0 database (Fick & Hijmans, 2017), and used to create annual rainfall and water temperature input layers respectively. These were then reclassified into suitability layers, using the control points outlined in Table 4.3, based on the values obtained from Conceição et al. (1998).

The data on groundwater or aquifer productivity, which determines the rate of groundwater abstraction was obtained from the British Geological Survey (BGS) database (MacDonald et al., 2012). According to MacDonald et al. (2012), a borehole for irrigation agriculture must be able to sustain at least 5 l/s to be suitable, and for the hand pumped type, a yield of 0.3 l/s is acceptable. Drought risk was also an important consideration, as many parts of Nigeria have experienced historic and even recent drought conditions. The drought severity data layer, computed as mean length multiplied by dryness of all droughts that occurred in an area between 1901 and 2008, was obtained from the World Resources Institute (WRI) (Gassert et al., 2013). The layer had five original classes, where class 1 represents low severity score (< 20) and 5 is extremely high (> 50). Both groundwater productivity and drought risk layers were reclassified to continuous values using the fuzzy function and control points in Table 4.3. The factor weights were assigned following an acceptable consistency ratio. Figure 4.4 shows seasonal suitability layers for the water requirement sub-model, which is common to both objectives of modelling i.e., to identify suitable sites for aquaculture aimed at: (I) poverty and (II) economic growth.

Table 4.3: Data reclassification and weights* for water requirement sub-model

Factor (unit)	**Weight**	**Control point**				**Reference (control point values)**
		a	b	c	d	
Rainfall (mm/month)	0.4167	≤ 90	≥ 180	n/a	n/a	van der Mheen (1999)
Groundwater productivity (l/s)	0.0833	≤ 0.5	≥ 5	n/a	n/a	MacDonald et al. (2012)
Water temperature (^oC)	0.4167	20	28	32	35	Conceição et al. (1998)
Drought risk (severity score)	0.0833	5	1	n/a	n/a	Handisyde (2014)

**Common to both strategic priorities*

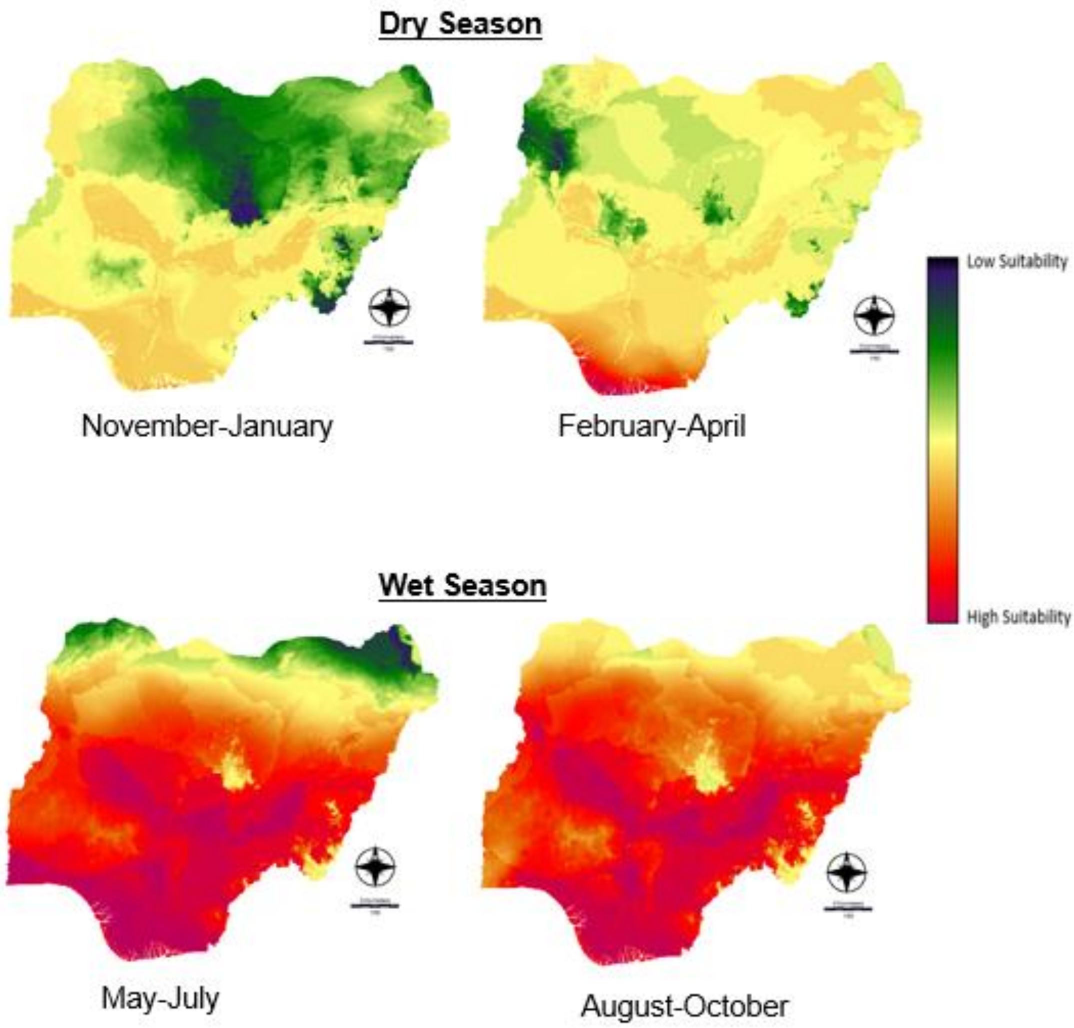

Figure 4.4: Seasonal water requirement suitability sub-models

Pond Construction

The structure and composition of soil can influence the suitability of an area for aquaculture, in terms of construction, water retention and pH (Salam et al., 2005). To accommodate the traditional method of pond construction in the study area, the range of optimum suitability, 15% to 35% soil clay content was adopted for this study (Table 4.4). The range of suitable clay content of different soil types reported for fishpond construction is 20% (low)– 60% (high) (Boyd et al., 2003; Hajek & Boyd, 1994). However, high clay content makes it difficult to use machinery, thus soils with 15% clay content can be considered optimal for pond construction (Tucker & Hargreaves, 2008).

In addition to soil composition, slope affects construction while the risk of flooding could affect decision on pond siting. The flood occurrence (number of floods recorded from 1985 to 2011) data layer for the study area had four classes: low (0-1), low to medium

(2-3), medium to high (4-9) and high (10-27) (Gassert et al., 2013). Figure 4.5 shows the suitability layer for the pond construction sub-model, which is common to both modelling objectives.

Table 4.4: Data reclassification and weights* for pond construction sub-model

Factor (unit)	Weight	Control point				Reference (control point values)
		a	b	c	d	
Soil clay (%)	0.4054	10	15	35	60	(Boyd et al., 2003; Tucker & Hargreaves, 2008)
Slope (%)	0.4806	0	0.5	2	8	(Aguilar-Manjarrez & Nath, 1998)
Flood risk (number of occurrence)	0.1140	4	1	n/a	n/a	(N. Handisyde, 2014)

**Common to both strategic priorities*

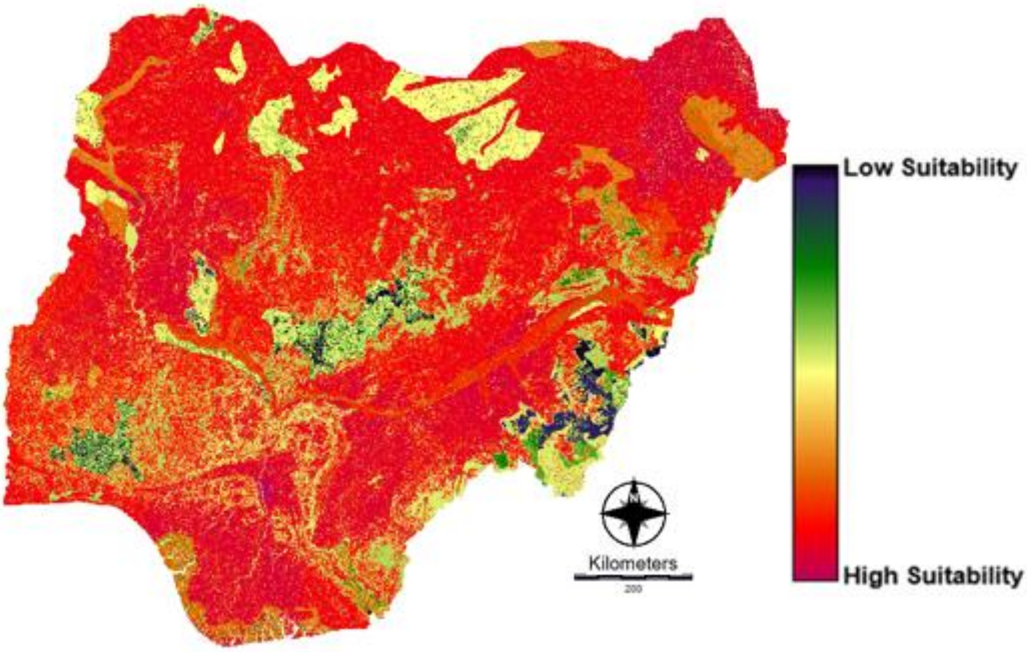

Figure 4.5: Pond construction suitability sub-model

Land Cover

Land cover data layer for 2015 was downloaded from the ESA Climate Change Initiative (CCI) land cover time-series v2.0.7 (ESA, 2017). The land cover classification was based on FAO's classification system in Table 4.5. Since the data layer had categorical information, values were standardized from 0 to 1, to ensure compatibility throughout the modelling process (Assefa & Abebe, 2018; Falconer, 2013; N. Handisyde, 2014). Land cover mapping enables the visualization of the impacts of different activities on the environment (ESA, 2017; Tappan et al., 2016). For example, mangrove destruction is one of the major negative impacts of aquaculture (De Silva, 2012). Therefore land change detection is important for spatial planning, so that future expansion of aquaculture will not adversely impact other land users. The layer for the land cover sub-model is given in Figure 4.6.

Table 4.5: Reclassification for land cover sub-model

Value	Label	Suitability class (score)
10	Cropland, rainfed	Suitable (0.85)
20	Cropland, irrigated or post-flooding	Highly unsuitable (0.15)
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	Unsuitable (0.50)
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland	Unsuitable (0.50)
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	Unsuitable (0.50)
60	Tree cover, broadleaved, deciduous, closed to open (>15%)	Highly unsuitable (0.15)
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	Highly unsuitable (0.15)
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	Unsuitable (0.50)
120	Shrubland	Suitable (0.85)
130	Grassland	Suitable (0.85)
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	Highly suitable (1)
170	Tree cover, flooded, saline water	Highly unsuitable (0.15)
180	Shrub or herbaceous cover, flooded, fresh/saline/brackish water	Highly unsuitable (0.15)
190	Urban areas	Highly unsuitable (0.15)
200	Bare areas	Highly suitable (1)
210	Waterbodies	Highly unsuitable (0.15)

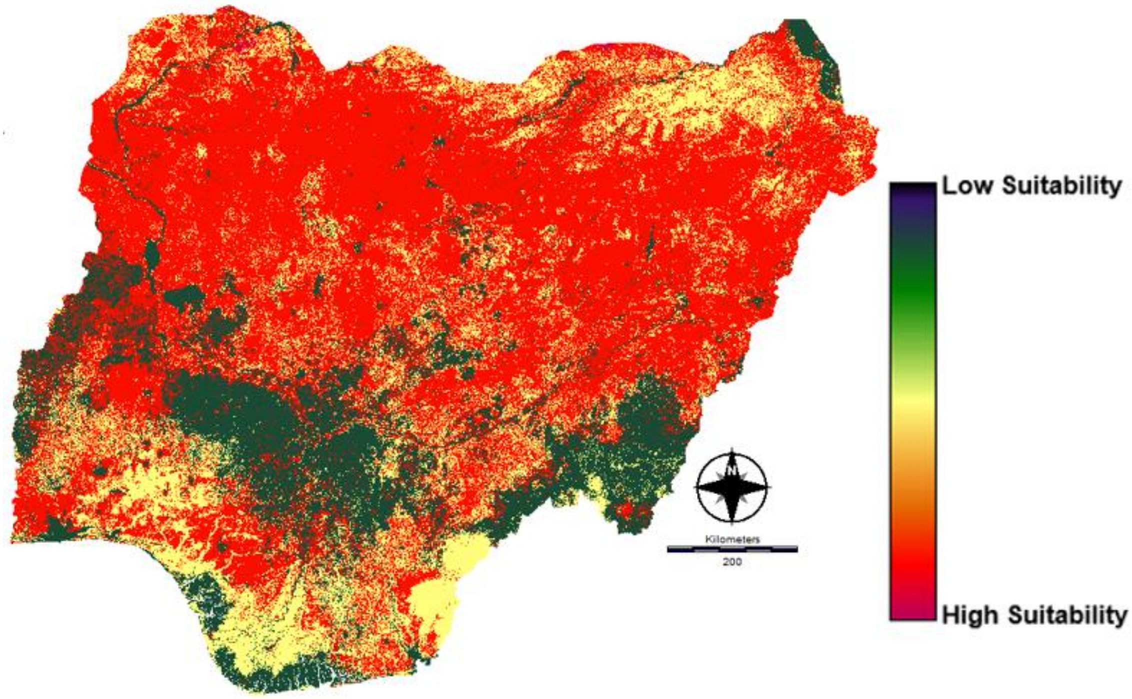

Figure 4.6: Land cover suitability sub-model

Social environment

Four factors were selected for the social environment sub-model as shown in Table 4.6. The first, population density was considered in terms of potential pollution (Falconer, 2013; Giap et al., 2005), meaning that the higher the population density within an aquaculture area, the more likely it could face household and other types of pollution. The input data layer was obtained from Landscan population distribution dataset (2018). Currently the two major means of transportation in the study area are road and airport (Onokala & Olajide, 2020). Consequently, a good aquaculture zone should be within reasonable distance of these facilities, to enable both national and international access. The data layer of major roads was created by digitizing roads on Google Earth [retrieved in 2019] and that of airports was from the repository of World Food Programme (Karakostis, 2019). Distance to road or airport was measured directly to the nearest cell, with suitability determined by the fuzzy function control points.

The layer, ‘share of local fish market’, was created by dividing artisanal fish catch (tonnes) in 2015 for each state (FDF, 2017) by their respective area (km^2). The assumptions here was that high artisanal fish catch in a state means less opportunity for aquaculture within that state. The factor weights and the control point values for reclassification are given in Table 4.6. The sub-models are shown in Figure 4.7.

Table 4.6: Factor weights and data reclassification for social environment sub-models

Factor (unit)	**Weight-Priority I**	**Weight-Priority II**	**Control point**				**Reference (control point values)**
			a	b	c	d	
Population density (persons/km^2)	0.30	0.30	0	100	500	5000	Adapted (Falconer, 2013; Giap et al., 2005)
Distance to major road (km)	0.30	0.30	n/a	n/a	10	50	Adapted (Díaz et al., 2017)
Distance to major airport (km)	0.10	0.30	n/a	n/a	10	100	Assumed
Share of local fish market [fish catch (mt)/km^2]	0.30	0.10	≥ 10	≤ 1	n/a	n/a	Assumed

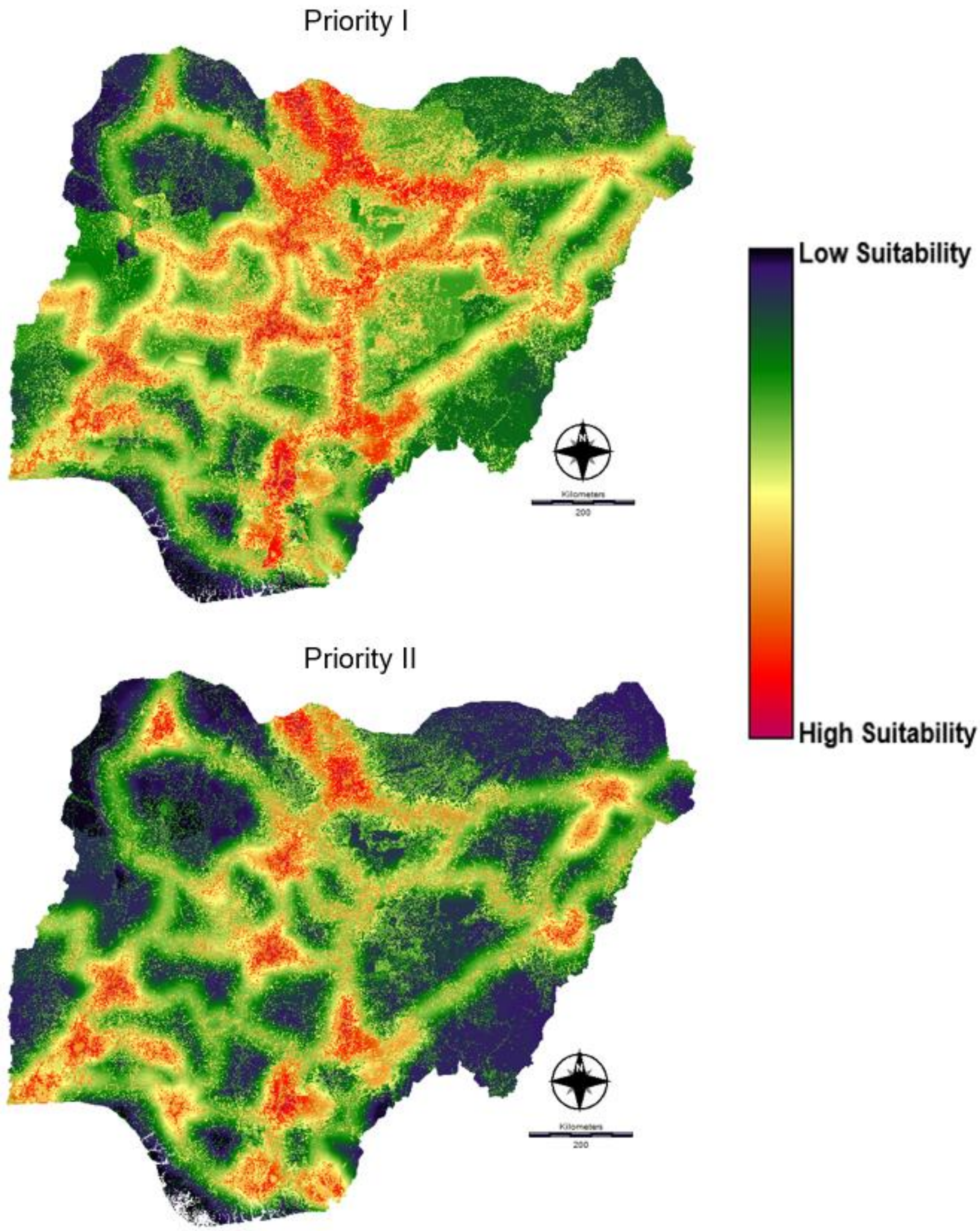

Figure 4.7: Social environment suitability sub-models for Priority I and II

Economic environment

For the economic environment sub-model, two factors were used: multidimensional poverty index (MPI) and price change (%) of fresh fish in each state. MPI is a measure of household poverty both in terms of income level and deprivation (UNDP, 2018). The assumption was that a high MPI indicates a high potential of aquaculture as a livelihood. The values of the control points used in this study were according to the range of values across the study area rather than some standard adapted from other studies. The price change of fish was calculated as the percentage difference of fresh fish price between 2008 and 2015 (FDF, 2017). For each strategic priority sub-model, the factors were combined based on the assigned weights (Table 4.7). The sub-models are shown in Figure 4.8.

Table 4.7: Factor weights and data reclassification for economic environment sub-models

Factor (unit)	**Weight-Priority I**	**Weight-Priority II**	**Control point**				**Reference (control point values)**
			a	b	c	d	
Multidimensional poverty index	0.75	0.50	0.01	0.64	n/a	n/a	Assumed
Price change of fish (%)	0.25	0.50	n/a	n/a	0	100	Assumed

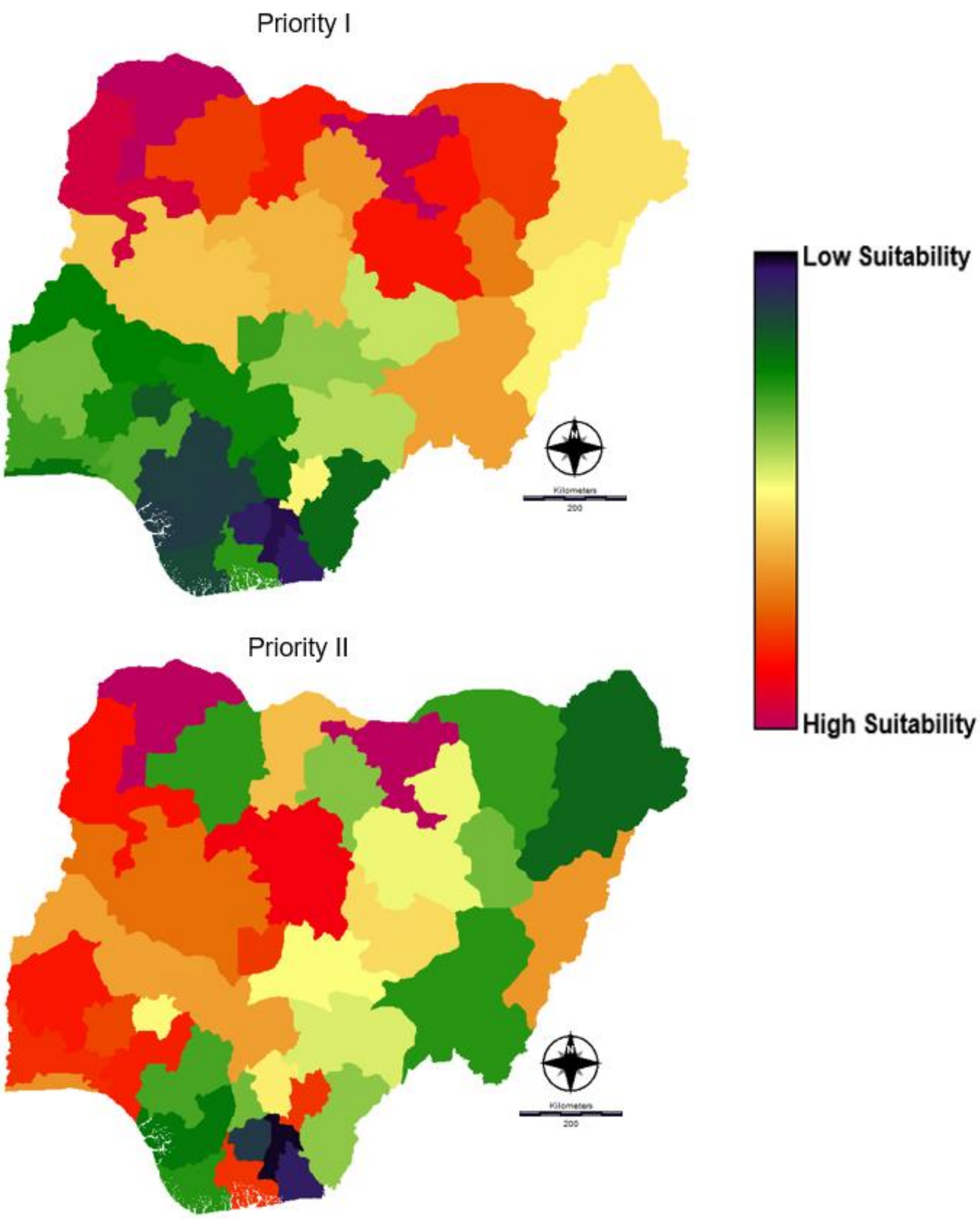

Figure 4.8: Economic environment suitability sub-models for Priority I and II

Constraint

The same constraint layer was used for both Priority I and II. This was created by combining the layers of urban areas, protected areas, waterbodies, and slope (Fig. 4.9). Urban areas and waterbodies were extracted from the LULC layers of ESA (2017), and protected areas, from the World Database of Protected Areas (UNEP-WCMC, 2019). All areas with slope greater than 8% were reclassified as a constraint.

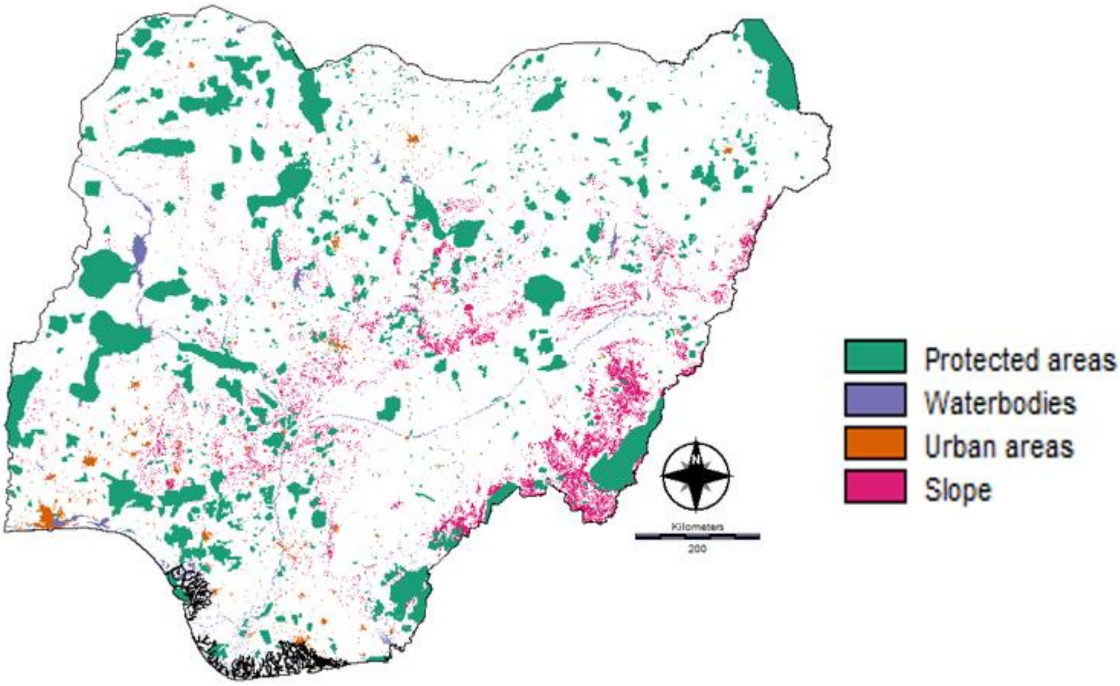

Figure 4.9: Constraint layer

4.2.2.4 Overall site suitability model

The five sub-models for each strategic priority were assigned a set of weights (Table 4.8). The WLC method of SMCE was used to combine the sub-models into the overall suitability model respectively.

Table 4.8: Weights assigned to the sub-models for strategic priorities I and II

Priority	**Water requirement**	**Pond construction**	**Land cover**	**Social environment**	**Economic environment**	**CR**
I	0.2566	0.1941	0.1941	0.1609	0.1941	0.03
II	0.2533	0.2260	0.2260	0.2260	0.0686	0.01

4.2.2.5 Suitable alternative zones and evaluation criteria

From the overall site suitability models, 5 zones or clustered areas with high sum of suitability scores were identified for each strategic priority using MOLA (Multi-Objective Land Allocation tool). MOLA runs an optimization algorithm that solves multiple objective, or as obtained in the present study, a single objective land allocation problem (Eastman, 2016b). To run the algorithm, the overall site suitability model was specified for one strategic priority at a time, with a total area of 100,000 ha to be identified and broken into 5 approximately equal zones.

Although the identified zones are the highest scoring clustered areas, these can be compared in terms of advantages and disadvantages, so further evaluation was necessary to establish which zones would be most appropriate for each strategic priority. The effect of season on the suitability of the zones for aquaculture was considered, given the variations in temperature and timings of rainfall between geographical locations in Nigeria. Since scenarios are based on past-to-present trends of drivers of change, the impact of long-term changes on the suitability of the zones was also considered. To investigate this, older datasets (circa 2000) were used to construct the same suitability model as the current one (circa 2020). Therefore, all the sub-models, including the constraint layer were expected to change between the old and current model dates, except ‘water requirement’ and ‘pond construction’ sub-models. The third criterion was the potential for conflict with other land uses (e.g., rice farming). The details of the 3 criteria are given in Table 4.9. A benefit criterion meant that a higher score on this criterion is preferrable. In contrast, a lower score on a cost criterion is preferrable.

Table 4.9: Set of criteria used in the present study to evaluate the alternative zones

Criterion (km^2)	Label	Cost/Benefit	Category	Rationale
Seasonal variation	C1	benefit	temporal	Aquaculture zone should have good water availability/quality that is consistent throughout the year
Long-term variation	C2	benefit	temporal	Aquaculture zone should have a land cover and local market that can support farming activities in the long-term
Overlap with rice-producing area	C3	cost	spatial	Aquaculture zone should be in areas with low potential for conflict with other resource users

Similar to the current data layers for land cover and population density, those for year 2000 were obtained from ESA (2017) and ORNL (2019) respectively. The data layer for major roads in Nigeria (c.2000) was from the repository of World bank (2009). Since all of the major airports in Nigeria were established before the year 2000 (Karakostis, 2019), the same data layer was used for both model dates. The 'share of local fish market' layer (c.2000) was created by substituting the artisanal fish catch per state in 2015 with those of 2008 as reported by FDF (2017). For the economic environment sub-model, MPI data at subnational level for Nigeria was unavailable prior to 2018, so the same data layer was used for both model dates. Also, the price of fresh fish data was unavailable for c.2000, therefore the same input layer as c.2020 was used. To update the constraint layer, urban areas, and waterbodies (LULC layer, 2000) were used to replace the current constraint layer. The metadata of the current dataset on protected area was filtered to create the c.2000 layer, by removing all protected areas designated after year 2000 because previous datasets were unavailable.

Having defined the criteria, the next stage involved scoring the zones against each criterion. For C1, seasonal 'water requirement' sub-models were developed in same way as the original sub-model, except that rainfall and water temperature layers contained average values for August-October (wet season) and February-April (dry season). Then, the area (km^2) of each identified zone which overlaps with portions (where suitability score ≥ 0.70) on the seasonal sub-models was computed separately for wet and dry seasons. The mean area of overlap was then standardized using Equation 4.3. In the case of C2, a layer generated to show only portions that maintained a suitability score ≥ 0.70 between c. 2000 and c. 2020 models was used as reference to estimate the overlapping area by each zone. For C3, the map of rice-growing areas in Nigeria was obtained from CGIAR rice database (https://ricepedia.org/) and made compatible with all other input data layers in this study (see Figure 4.10). Like C1 and C2, the overlapping area by each zone was computed. Since C1 and C2 are benefit criteria, the standardization was achieved with Equation 2, and for a cost criterion C3, Equation 4.4 was used (Voogd, 1982).

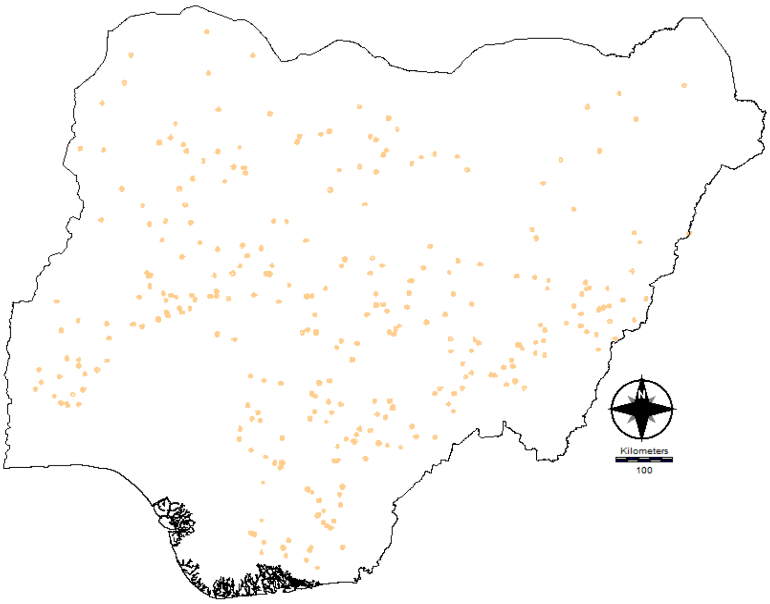

Figure 4.10: Data layer of rice-producing areas in Nigeria. Each point represents approximately 60 km^2

$$Standardized\ score = \frac{actual\ score}{maximum\ score} \qquad \text{(Equation 4.3)}$$

$$Standardized\ \ score = 1 - (\frac{actual\ score}{maximum\ score}) \qquad \text{(Equation 4.4)}$$

4.2.2.6 Weighting of evaluation criteria

After scoring the zones against each criterion, the criteria must be assigned weights to enable a SMCE. The swing weighting method (von Winterfeldt & Edwards, 1986) as adapted by Ram et al. (2011) was used to generate criteria weights in each scenario. However, the exercise was conducted online, which involved a survey in four parts with two groups of experts, each group consisting of 7 participants (see Appendix B). Group 1 specialized in environmental management of aquaculture, and Group 2 in aquaculture society/technology. In Part 1, each participant was presented with a description of the three criteria and asked to assign a weight of 100 to the criterion they thought was most important. Then weight the remaining two criteria relative to 100. Part 1 was assumed to represent a normal situation in which the challenge to spatial planning is minimal (scenario S3). In Parts 2, 3 and 4, the participants were presented with three alternative scenarios (S1, S2 and S4 as excerpts, respectively). For each, following the same weighting procedure as Part 1, participants were asked to consider the scenario presented, and weight the criteria again. The weights were then standardized for each

Group and the mean values recorded. This meant that four sets of criteria weights were generated, one for each scenario.

4.2.3 Choice phase

In the choice phase, the five alternative zones were evaluated through weighted summation (Equation 4.5). Therefore, the output for each strategic priority is a ranking of the five zones based on their respective performance score in each scenario.

$$Pi = \sum Xc \,.\, Wcs \qquad \text{(Equation 4.5)}$$

Where Pi = Performance of zone i in terms of criterion c under conditions of scenario s. Xc is the criterion score, while Wcs is the relative importance (weight) of criterion c in scenario s.

Finally, sensitivity analyses were conducted to assess the robustness of the rankings. This was based on the idea that the ranking of a set of alternatives, termed zones in the present study, is dependent on their criteria scores and weights, so any change in scores and/or weights results in a change in the ranking (Janssen & Van Herwijnen, 2006). In the present study, changes were scenario-based, which was reflected in weights, since variation in scores can only be associated to potential measurement errors. The implication was that, for each strategic priority, the criteria score of a zone is the same in all scenarios, while the criteria weight differed between scenarios. The sensitivity analyses were conducted using DEFINITE v3.1 (Decision making software for a finite set of alternatives) [SPINlab, Amsterdam]. The software provides options for analysis, including multicriteria, cost-benefit and graphical methods for comparing predetermined alternatives and ultimately indicates the best alternative.

4.3 Results

4.3.1 Aquaculture site suitability models and the alternative zones identified

The overall site suitability models show areas suitable for aquaculture with spatial variability between the two strategic priorities (Figure 4.11, A and B) based on the suitability factors used in this study. For Priority I, i.e., mapping suitability of areas aimed at poverty alleviation, the areas with high suitability were localized across northeast-to-west. This pattern was similar but occurred in the far south for Priority II, where the target was to locate suitable areas for expansion that will focus on economic growth (GDP). The five alternative zones identified for Priority I and II (Figures 4.11C and D) respectively, further display the spatial variability in the overall suitability models. The respective zones signify the five top clusters (approximately 20,000 ha each) with the highest sum of suitability scores and potential to be designated as aquaculture zones.

4.3.2 Criteria weights and the ranking of zones

The outcome of the swing weighting exercise for the different scenarios is given in Table 4.10. The criteria weights in scenario S3 reflected those expected under normal circumstance in which the challenge to spatial planning is minimal, unlike in S1, S2 and S4 with bigger challenges. Criterion C1 (seasonal variation in suitable areas for aquaculture) was assigned the most weight, consistently greater than 0.4 across the four scenarios. Generally, the order of relative importance or weight assigned to criteria across scenarios was C1>C2>C3. In contrast, the difference between the highest and lowest weights (i.e., range) is greater in C3.

Table 4.10: Criteria weights (mean) elicited from the two groups of aquaculture experts

Criteria	**Scenario**				**Range**
	S1	S2	S3	S4	
Seasonal variation (C1)	0.452	0.417	0.453	0.405	0.048
Long-term variation (C2)	0.340	0.278	0.336	0.345	0.067
Overlap with rice area (C3)	0.209	0.306	0.211	0.250	0.097

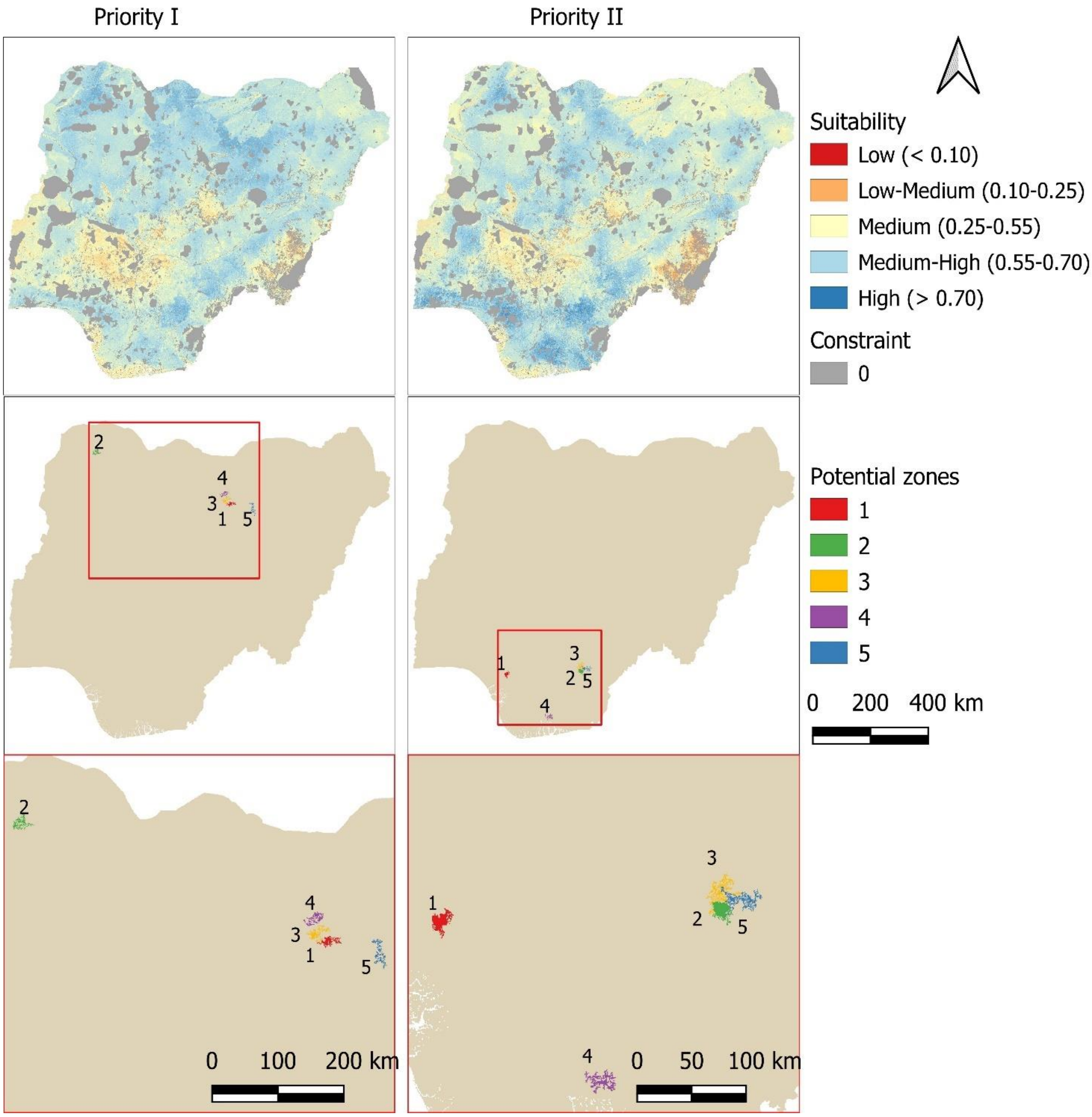

Figure 4.11: Suitability modelling outputs for Priority I and II. 'A' and 'B' are the overall site suitability models. The location of the five alternative zones for Priority I are shown in 'C' (middle) and zoomed ('C' bottom) and similarly for Priority II, in D (middle and bottom).

The results in Figure 4.12 show the ranking of the 5 alternative zones in S3, which largely represents the rankings in other scenarios. However, the performance scores vary slightly between scenarios based on individual and all three evaluation criteria. For Priority I, zone 5 ranked highest with performance score slightly more than zone 1 in all four scenarios. Zone 2 was consistently the lowest ranking across scenarios, while zones 3 and 4 were tied in ranking. In contrast to Priority I, zone 4 stood out as highest-ranking zone for Priority II, while others scored closely to each other.

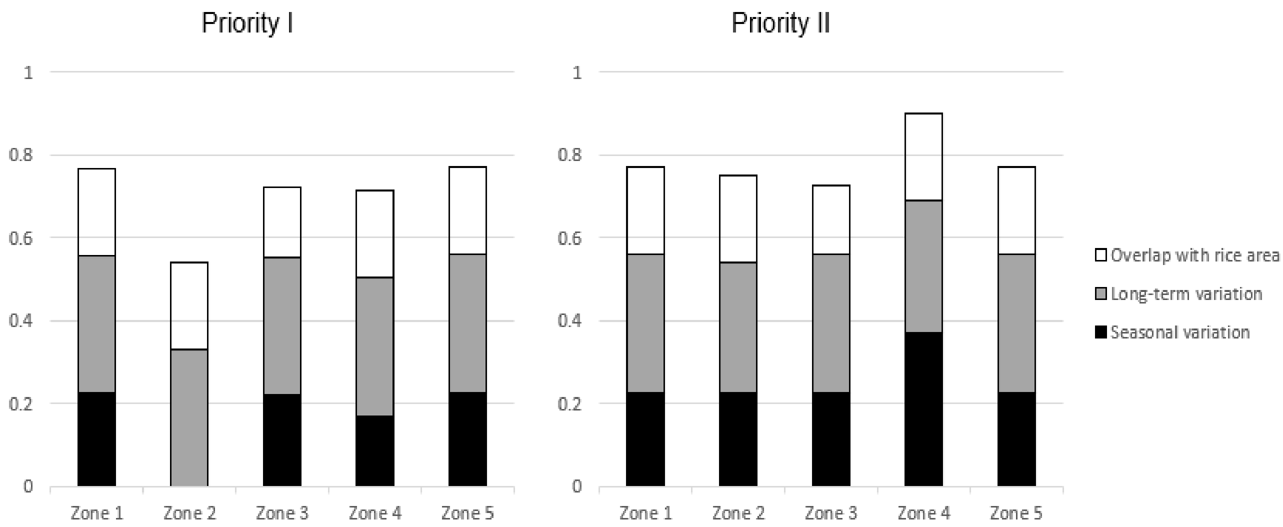

Figure 4.12: Ranking based on performance score of the zones in scenario S3. The contribution of each criterion performance is indicated by black, grey, or blank stack.

4.3.3 Stability of the rankings

Figure 4.13 [I(a), I(b) and I(c)] are results of sensitivity ranking of the 5 zones for Priority I. The results mean that, at the original and below the weight assigned to 'seasonal variation' criterion [I(a)], zone 5 ranks slightly above zone 1. Note that as the weight reduces in I(a), there will be proportional change in the other criteria weight to sum up to 1 or 100%. In contrast, as the weight in I(a) increases, zones 5 and 1 become tied in rank. Overall, the result shows that the ranking of zone 5 is stable in any scenario since no rank reversal was observed in I(a), I(b) & I(c). Looking at I(c), unlike zone 5, zone 1 appeared to be overtaken by zones 4 and 2. Although this reversal occurred at 0.9, which is far away from the original weight of 0.2, as well as from the most weight assigned (0.3 in scenario S2). For Priority II, the ranking of zone 4 is very stable, because only in extreme cases II(a) and II(b), that a weight of less than 0.1 or greater than 0.8 respectively caused zones 1 and 5 to rank higher. These are widely outside the range of weights elicited in all the four scenarios.

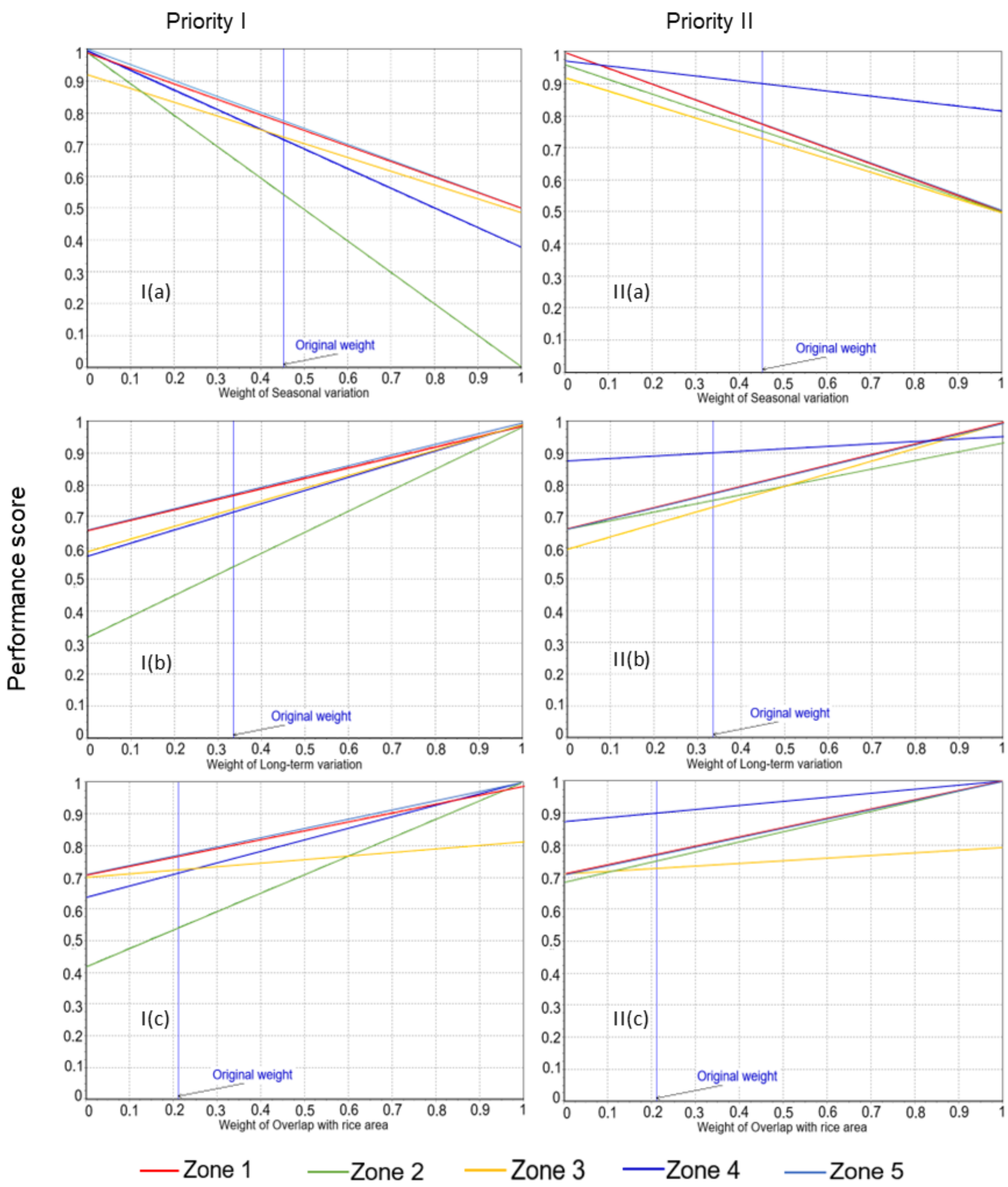

Figure 4.13: Sensitivity of the rankings to changes in criteria weights. The original weights are those elicited in scenario S3.

4.4 Discussion

The identification of specific zones suitable for aquaculture development is a strategic problem. This is a long-term planning issue, involves many different stakeholders and requires environmental assessments. The process must be relative to the possible future developments of other activities in the surrounding to ensure sustainability through the anticipation of conflict at the planning stage. Such issues and uncertainties are especially important considerations where environmental data is scarce, coupled with frailty of land use legislation. This study has shown that an approach that combines scenarios and SMCE can be useful to identify and prioritize suitable zones for aquaculture development even in data-poor environments. The demonstration of this approach was at a national scale and focused on Nigeria. Falconer et al. (2020) reports that site suitability modelling research in aquaculture at a national scale is limited by data availability and often with little application potential for decision support. The systematic nature of the approach developed in this study may allow easy adaptation for other countries or at subnational scales.

4.4.1 Overall site suitability models

Based on the scenarios of Nigerian aquaculture described by Yakubu et al. (2022), site suitability models for freshwater pond system were developed separately for Priority I and II. Priority I was to identify areas where aquaculture could be developed to maximize its contribution to the fight against poverty. Whereas Priority II focused on locating areas with high potential to support large-scale aquaculture business, to boost its contribution to GDP. Previous studies have used GIS-based models to support socio-economic assessment of aquaculture potential. Using a GIS-based Bayesian probability model, Van Brakel & Ross (2011) estimated that aquaculture development could significantly increase the income of poor farmers in Cambodia, provided their access to market is improved. Other similar studies that simulated the potential economic benefits of aquaculture includes Salam et al. (2003) and Ferreira et al. (2015). Although, more specific assessments such as effects of season are useful to support decisions on resource allocation (Falconer et al., 2018), the overall site suitability results here can be used to characterize an area. This minimizes the task of manual survey, thereby reducing costs both in terms of money and time.

There are several studies that have used scenario planning to structure problems for MCE (Marttunen et al., 2017), however, those with spatial dimension as in SMCE are rare. To the authors' knowledge, the present study is one of the first attempts in aquaculture research to integrate scenarios with SMCE. This is a useful consideration in the EAA (Ecosystem Approach to Aquaculture) discourse since the identification and allocation of suitable areas in the form of aquaculture zone is a critical step in the EAA implementation process. The conversion of croplands and other land use/cover for aquaculture expansion are being restricted or even prohibited around the world (Filipski & Belton, 2018). In such areas, and where similar restrictions may be considered in future, the result of this study further highlights the importance of a systematic and strategic decision analysis in aquaculture development planning. Similar to Smith & Brennan (2012), this study emphasizes the risk that may be associated with using historical maps of aquaculture suitability for evaluating strategies or for decision making during project planning. Land use and land cover (LULC) time series data have been used to examine impacts of changes on environmental resources, population distribution, census planning, urban and regional development, climate modelling and agriculture/aquaculture (ESA, 2017). The outputs from the present study employed LULC change as one of the factors responsible for long-term variations the site suitability model dates.

4.4.2 Potential zones for aquaculture, evaluation and ranking under different scenarios

Several studies on aquaculture site assessment have developed different methodologies for producing suitability and site selection models (e.g. Aguilar-Manjarrez & Nath, 1998; Asmah et al., 2021; Barillé et al., 2020; Díaz et al., 2017; Falconer et al., 2013). However, many do not go as far as prioritizing areas for the development of sites or zones, instead leaving that open for users to interpret the results themselves. The present study considered that planners and other decision makers alike may want to further narrow their options of potential zones, rather than using the original suitability models to decide on areas to physically survey during planning. In view of this, more specific and distinct areas were located within the GIS environment. The five locations for each of the two strategic priorities, therefore, represent areas that can be considered as potential zones for aquaculture development in the study area. These zones might also be considered as alternatives whereby they are compared before selection is done based on their performance scores against the evaluation criteria used. The set of evaluation criteria in this study had spatial and temporal elements to demonstrate the importance of flexibility in measuring the performance of alternatives. The criteria, seasonal and long-term variations in highly suitable areas, can generally apply to many other study areas. However, the spatial criterion (overlap with rice-producing area) was identified based on understanding of the spatial issues in Nigeria.

SMCE is the focal point of this study. Since the outputs of SMCE depend on the values of factors or criteria and weights assigned, these values and ultimately the SMCE outputs are open to different interpretations influenced by stakeholders' perspectives. The present study addressed such issues by adopting a scenario-driven approach, which first allowed for poverty alleviation and GDP to be defined as the strategic priorities based on scenarios by Yakubu et al. (2022), thus enhancing the usability of the resulting spatial models. As noted by Falconer et al. (2020) and Gonzalez & Enríquez-De-Salamanca (2018), the development of spatial models to support environmental assessment and planning decisions must begin with the "What", "Why" and "How" the models will be used in real world decision making. Secondly, the scenarios guided the identification and weighting of the suitability factors during the development of the overall site suitability models. Thirdly, the scenarios were used to elicit weights from the expert groups for evaluating the alternative zones. For example, scenario S2 emphasized a high conflict potential between aquaculture ponds and other resource users, which may have improved C3 weighting. Overall, the indication of a criterion's relative importance was consistent across the four scenarios (S1 – S4), which suggests the potential views of most stakeholders, if the weighting was done in a real-world setting. Ram et al. (2011) obtained similar results, having one of their three criteria scored least by decision makers consistently across 12 scenarios, while the relative importance of the remaining two criteria could easily be justified. Finally, a sensitivity analysis was conducted to assess the effects of changes in criteria weights on the performance scores or rankings of the potential zones that were identified in this study.

4.4.3 Limitations of the study and recommendations for further study

The availability and quality of data is a key issue in aquaculture spatial modelling (Falconer et al., 2020). However, the efforts of the research community, national authorities, and international organizations to increasingly make data available on open-source databases is commendable. This study utilized open-source datasets and it is expected that the approach developed can be enhanced as more data become available. For example, the long-term variation in highly suitable areas between the two dates, c. 2000 and c.2020 may significantly change, if different set of temperature and rainfall data was used, rather than the historical mean data (1970-2000) used for both dates. For the suitability factors of the overall model, the datasets for c. 2000 ranged from 2000 to 2009 and for c. 2020, the datasets were between 2015 and 2020. A consistent and up to date dataset may produce some increased visibility in the change observed in the model outputs between dates. Therefore, addressing such uncertainties, including those arising from measurements of factors or criteria could be an important validation of the model outputs. However, based on the scope of this study, only the stability in the ranking of potential zones, as a function of criteria-weighting between scenarios, was assessed through sensitivity analysis.

The performance of each potential zone identified is the sum on all three criteria against which the zone was evaluated. But decision makers may as well choose to base their decisions on a particular criterion, in which case it is useful to view performance on each criterion. However, given the large study area, it can be argued that more than three criteria would be required to facilitate real world application of the approach developed in this study. To address similar limitation, González Del Campo (2017) developed an online GIS-based tool for identifying plan-specific environmental criteria in Ireland, emphasizing the need for exploring the sensitivity of a range of these criteria. So, the more criteria are set for evaluation that meet the needs of most stakeholders, the easier it becomes to compare alternatives such as the zones identified in the present study and ultimately reach a decision. Therefore, defining more evaluation criteria is both a subject of and useful for further studies in aquaculture spatial planning.

Apart from the issues with temporal resolution of the dataset, the spatial resolution is also very important. For example, a finer spatial resolution of the data layer of rice-producing areas may increase the power of the C3 criterion to differentiate between zones, and more specifically for site selection. However, it is also important to consider the balance between the quality and number of criteria in evaluating alternatives. As more data become available, further studies in the same study area or elsewhere, may employ additional criteria such as: distance between potential zones or between zones and protected areas, proportion of zone already used for aquaculture, etc. Also, a very important aspect to support aquaculture sustainability in regions with weak natural resource legislation is to better understand the level of spatial association between existing aquaculture ponds and other land uses.

4.5 Conclusion

This study explored the use of scenarios for problem structuring in GIS-based aquaculture site suitability modelling to enhance the scope of the resulting decision support models. The models were designed and built for identifying terrestrial zones that are suitable for aquaculture with respect to different economic goals rather than the common use of already developed suitability models in testing different scenarios to portray usability. Therefore, a new approach has been developed and applied by locating and comparing alternative zones with high potential for aquaculture development in Nigeria. The results can be used by planners to integrate aquaculture in land use planning, and the approach enhances the applicability of aquaculture site suitability models, by providing more flexibility and decision options for stakeholders during aquaculture development planning. Although, this study considered a single objective multi-criteria issue, i.e., land allocation for aquaculture development, multiple objective decision problems which are either conflicting or complementary may be addressed in future studies.

CHAPTER 5 EXPLORING DRIVERS OF FARMERS' PERCEPTIONS OF AQUACULTURE CLUSTER IN NIGERIA AND IMPLICATIONS FOR SUSTAINABLE EXPANSION

5.1 Introduction

The role of sustainable aquaculture is recognized in discussions around future food security and environmental health (Béné et al., 2016; Simmance et al., 2022; Troell et al., 2014). Despite the rapid growth of global aquaculture and some improvements in addressing its sustainability challenges, more work needs to be done to achieve the desired targets (Naylor, Hardy, et al., 2021). One of the key targets is to expand aquaculture areas sustainably and minimize conflict with other activities in the long term (Aguilar-Manjarrez et al., 2017; Falconer et al., 2018). This is complicated as spatial issues are location specific. Thus, while the role of spatial planning has been demonstrated in promoting aquaculture growth, the tools, or methods for implementation vary with the physical and socioeconomic factors characterizing the location under consideration (Falconer et al., 2020). In developing regions like Africa, aquaculture activity is dominated by small-scale farmers, most of whom are producing and marketing their products with limited access to affordable inputs, financial and transport services (Kassam et al., 2011). Cluster management is deemed to be a promising way to address such difficulties, because it encourages group of farmers to interact, pool resources and implement similar production standards (Ha et al., 2013; Joffre et al., 2020; Kassam et al., 2011). However, the process to identify and designate such clusters must have a good scientific basis to allow for successful monitoring and ensure sustainable production (Aguilar-Manjarrez et al., 2017; Corner et al., 2020).

Generally, a cluster can be defined as a geographical area with interconnected companies and supporting institutions, in which firms receive economic benefits that are not obtainable by those firms outside the area (Porter, 2000). According to Tveteras (2002), these economic benefits often lead to increased productivity of firms or more specifically, increased capacity for innovation and growth that is sustainable. The United Nations Industrial Development Organization (UNIDO, 2013) describes how a cluster approach to economic development is useful in achieving inclusive growth. The three main economic benefits, also known as agglomeration economies are; better access to specialized labour and technical support, stronger value chain, and ease of sharing knowledge among actors (Tveteras, 2002).

Kassam et al. (2011) defines an aquaculture cluster as a group of farms or farmers located in the same area, often sharing the same water source and adopt the same farming practices and species. An aquaculture cluster can also be referred to as Farmers' Organization (FO) or a grouping of FOs in the same locality including cooperative, association, union, informal group, club etc. (Joffre et al., 2019; Kassam et al., 2011). Cluster farming is believed to be a mechanism that have contributed to aquaculture growth in several Asian countries, such as Bangladesh, India and Vietnam, primarily through reduction in production cost and improved access to market (Kassam et al., 2011). Other benefits of aquaculture clustering highlighted in the literature include increased use of modern inputs (Hu et al., 2019; Zhang et al., 2019), better access to information and higher adoption rates of better management practices (Joffre et al., 2019), higher profits, including export performance (Gaasland et al., 2020; Umesh et al., 2010), and improved access to government support (Ha et al., 2013).

However, aquaculture clustering around the world is largely unplanned as it often precedes interventions from government and non-governmental agencies. The rapid expansion of area employed for aquaculture in Bangladesh has been described as spontaneous because farmers often convert rice paddies into fishponds to achieve higher returns, and production is believed to have clustered overtime (Filipski & Belton, 2018; Zhang et al., 2019). A similar trend is seen in Vietnam where shrimp farms have replaced several rice-producing and mangrove areas (Ha et al., 2013; Joffre et al., 2019). In India, shrimp farming in unorganised clusters faced frequent disease outbreaks until a government-collaborated project from 2002 significantly reduced disease risks through the establishment of farmer clubs (Umesh et al., 2010).

Clustering is also starting to occur in Africa where aquaculture is still an emerging sector. In Nigeria, fish farm area is increasing, with significant clustering of production facilities within urban areas (Achoja, 2019; Adeogun et al., 2007; Miller & Atanda, 2011). Such a pattern of development may become unsustainable with increasing urbanization. As urban sprawl occurs, there will be limited suitable area for aquaculture expansion or pressure to change to other land use. Hence to devise strategies that would support a careful planning and management of aquaculture clusters in Nigeria, it is imperative to understand how existing aquaculture clusters have formed, the advantages and disadvantages experienced so far and how they are perceived by the farmers and public. However, due to Covid-19 restrictions which have reduced the chances of conducting detailed fieldwork, investigating farmers perception of aquaculture cluster appears more feasible. Perception can be complex and based on different factors that can be difficult to untangle. Machine learning methods such as logistic regression and Classification & Regression Trees (CART) offer a chance to identify the key ones from a set of factors. For example, Alexander et al. (2016) and Thomas et al. (2018) used logistic regression to assess public perception of aquaculture, while Ouréns et al. (2022) applied random forest to understand stakeholders' perceptions of the governance of their local fisheries.

The aim of this study is to gain insight into the views of Nigerian fish farmers on aquaculture clusters as well as the requirements for effective cluster management across the country. To this end, a survey was conducted to answer the following questions: (1) How do fish farmers in Nigeria perceive aquaculture clusters? Are farmers likely to remain, if already in a cluster, and if not, to join such clusters? (2) What factors influence fish farmers perceptions of potential benefits and limitations of cluster farming in Nigeria? The results of this study can help to raise awareness on the benefits of a planned cluster-based approach, and to facilitate communication between the different stakeholders involved in the aquaculture sector.

5.2 Materials and methods

5.2.1 Data collection

A framework for understanding the process of adoption of agricultural innovation (Meijer et al., 2015) was adapted in the present study. Here, a questionnaire (Appendix C) was designed using '*Jisc*' online surveys [www.jisc.ac.uk/online-surveys]. The questionnaire was divided into four sections: (i) Farm characteristics (ii) Farming practices (iii) Farmers' attributes (iv) Perception of aquaculture clusters, each section for one category of data respectively (Figure 5.1). The data was collected from November 2021 to January 2022. To avoid respondent fatigue (O'Reilly-Shah, 2017), the questionnaire was designed to ensure ease of completion while maintaining the scope of the study. Demographic variables such as age, gender and income are important considerations, but were not included because their distributions would most likely be skewed based on the results of various surveys previously conducted (Adeogun et al., 2007; Ofuoku et al., 2008; Ogidi, 2016; Omeje et al., 2020; Subasinghe et al., 2021). Instead, the present study employed two demographic variables: education level and farming experience (years) deemed to have relatively normal distribution.

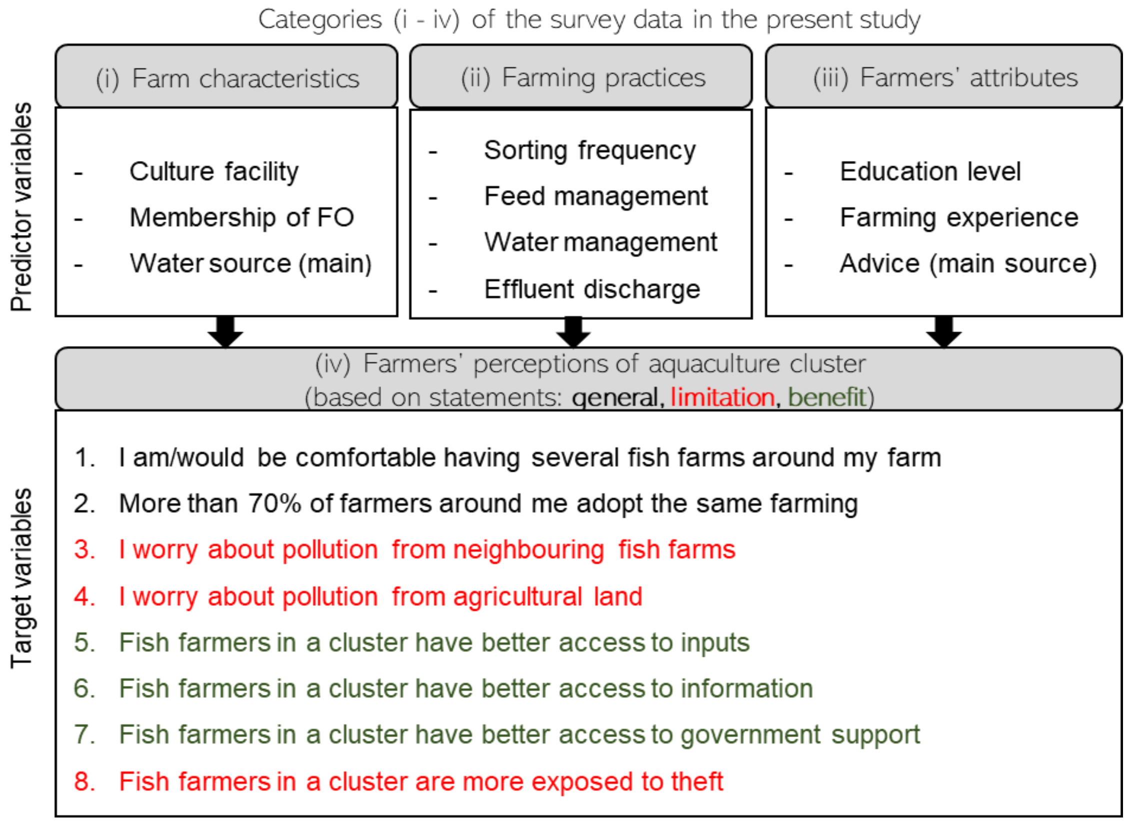

Figure 5.1: Categories of data collected in the present study using questionnaire (Adapted from the analytical framework for agricultural innovation adoption by Meijer et al. (2015).

The eight statements used to elicit farmers' perceptions about aquaculture clusters can be split into: general (statements 1 and 2), potential limitations (statements 3, 4 and 8) and potential benefits (statements 5, 6 and 7). Since the aim of this study was to understand farmers' perceptions of aquaculture clusters rather than to evaluate impacts of clustering on aquaculture business in Nigeria, the statements were derived from the literature. For example, considering the link between knowledge and perception (Meijer et al., 2015), statement 1 was intended to map farmers' understanding of the concept of cluster farming to the perception of their own farm surrounding. This informed statement 2, which was about farmers' perception of the activities of other farmers. There are designated agricultural development zones across Nigeria (Akinsola & Oladele, 2004; Ofuoku et al., 2008; Ogidi, 2016). Because aquaculture is considered a subsector of agriculture, the continuous expansion of both activities in proximity without a properly defined integrated approach or land use plan may become unsustainable (Yakubu et al., 2022). Such insight therefore justifies the statements 4 & 8 and altogether, designed to elicit farmers' perceptions of aquaculture clusters.

The link to the questionnaire was shared with known farmers directly as well as with contacts in the aquaculture industry through email and social media platforms. Although it was believed that some farmers have little or no access to the internet, the response rate during the first month of launching the survey was much lower than expected. This may have resulted from the increased use of questionnaire across many disciplines especially public health, to collect research data during the Covid-19 pandemic (de Koning et al., 2021). To overcome this challenge, three field representatives, one each in the north, north central and south of Nigeria were deployed to administer the questionnaire using a paper and pencil version. At the end of the survey, a total of 152 responses were collated for analysis (Table 5.1).

Table 5.1: Number of respondents by region and state in Nigeria

Region	**State**	**Number of Respondents**
North	Kaduna	1
	Katsina	1
	Kebbi	72
North central	Abuja (Capital)	6
	Kwara	7
	Niger	19
South	Abia	1
	Delta	30
	Edo	3
	Lagos	2
	Ogun	5
	Oyo	4
	Akwa Ibom	1
Total	**13**	**152**

5.2.2 Data analysis

The question on how farmers perceived aquaculture clusters, including their likelihood to remain in or join a cluster was addressed using descriptive statistics (measures of frequency). All analysis was conducted using the ‘R’ statistical software (R Core Team, 2020). The descriptive analysis was characterized by each of the four categories in the questionnaire. Next, Random Forest (RF) method was used to model the relationship between the predictor and target variables as well as compute the importance score of each predictor variable. The RF method was chosen over others such as Logistic Regression because RF does not assume normality in a dataset, thus able to capture non-linear relationships and produces more stable variable importance ranking (Schonlau & Zou, 2020).

5.2.2.1 Random Forest for modelling predictors of farmers’ perceptions

RF is a non-parametric machine learning algorithm that can handle dataset with small observations and many predictors, while minimizing overfitting (i.e., fitting a model too closely to a particular dataset, such that it results in poor performance on a new dataset) (Breiman, 2001). The RF method builds on CART, by improving on its limitation of producing a single tree which gives highly unstable predictions. This instability is due to significant variability in the tree structure with slight changes in training samples (Strobl et al., 2009).

RF works by building and aggregating multiple trees from the same training dataset, thereby forming an ensemble of classification or regression trees (Breiman, 2001) . Every tree in the RF is built independently by random selection of a subset of *n* observations with replacement (bootstrapping) (Schonlau & Zou, 2020). Prediction by a RF model is therefore a ‘majority vote’ on all the prediction aggregated from the individual trees for classification. In the case of regression, a RF model prediction is a weighted/unweighted average of predictions by the individual regression trees. This ability to aggregate outcomes of many different trees makes RF a very powerful tool for prediction (Strobl et al., 2009). However, the accuracy of prediction depends on the RF model’s hyperparameters, mainly number of trees (*nTree*) in the forest, size of tree (*nodesize*) and number of candidate variables at each split, denoted by *mtry*. According to (Strobl et al., 2009), the use of default values for these parameters is mostly sufficient to produce high prediction accuracy. In the R package, *randomForest,* the default values for classification trees are *nTree* = 500, *nodesize* = 1 and *mtry* = sqrt(*p*), where *p* is number of predictor variables (Liaw & Wiener, 2002).

In the present study, RF was used to test the influence of the predictor variables on farmers' perceptions (i.e., the likelihood that they will agree or disagree with the statements about potential benefits and limitations) of an aquaculture cluster (Figure 5.1). To keep the tree size manageable and allow ease of interpretation of results, the standard five-point Likert scale response was collapsed into three response classes as follows: 1 and 2 = agree, 3 = undecided, 4 and 5 = disagree. The RF modelling focused only on statements (or target variables) that achieved at most 80% of the observations among the three response classes. Although this threshold was set arbitrarily, it should be noted that unbalanced observations between response classes will tend to guide the prediction of RF and most statistical models in favour of the class with the most observations (Strobl et al., 2009). Considering this, it was assumed that above the set threshold, the classification of farmers' perceptions based on a target variable (statement/response) will be unaffected no matter the different permutations of the modelled predictors.

The survey data was split into 80% for training and 20% for validation, while the RF algorithm was allowed to run on default settings. This means that, in each bootstrap of the 500 individual trees, the RF algorithm takes 80% (with replacement) of the dataset for training and the remaining 20% as out-of-bag samples for validation (to measure prediction accuracy). Here, the dataset contains 152 observations with 10 predictors for classifying responses (farmers' perception) based on one statement at a time. One RF model is therefore built for each statement that satisfies the previously set threshold, i.e., statements in which no response class had more than 80% of the 152 observations. For every RF model built, the Out-Of-Bag (OOB) samples is used for validation in two ways. 1) Ordinary validation based on prediction by the whole ensemble of trees. 2) OOB validation based on only those trees that do not contain an OOB samples in their bootstrap training samples. The importance score of each predictor variable was also computed, which means that variables with a higher score are more relevant to the RF model accuracy than those with lower scores.

5.3 Results

5.3.1 Characteristics of farm and farming practices

The descriptive statistics for farm and farming characteristics are presented in Figure 5.2 and 5.3 respectively. About 50% of the farmers use earthen pond as the major grow-out facility (Figure 5.2). Many farmers (72%) belong to at least one FO, of which 35% indicated cluster, while 28% did not consider themselves as members of any FO. Borehole was the main water source (49%), followed by Rive/Lake (36%) and Well (11%).

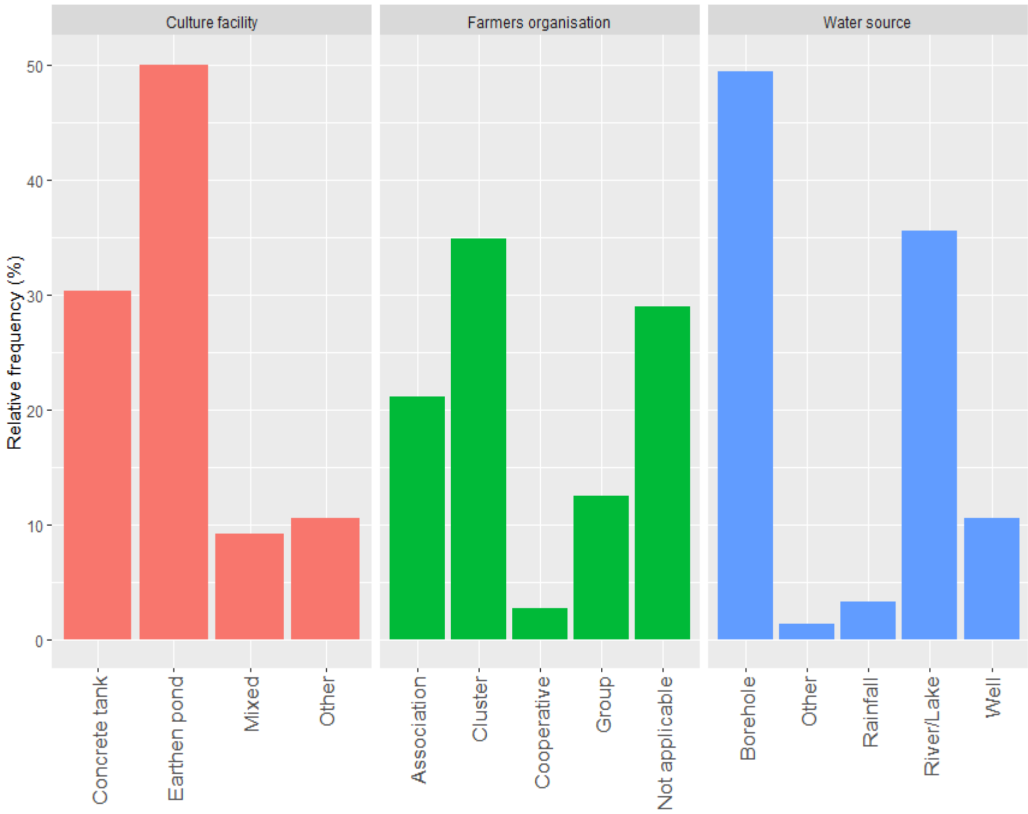

Figure 5.2: Farmers' response under the 'farm characteristics' category. The different colour of bars between the 3 predictor variables in the chart are only for visualization purposes; and not intended to convey additional information.

Figure 5.3 shows that over 60% of farmers sort (grade) their fish one or two times before harvest. The common feed management methods were ad libitum feeding, estimated based on biomass or without any reference (randomly). For water management, 51% of farmers use the manual exchange method of culture water through pumping in and out using machine. Water management by flow-through is also popular among farmers, especially those who indicated River/Lake as their main water source. On the other hand, 77% of farmers discharge effluent to agricultural land. Farmers who answered 'other' (5%) all specified 'back to River' as destination of pond effluents.

Figure 5.3: Farmers' response under the 'farming practices' category. The different colour of bars between the 4 predictor variables in the chart are only for visualization purposes; and not intended to convey additional information.

5.3.2 Farmers' attributes

Majority of the farmers had at least secondary school education, with 45% above secondary level (Figure 5.4). Similarly, many farmers have over 2 years farming experience, 54% with 2-5 years and 34% beyond 5 years' experience. For the main source of advice on how to tackle farming challenges, many farmers (44%) rely on extension agents while 37% reported personal source.

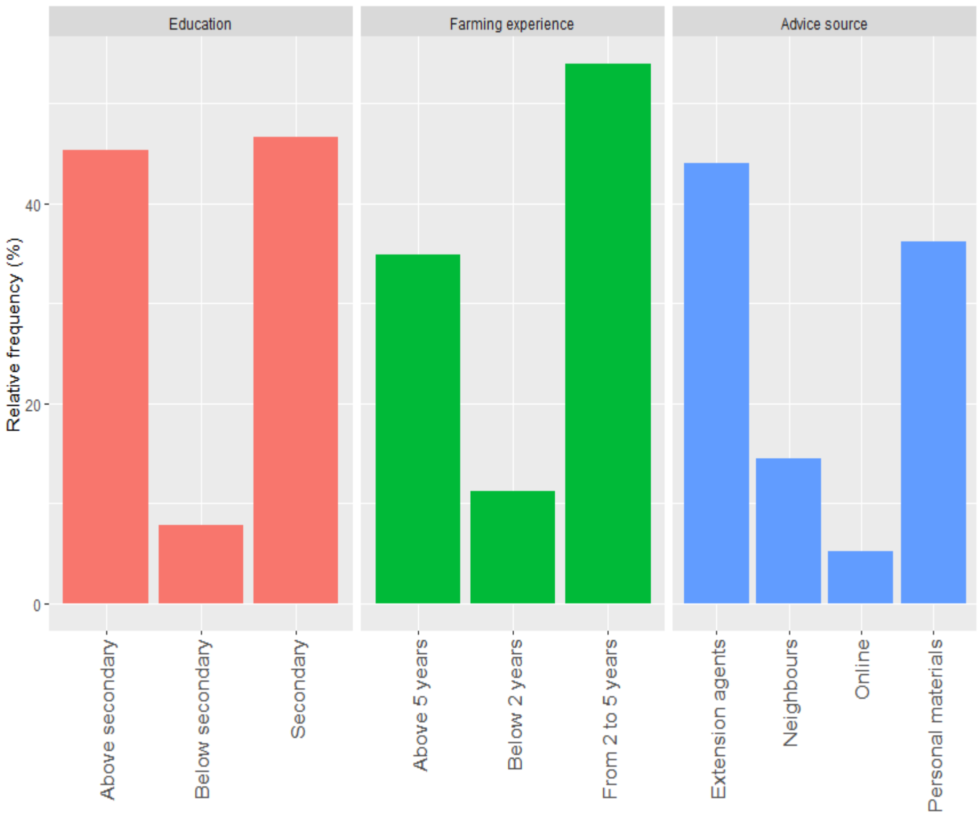

Figure 5.4: Farmers' response under the 'farmer's attributes' category. The different colour of bars between the 3 predictor variables in the chart are only for visualization purposes; and not intended to convey additional information.

5.3.3 Farmers' perceptions of aquaculture clusters

Overall, most farmers had a positive perception of aquaculture clusters (Figure 5.5). More than 80% of farmers agree with the potential benefits of aquaculture clusters based on response to statements 5, 6 & 7. Interestingly, farmers remained positive about the potential limitations of aquaculture clusters. Most farmers (55%) disagreed with statement 8 (fish farms in a cluster are more exposed to theft), while many did not agree with the other statements 4 and 3 on potential limitations of aquaculture clusters. There is some disagreement among farmers (18%) with the general statement 1, about having several fish farms in the vicinity of their farms, although majority were positive. Most farmers (83%) agreed that there is uniformity in how farming is practiced in their area, while 13% were undecided and only 4% disagreed.

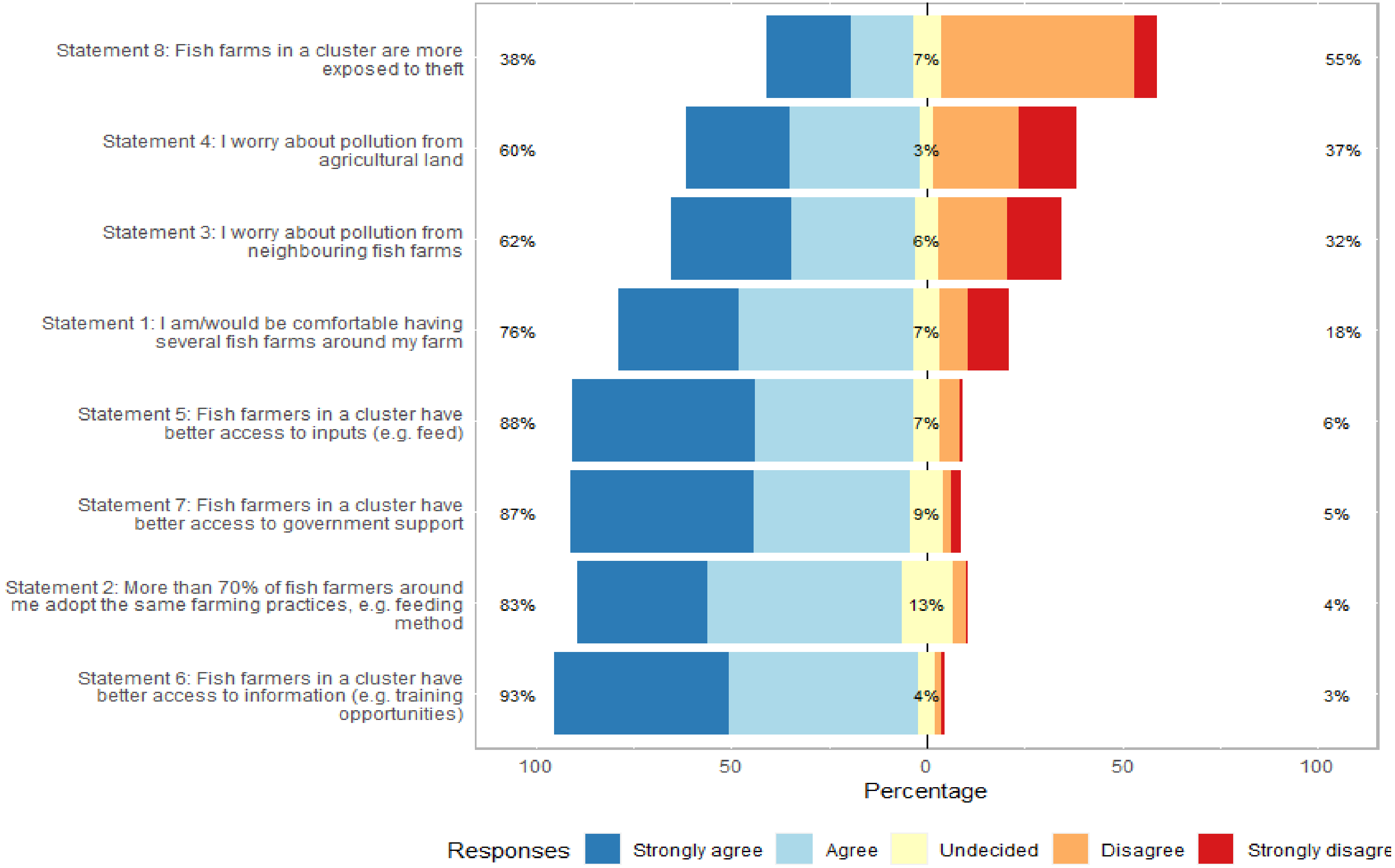

Figure 5.5: Farmers' perceptions of the concept, potential benefits, and limitations of aquaculture clusters. The percentage values are cumulative values for the two response classes on either side of the Likert scale for each statement.

As for whether famers are likely to remain in or join a cluster, Figure 5.6 shows farmers' responses to statement '1' according to membership of FO. About 90% of farmers who identified with Cluster and Group tend to have a positive perception compared to the other two FOs. Also, majority (75%) of farmers in Cooperative were positive, while farmers (53%) in Associations had a negative perception about having several farms in their farm area. On the other hand, up to 65% of farmers who do not belong to any FO (Not applicable) had a positive perception.

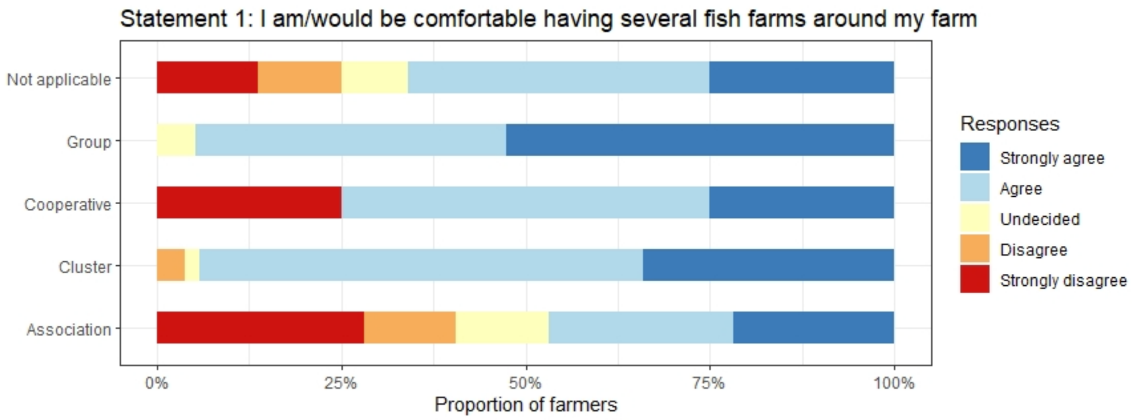

Figure 5.6: Farmers' perceptions of aquaculture clusters (based on response to statement 1) by membership of FO.

5.3.4 Factors influencing farmers' perceptions of aquaculture cluster

A total of 4 RF models were built, one for each target variable: statement 1, 3, 4 and 8. These were the statements for which no response class had more than 80%, thus did not exceed the set threshold. There were 500 trees (*nTree*) in each model and *mtry* of 3. The ordinary and OOB prediction accuracy are given in Table 5.2. It can be observed that OOB accuracy of RF model is highest for statement 1 and least for statement 8. As mentioned earlier, the OOB prediction is more reliable, since all the individual trees involved in its prediction do not contain the training samples.

Table 5.2: Prediction accuracy for the models

Target variable	**Prediction accuracy (%)**	
	Ordinary (95% CI)	OOB
Statement 1	80.00 (0.59-0.93)	74.02
Statement 3	96.00(0.80-0.99)	70.08
Statement 4	84.00(0.64-0.95)	67.72
Statement 8	72.00(0.51-0.88)	66.14

Out of the 10 predictor variables, main source of advice (*AdviceSource*) and destination of effluent discharge (*Discharge*) were the top two most important in 3 of the 4 models (Figure 5.7). The importance score for each variable in the respective models show the mean decrease in prediction accuracy (i.e., increase in the chances of misclassifying farmers' perceptions) due to the exclusion of that variable. Extending the ranking to top 5 (based on frequency) most important variables across the models will include education level (*Education*), years of farming experience (*Experience*) and membership of farmers' organization (*FO*). In contrast, Culture facility (*Facility*), main water source (*WaterSource*) and Feed management method (*FeedMgt*) are the bottom 3 variables with negative to small positive values. This means that the importance of these variables varies randomly around zero. However, on a model-by-model basis, rankings of the variables vary. For models of statement 1 and 3, *FeedMgt* and *WaterSource* ranked in top 5 respectively, while *Facility* was consistently in the bottom 3 for all 4models.

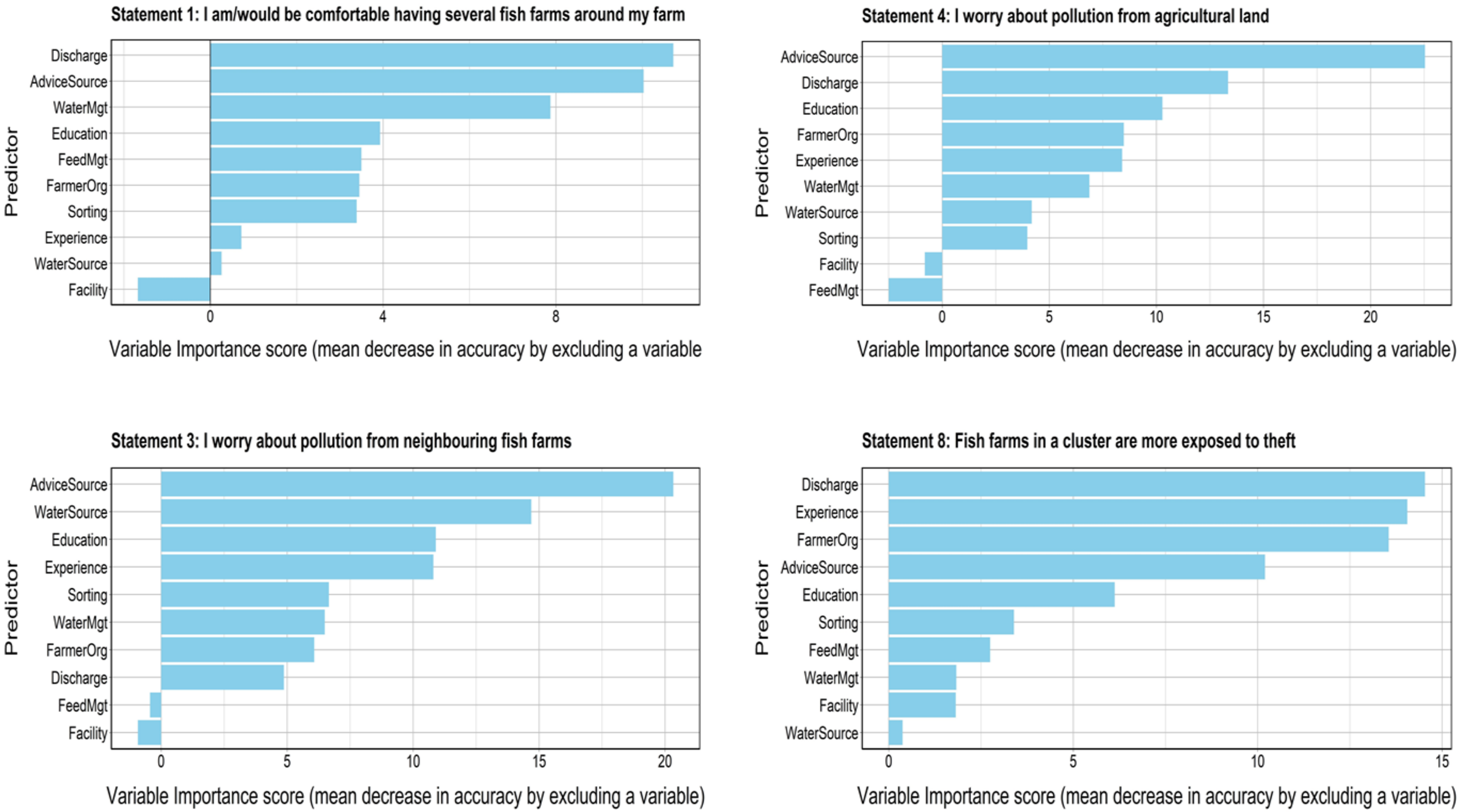

Figure 5.7: Variable importance score of the Random Forest models for predicting farmers' perceptions of the concept and potential limitations of aquaculture clusters. Only the model for statement 8 did not show any negative score for variable importance, which may be related to both the low OOB prediction accuracy compared to others, and somewhat balanced observations between the left and right side of the Likert scale.

5.4 Discussion

In this study, random forest models were developed and used to identify the main drivers of farmers' perceptions about aquaculture clusters. Interesting findings were made during the model design, development, and evaluation. At the design stage, predictor and target/response variables were characterized using survey data. Difference was found between farmers in terms of the type of culture facility, membership of FO and water source. Earthen pond aquaculture dominates the options of culture facility, while borehole is the most used source of culture water. Although, this does not necessarily mean that most ponds are reliant on boreholes in the study area. These findings are in line with previous studies such as (Dauda et al., 2017; Offem et al., 2010; Ogidi, 2016), that sought to describe fish farming activities at subnational level in Nigeria.

It is surprising however, that membership of cooperative societies had very low frequency. This may have resulted from a limitation in the questionnaire employed in this study, whereby farmers were not allowed to select more than one option in answering what FO they belonged to. Ofuoku et al. (2008) reported over 20% more membership of cooperative society than association membership in Delta state. Although, they found that, while fish farmers joined cooperative societies for economic benefit (i.e., access to credit), those in associations want social benefits in addition, including access to information. Also, the findings of Olaoye et al. (2013) that the number of cooperative membership almost double non-membership in Oyo state Nigeria referred to cooperatives as some registered or formal group of farmers who aim for improved access to inputs and technology. Mercy Corps (2017) defined cooperative society as a credit association registered (limited liability) under the Nigerian Cooperative Societies Act. Due to the subtle difference between a cooperative society, an association, and a formal group, it will be useful therefore to clarify fish farmers responses regarding membership of FO in future surveys. Considering the foregoing points, the second objective of the present study used membership and non-membership of FO rather than the different types of FO in modelling famers' perceptions of aquaculture clusters.

Variations exist between farmers regarding the number of times they sort or grade fish before harvesting, as well as where they discharge farm effluents. The large number found here for farmers having at least secondary school education and over 2 years of farming experience is like the findings of several local studies on the socioeconomics of fish farmers in Nigeria. The sorting of fish is a typical farming activity that depends largely on adequate availability of water and ease of exchanging culture water. Farmers who sort more than twice may be associated with relatively more of these advantages. Most farmers indicated ‘agricultural land’ as point of effluent discharge, although this includes vegetated land. The other options, except ‘bare land’ were associated mostly with farms that are close to waterbodies. This suggests some correlation between water source and effluent discharge. Also, that farms fed by waterbodies have same as their effluent receiving environment. This could be confirmed by the study area description in Achoja (2019), who characterised farms in Delta state based on their concentration around waterbodies, while comparing with a control group away from waterbodies.

The results in Figure 5.5 show that most farmers had a positive perception of the potential benefits of an aquaculture cluster, irrespective of their personal and farming conditions. However, the perceptions tend to become divided when focus turned to the potential limitations. Similarly, Figure 5.6 suggests that farmers who are not members of a farmer organization are willing to be part of an aquaculture cluster, while majority of those already in a cluster are very likely to remain. This reiterates the abundance of opportunities for intervention by leveraging on existing aquaculture clusters to improve production and trade. However, it is interesting to see the divide in farmers’ perceptions between the potential benefits and limitations of aquaculture clusters. Better still, is the fact that a farmer’s non-membership of FO does not influence what they think about the potential benefits of cluster farming. Stakeholder consultations that seek to plan the use of cluster management should probably be more concerned with addressing the risks that farmers may perceive rather dwelling on the positive side. It is however important to first seek to evaluate the actual situations in the different fish farm clusters that already exist rather than relying on those reported from other countries. Also, a better understanding of the trends in aquaculture clustering at both spatial and temporal scales would be insightful. Such studies in Bangladesh (Zhang et al., 2019) revealed useful information for effective planning, in that a change in cooperative behaviour between high and low clustering regions was observed within the period investigated.

In the 4 RF models, OOB accuracy is highest for the model of statement 1 (Table 5.2). The value decreased for the model of statement 3 and so on. Looking at Figure 5.5, the differences in observations on the Likert scale as one moves from statement 1 upwards corresponds with the order and magnitude of the decrease in OOB accuracy of the respective models. This is because for supervised machine learning algorithms like RF, the chances of misclassification of farmers’ perceptions are significantly low where majority of observations occurred in one response class, as is the case for statement 6 and others in the lower half of Figure 5.5. It seems unreasonable therefore to include these when modelling to find the key variables influencing farmers perception. This study found two main drivers of farmers' perceptions of aquaculture clusters: main source of advice (*AdviceSource*) and destination of effluent discharge (*Discharge*), each in the farming practice and farmers' attribute categories. For top 5 important variables, while these categories contributed 2 predictor variables each, only membership of FO represented the farm characteristics category.

Overall, this study found that farmers' perception of the concept of cluster-based aquaculture development is positive. However, as previously mentioned, there is need for further studies to allow for better understanding of the realities of farmers in existing aquaculture clusters in Nigeria. Although some interest is starting to develop in evaluating the impacts of clustering on profits, other areas are lacking. For example, understanding the mechanisms of interaction between farmers in aquaculture clusters, public perception, and the potential for conflict with other users of the same natural resource, particularly waterbodies. Furthermore, understanding how management practices could vary between farms in clusters and those in non-clusters and how much difference this makes, is key in ensuring acceptability of cluster-based aquaculture interventions. Joffre et al. (2019) showed the advantages of reliance on the diversified sources of information in existing farmer clusters for the improvement of planning and management of aquaculture growth. The present study found that extension agents represent the most source of information for farmers, with a relatively fewer indications of interaction between farmers when tackling farm management issues. Although, it is important to state that extension agents in this context not only refers to those from government but individuals or company representatives who supply inputs. Based on evidence from similar study (Joffre et al., 2019), the frequency of interaction and trust is relatively higher between clustered farmers and input retailers compared to those not in clusters.

5.5 Conclusion

In this chapter, a survey of fish farmers in Nigeria was conducted to understand their perceptions of aquaculture clusters. Farmers are a key stakeholder in aquaculture policy development and implementation. It was hypothesized that the following factors influenced what farmers think about aquaculture clusters: farmers' membership of a formal organization, the type of fish culture facility and the production practices they adopt, including the years of farming experience and level of education. The assessment of perceptions was based on their extent of agreement with a series of statements in the survey about the concept, potential benefits, and limitations of aquaculture clusters. It was found that majority of farmers in Nigeria have a positive perception about aquaculture clusters irrespective of variations in the factors that were tested in this study. Also, many farmers indicated willingness to remain in or join an aquaculture cluster. However, the classification of farmers by extent of agreement using random forest models showed that farmers main source of advice and where they discharge farm effluent are the two most important factors determining how positive they think about aquaculture clusters. Therefore, a deliberate attempt by planning authorities to organize existing aquaculture clusters or create new ones should consider these factors to help maximise the chances of success. Further study may focus on farmers that are in existing aquaculture clusters to evaluate the actual benefits they derive, or the issues commonly faced. The perspectives of other value chain actors as well as the public would also be useful. This is because, the success of a cluster-based aquaculture development not only depends on the horizontal coordination that is enabled but also as Ha et al. (2013) found, on the nature of vertical coordination with other actors along the value chain. Finally, the role of government cannot be overemphasized in creating an enabling environment towards a private sector-led aquaculture cluster development.

CHAPTER 6 ASSESSMENT OF LAND USE CHANGE IN A POTENTIAL ZONE FOR AQUACULTURE USING GOOGLE EARTH ENGINE

6.1 Introduction

Public concerns have increased about the use of natural resources such as land, due to increase in human population and environmental change (Stehfest et al., 2019). Land use is closely associated to important topics like food security (FAO, 2018a), energy systems, ecosystem services, and rural-urban migration (Hertel, 2011), hence critical to the different dimensions of sustainable development (Stehfest et al., 2019). Aquaculture in both coastal and inland areas has been expanding in many parts of the world. The expansion process is largely spontaneous as they mostly occur around areas with existing farms (Zhao et al., 2022), and in some places, where croplands are easily converted (Filipski & Belton, 2018; Joffre et al., 2019; Ottinger et al., 2016; Yu et al., 2020). Moreover, aquaculture is often considered traditionally as part of agricultural zones (Gona et al., 2018; Ofuoku et al., 2008). However, to plan for a sustainable expansion of aquaculture, land allocation should be done strategically. In strategic planning, the focus is on how conditions might change in the future and using knowledge of past- to- present trends to inform alternative strategies towards a defined goal (Schoemaker, 1995). According to (FAO, 1993) land use conflicts are simply the consequence of a mismatch between land use and land suitability. This indicates the significance of well-informed land use planning, especially because aquaculture appears to be less flexible due to its deeper interaction with the environment compared to other activities like crop farming.

Land use sustainability is defined as a measure of the likelihood that a particular land use will remain physically, economically, and socially suited to a particular location in the long term, over 25 years (Smyth & Dumanski, 1995). Mapping land suitability for different activities in an area of interest is a key step in land use planning (FAO and UNEP, 1999). However, detailed appraisal of such suitability maps will be required to help design a land use plan that is not only based on present issues but look at future land demands by different activities. Smyth and Dumanski (1995) developed a framework for assessing sustainability of current and alternative land uses, while emphasizing the importance of 3 aspects: 1) How to assign relative importance to socioeconomic and environmental factors at the area of interest, 2) Understanding the trends of change in these factors and 3) Projecting potential future changes in trends through modelling of past- to-present events or use of geographical evidence (change that occurred at a comparable site). This information is then used to identify sustainability indicators and thresholds against which the current or alternative land use sustainability is measured.

Spatially explicit Land Use Change (LUC) models have been used to reflect interactions of factors that drive land use change (Veldkamp & Lambin, 2001). LUC models are said to be spatially explicit when the input data/model outputs are fully attributable to a specific location on the globe, e.g., a model that predicts change in a parcel of land, based on the presence of water, mountain, specified population density, or market in its surrounding rather than the use of distance to these features as driver variables (Briassoulis, 2019; Irwin & Geoghegan, 2001; Ren et al., 2019). In essence, spatial data is required for non-spatially explicit factors (proxy variables) to be estimated, e.g., elevation, slope, transportation cost, etc. Non-spatially explicit modelling results from inadequate data – poor quality or difficulty in collection/use of data, for example, how to assign location to policy change, new legislation, or inflation to be used as model inputs. More broadly, LUC modelling approaches can be classified into two groups: Statistical (pattern-based), which extrapolates historical patterns into the future and Structural (process-based), which simulates the consequences of changes in human activities (Ren et al., 2019; Veldkamp & Lambin, 2001). For a comprehensive account of LUC modelling approaches, see Briassoulis (2019).

Earth observation technologies provide time series satellite data from as far back as 1972 (Landsat 1) in the form of remotely sensed imagery (Belward & Skøien, 2015), offering opportunities to meet the complex information needed for policymaking (Gómez et al., 2016). Subsequent missions like the European Space Agency's (ESA) Copernicus offer satellite data for free, including Sentinel-2 Multispectral Instrument (MSI) images at high spatial (10m) and temporal (10-day) resolutions (Ottinger et al., 2016). In addition, the advent of Google Earth Engine (GEE), a powerful platform on which satellite data can be accessed, processed, analysed, and visualized, within a significantly reduced time than traditional methods has created more opportunities for research (Gorelick et al., 2017). This suggests improved accuracy over the years (Noi Phan et al., 2020) as researchers have been working to answer important questions including when, how, and where LUC is occurring at different spatial scales. Although, decision on the period to investigate, the nature of information to extract and analysis depend on the purpose and object of study (Briassoulis, 2019).

For LUC detection, which is prior to modelling LUC as a function of driving factors, available and consistent land use maps for different dates are best used (Sexton et al., 2013; Wulder et al., 2008). The first global land use map at 10 meters spatial resolution was in 2020 (https://esa-worldcover.org/en). Where analysis-ready land use maps are unavailable due to lack of time series data or inconsistent resolution, various remote sensing techniques such as change in spectral index, spectral distance, or statistical metrics can be used to detect change between two dates (Gómez et al., 2016). Spectral index methods take advantage of the fact that every Land Use/Land Cover (LULC) present their highest and lowest reflectance values in different spectral bands within a multispectral satellite data (Hatfield & Prueger, 2010). Therefore index-based methods involve the computation of a normalized difference between two or more bands to enhance the contrast of signal between a specified LULC and its background (Xue & Su, 2017). One of the most applied spectral indexes is the Normalised Difference Vegetation Index (NDVI), which ranges between -1 and +1 (Karnieli et al., 2010; Sonobe et al., 2018).

The aim of this study was to model the intensity and spatial distribution of LULC change at a high resolution in a potential zone for aquaculture. This can be used to inform land use planning. More specifically, the objectives were: 1) To calculate spectral indexes of built-up area, vegetation, and water from multitemporal Sentinel-2 images within a potential zone for aquaculture development, 2) To detect spatial and temporal changes in these indexes, and 3) To compare the changes to the situation in a reference zone.

6.2 Materials and Methods

6.2.1 Study area

In this study, a previously identified zone suitable for aquaculture which occurred in Edo state of Nigeria (Figure 6.1) was selected as the assessment site. For the reference site, a popular location for aquaculture in Delta state was identified. Both states are located within the same agroecological zone (humid forest).To ensure consistency, an area of

100 km^2 was defined for each site as shown in Figure 6.1. Based on measurements taken on Google Earth, the average area of aquaculture ponds in the reference site is 0.015ha. Hereafter, the assessment site will be abbreviated as 'PS' and the reference site as 'RS'.

The physical geography, including elevation, tree canopy structure, weather and climate of the sites are characteristic of tropical humid forest. As described by Faber-langendoen et al. (2016), tropical humid forest agroecology in Africa has predominantly tall trees up to 45m in a dense, multi-layered forest and are primarily semi-evergreen with deciduous trees comprising up to 25% of the main canopy. The soils are often deeply weathered, reddish or yellowish clays. Rainfall is abundant and well-distributed throughout most of the year. Water stress is very low, with no regular annual dry season and mean monthly temperature around 25^{o}C (NIMET, 2018).

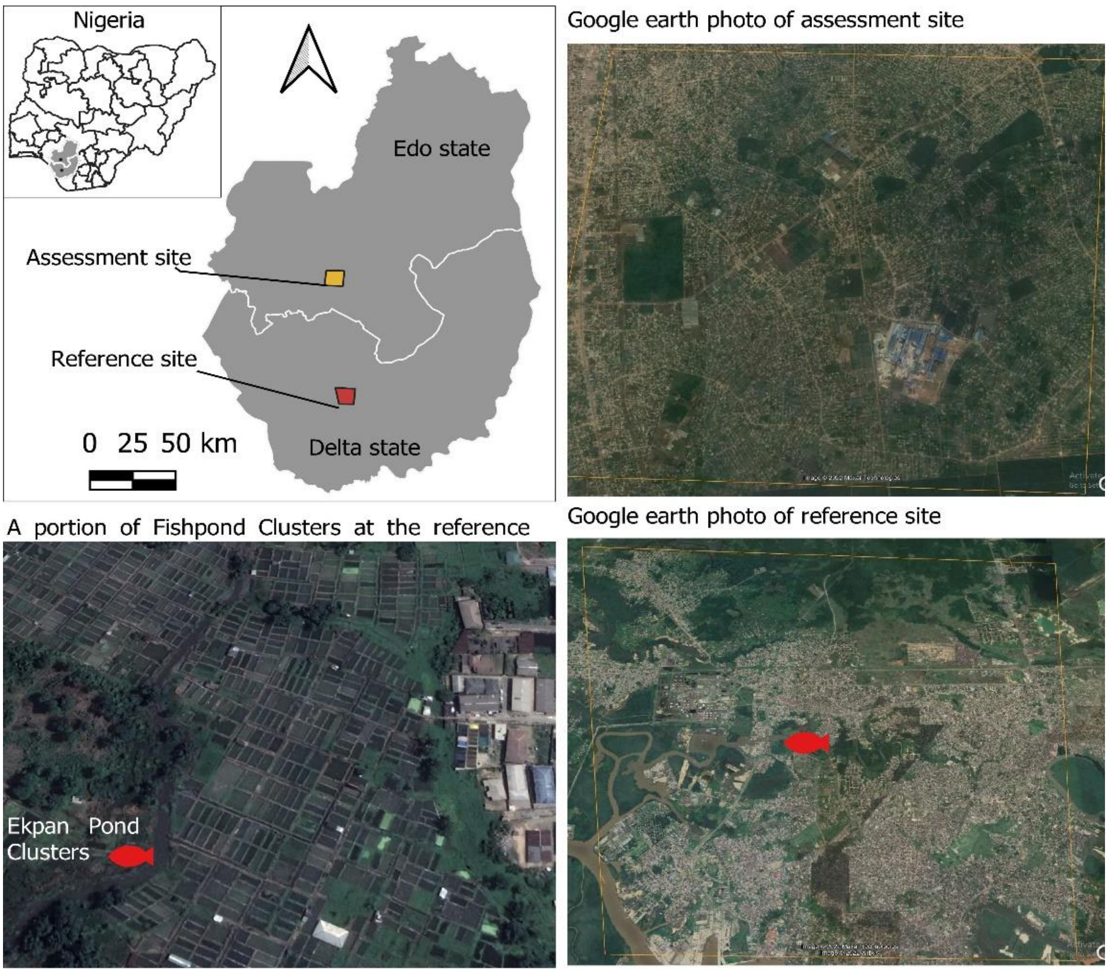

Figure 6.1: Map of the study area showing the assessment site (Edo state) and reference site in Delta state, with example of Fishpond clusters.

6.2.2 Data

The dataset used in this study was Sentinel-2 MSI Level-1C (Top-of-Atmosphere, ToA reflectance) images hosted on GEE. The data was collected for the year 2016 to 2021. Sentinel-2 is second of the Sentinel series in the Copernicus programme and comprises a constellation of two polar-orbiting satellites (ESA, 2022). The satellites have a large swath width of 290 km and high revisit time of 10 days at the equator with one satellite, and 5 days with 2 satellites under cloud-free conditions. Each image tile spans 100 km by 100 km and projected in UTM/WGS84. The MSI sensors onboard Sentinel-2 satellites collect images with 13 spectral bands (spatial resolution of 10 m to 60 m) ranging from visible to near-infrared and short wave-infrared spectrum. The bands that were used in this study are given in Table 6.1.

Table 6.1: Sentinel-2 bands used in this study

Band	**Description**	**Spatial resolution (m)**
B3	Green	10
B4	Red	10
B8	Near-infrared (NIR)	10
B11	Short wave-infrared 1 (SWIR1)	20

6.2.3 Methods

The geometries of the assessment and the reference sites (PS and RS) were specified. For each site respectively, Sentinel-2 Level-1C dataset hosted on GEE was filtered (Appendix D). The images collected were those with less than 30% cloud cover from 1 January to 31 December of each year (2016-2021). It is important to mention that Sentinel-2 data was the preferred option because it provides the highest spatial resolution of the freely available satellite data. However, because the first Sentinel-2 satellite was launched in 2015 (Ottinger et al., 2016), only a 5-year time series data was available at the time of this study.

6.2.3.1 Analysis of temporal change in spectral indexes

Cloud pixels were masked out using the QA60 band available in the Sentinel-2 image collections of each year. The QA60 band is a 60 m spatial resolution cloud mask for opaque and cirrus clouds. Masking cloud in an image makes the cloud pixels become transparent, therefore excluded from analysis and visualization (Zhu et al., 2015). After masking is completed over the image collection for each study year, three spectral indexes (Normalised Difference Built-up Index - NDBI, Normalised Difference Vegetation Index - NDVI, and Modified Normalised Difference Water Index - MNDWI) were then computed (Table 6.2). The value of all the indexes range between -1 and +1, with thresholds corresponding to different features on the Earth's surface (Gómez et al., 2016). Since GEE now makes it feasible to compute spatial metrics like mean and median over large area and time series images (Noi Phan et al., 2020), monthly mean of NDBI, NDVI and MNDWI was calculated for both PS and RS. Seasonal variation was investigated using the image collections for 2021. On the other hand, annual variation was based on the values in December of every year. December and January were the two months with the most images in the yearly collection that met the cloud cover condition set above. No image was found for May, June, August, and September.

Table 6.2: Formulae of the three spectral indexes used in this study. ρ in the formulae represents the ToA reflectance of the respective bands

Spectral index	Formula	Reference
Normalised Difference Built-up Index (NDBI)	$\frac{\rho SWIR1 - \rho NIR}{\rho SWIR1 + \rho NIR}$	(Zha et al., 2003)
Normalised Difference Vegetation Index (NDVI)	$\frac{\rho NIR - \rho Red}{\rho NIR + \rho Red}$	(Rouse et al., 1974)
Modified Normalised Difference Water Index (MNDWI)	$\frac{\rho Green - \rho SWIR1}{\rho Green + \rho SWIR1}$	(H. Xu, 2006)

Higher positive NDBI values indicate built-up area, while those near zero or negative represent other land features (Zha et al., 2003). NDVI values near zero indicate bare soil, while higher positive values range from sparse vegetation (0.1 - 0.5) to dense green vegetation (0.6 and above). Negative values indicate features like water and sometimes cloud (Xue & Su, 2017). Higher positive values of MNDWI indicates water, while soil, vegetation and built-up area all have a negative value because soil reflects SWIR1 band more than NIR and vegetation reflects more SWIR1 than Green band (H. Xu, 2006).

6.2.3.1 Mapping the spatial distribution of land use change

To detect areas that changed between 2016 and 2021 based on the values of NDBI, NDVI and MNDWI, the corresponding image collection was further filtered for cloud cover. This is because optical remote sensing is affected by cloud cover, as they attenuate the amount of light that hits and reflects off the Earth’s surface, thus influences spectral indexes (Zhu et al., 2015). For example, although negative NDVI values indicates water, some negative pixels might be due to cloud. Therefore, all the images that had less than 3% cloud were used to create a median composite image, which enabled the change analysis at the assessment and reference sites (Appendix D). An arbitrary threshold of 0.2 was used to display areas that changed between 2016 and 2021.

6.3 Results and discussion

6.3.1 Temporal change in spectral indexes

The top row of Figure 6.2 shows the monthly mean values of NDBI (a), NDVI (c) and MNDWI (e) for PS and RS based on images obtained for the year 2021. Similarly, the bottom row (b, d, and f) gives the annual mean of NDBI, NDVI and MNDWI respectively from 2016 to 2021. Both monthly and annual NDBI values ranged between 0.02 and 0.16 in the PS, with the highest monthly value observed in October. Similar trend was observed at the RS, except that the NDBI values were relatively lower. Since it is not expected that significant changes in built-up area will occur within few months given the 100 km^2 study area, other features such as vegetation may have caused the slight variations in NDBI values between months. No marked difference in the mean NDBI values was observed between 2016 and 2021. Also, given that the values are low or near zero, changes in other features rather than built-up area had stronger influence on the trends observed at both sites.

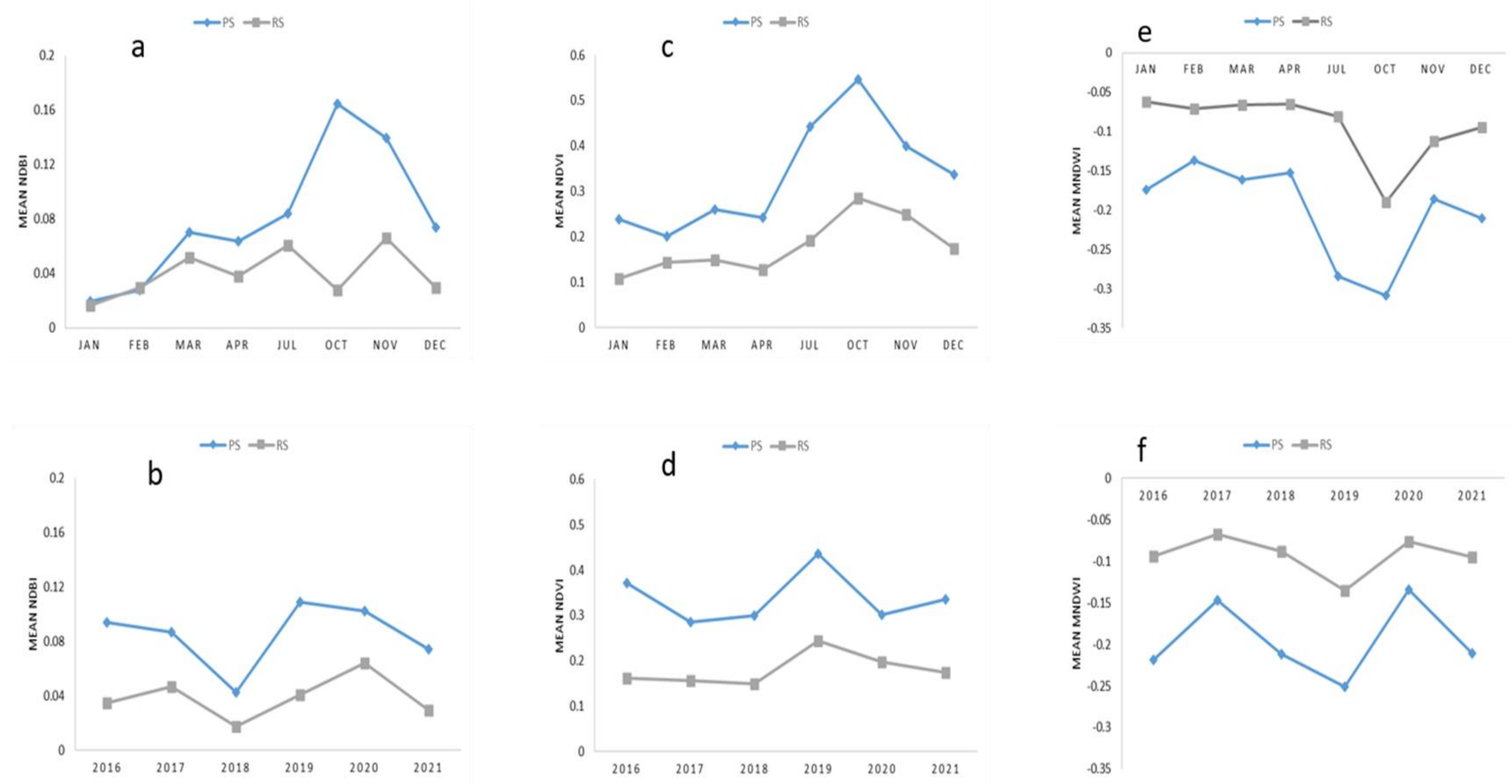

Figure 6.2: Mean values of NDBI, NDVI and MNDWI for the assessment site (PS) and reference site (RS). Seasonal in the top row and annual in the bottom row.

For NDVI on the other hand, there was a clear seasonal variation at the PS, with values ranging from 0.25 to 0.55. This occurred around the end of the rainy season and may explain why the NDBI values for October was highest in Figure 6.2 (a). Interestingly, similar trends in temporal (seasonal and annual) changes were observed in both sites for all three indexes. Because both sites occur in the humid forest area, vegetation is a major land cover, thus largely influences changes that are observed through temporal assessments. Alatorre et al. (2016) found similar trend in mean NDVI values from 1990 to 2010 while studying a mangrove area known for shrimp farming in Mexico. The portions of the mangrove with dense canopy had NDVI values between 0.25 and 0.30, while the values of sparse vegetation and bare soil were consistently around 0.15 and 0.05 respectively throughout the period under investigation. Therefore, there is need to differentiate between agricultural land use and forest cover in the NDVI images generated in the present study. In a trend analysis of vegetation productivity (NDVI) in Nigeria using MODIS data (2000 – 2021), Kießlich et al. (2021) disaggregated the NDVI change by climatic and human factors. The authors found that the score of NDVI change reduced by almost half in Edo and Delta states when only human-related change was considered.

Further explanation of the trend in the mean values of NDBI and NDVI in the present study can be seen Figure 6.2 [(e) and (f)]. The MNDWI values are near zero or negative, indicating that changes in vegetation cover determines the seasonal and long-term trend of spectral indexes in both the PS and RS. To detect water features using different water indexes in multiple countries in Europe, Worden and de Beurs (2020) noted how seasonal variations in the index values are influenced by type of water body or their location. This suggests that changes in the dominant land cover tends to obscure any change in water area, although the MNDWI is designed to remove background noise such as built-up area (H. Xu, 2006). Hence, to extract each LULC based on values of the calculated indexes, appropriate thresholds must be determined and applied using suitable algorithms aided by validation samples (Y. Xu et al., 2021).

6.3.2 Spatial change in spectral indexes

The images of NDBI, NDVI and MNDWI at the assessment site (PS) generated for 2016 and 2021 are shown in Figure 6.3. looking at the NDBI (black circles), a visible change in built-up area can be observed within the 5-year period investigated. Using a threshold of 0.2 showed areas with ± 0.2 change in NDBI value. Note that some of these areas that changed might represent other land feature like vegetation and bare soil. Since the aim of the present study was to analyse the spectral indexes and differences between PS and RS, it suffices to assume that most positive NDBI values are built-up areas. Therefore, the results show that the intensity of built-up area and rate of change at PS are higher than those at RS (in Figure 6.4).

An increase in NDVI values was observed between 2016 and 2021, although some areas (red circles) showed a decrease, indicating some loss in vegetation. Although vegetation is denser at the PS, the areas that changed is more localised than RS. As for occurrence of water surface, no visible area was detected at PS since the MNDWI values were mostly zero to negative. However, it will be worth investigating the areas that indicated a change of ± 0.2 in MNDWI values through visual inspection of high-resolution Google Earth images or field visit. In the case of RS, water surfaces were very visible, with MNDWI values of 0.18 to 0.40.

Clearly, PS and RS are different in terms of density of the 3 LULC investigated. Also, the rate and spatial distribution of change are different. However, they are generally comparable being in the same geopolitical and agroecological zones. These findings suggest that a land use planning exercise at the PS would benefit from understanding the interaction between aquaculture activities and other land uses at the RS. Following the concept of land use sustainability proposed by Smyth & Dumanski (1995), it means that after satisfying all the conditions of site suitability for aquaculture at PS, the thresholds of sustainability can be derived from the lessons learned at RS. Such approach is based on the understanding that sustainability cannot be measured in absolute terms, therefore needs to be adaptable in space and time. Importantly, certain factors or criteria used to determine the suitability of an area for aquaculture will be the same as those that are used to measure sustainability. The difference is that for sustainability, the potential future change in these factors is predicted for a stated period, including the likelihood of change as well as potential impacts on future suitability for aquaculture. It should be recalled that only LUC detection was attempted in the present study, which is necessary for modelling the influence of driving factors (cause-and-effect relationship) and subsequent prediction of future change. Also, that no known aquaculture pond cluster exists in PS as opposed to RS.

Therefore, the application of the above sustainability assessment approach in this context may simply be to use LUC drivers at RS (due to the presence of aquaculture ponds) as evidence to identify indicators and thresholds of sustainability at the PS. For example, at RS, the knowledge of how much mangrove area was lost to aquaculture ponds over the years or at what stage of development the conversion of aquaculture ponds to other land use began along with the drivers/impacts, can help to predict sustainability issues at the PS. The scenario-driven approach in Chapter 4 demonstrated the use of historical data (long-term variation in suitability) as a criterion to support zone allocation for aquaculture. In the present chapter, the use of geographical evidence, i.e., comparable area where aquaculture pond is one of the land use classes, as an alternative or a complement, could improve the outcomes of LUP for aquaculture development.

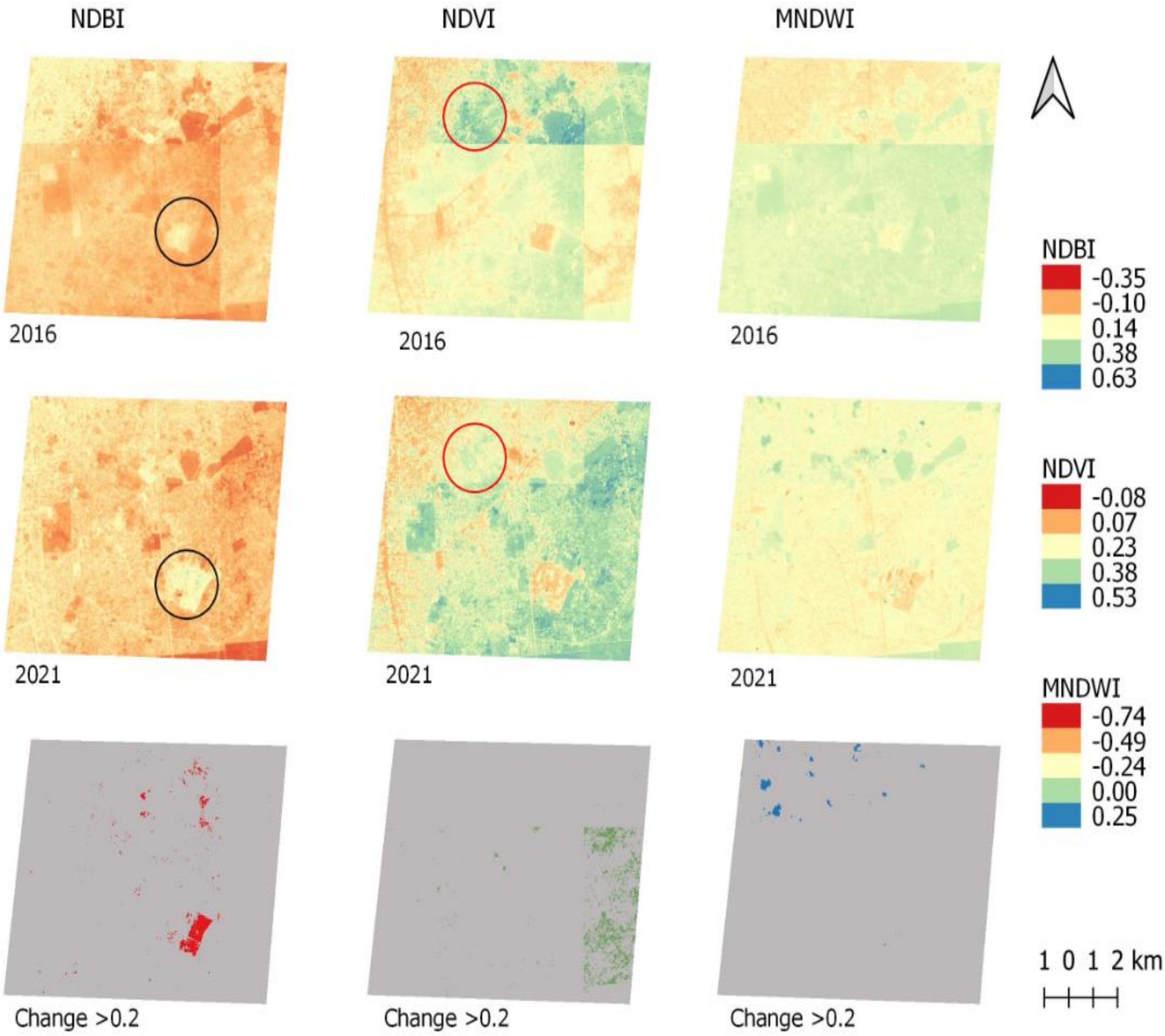

Figure 6.3: Detected change in the spectral indexes of built-up area, vegetation, and water features between 2016 and 2021 at the assessment site. Black circles represent an increase and red, a decrease. The values of each feature should be compared in vertical order between years and not horizontally (between spectral indexes).

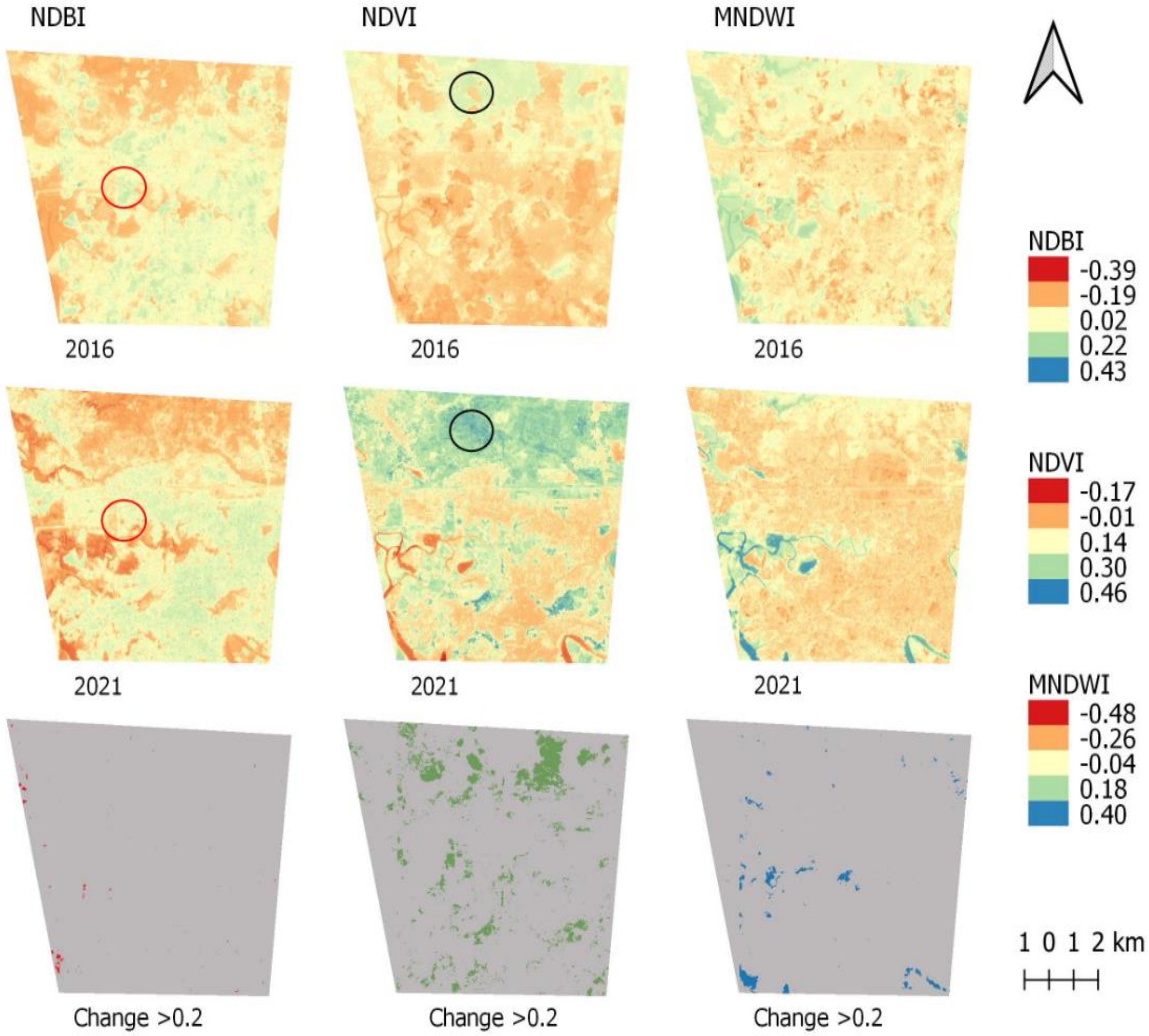

Figure 6.4: Detected change in the spectral indexes of built-up area, vegetation, and water features between 2016 and 2021 at the reference site. Black circles represent an increase and red, a decrease The values of each feature should be compared in vertical order between years and not horizontally (between spectral indexes).

6.4 Conclusion

Using remote sensing and GIS technologies combined with the power of GEE, Sentinel-2 multispectral images were analysed to explore changes in LULC at a potential zone for aquaculture in relation to a reference zone. Specifically, the study focused on built-up areas, vegetation, and water surfaces and compared changes with those at a reference zone with high concentration of aquaculture clusters. While the intensity and rate of change of built-up area and vegetation were higher at the potential zone, water surfaces were significantly higher at the reference zone. The comparison was based on the premise that land use change is a very good indicator of economic and social activities in a specified area. Therefore, the ability to link aquaculture development to land use change in one location can provide evidence for assessing aquaculture sustainability in a comparable location, where planning is on-going to develop aquaculture. The actual extraction of LULC based on the values of the indexes generated in this study will be useful to quantify change. In turn, this will aid the detection of aquaculture expansion, and the creation of land use maps of the study sites that include aquaculture pond as a land use class will be possible. These are key to understanding the complexity of land use systems, and in this context for planning a sustainable expansion for aquaculture.

CHAPTER 7 GENERAL DISCUSSION

Robust information such as location and farm area, volume of production, farming practices, value chain actors, etc., is required for effective management of aquaculture at different administrative levels (FAO, 2017). However, obtaining such information from individual farmers over a large area can be difficult (Nash, 1995). Spatial planning has been described as a promising way to facilitate improved data collection to guide sustainable production (Aguilar-Manjarrez et al., 2017; Waite et al., 2014). Nevertheless, the rapid growth of human population and its interface with geopolitical and climate change means that the future is ever uncertain, thus planning must be strategic. Using Nigeria as a case study, this research project examined the past and present states of the aquaculture sector to inform site suitability modelling, generate different development options and indicators of long-term suitability of sites that can support plans for aquaculture expansion in a sustainable manner.

Different decisions are made throughout the spatial planning process, each stage with its own issues to be resolved. In simple terms, decision-making is about how to choose between two or more alternatives. But neither a blueprint spatial plan (e.g. an estate redevelopment) nor strategic spatial plans (e.g. land use zoning) can be referred to as simple decision-making exercise (Faludi, 2000). The complexity of spatial planning is not only determined by the uncertainties of the future but also by the fact that, for the same activity, spatial issues may vary between locations, scale, and time points (Airey & Doughty, 2020). Also, the process often involves many different stakeholders, including from other sectors, thus could be influenced by complications from multiple objectives, differences in value judgement or special interest by powerful individual/group (Airey & Doughty, 2020; Faludi, 2000; FAO, 1993; Gonzalez & Enríquez-De-Salamanca, 2018). Moreover, because spatial planning is a process, the design stage (where alternative courses of action/suitable areas are identified for different activities) is faced with decision problems that differ from those occurring at the implementation stage (Rudolf & Grădinaru, 2019). Hence, the need to understand what tools are required, how these can be developed or adapted and how to apply them to facilitate decision-making (Aguilar-Manjarrez et al., 2017; Falconer et al., 2020; Gonzalez & Enríquez-De-Salamanca, 2018). The significance, and ways of addressing some of these dimensions of complexity, specifically for aquaculture spatial planning, were demonstrated in this research project through a series of studies.

The future is uncertain, yet it is critical for planning authorities to create both short and long-term plans. As such, the design of land use plans is often based on projections of future demand for land by different activities (FAO and UNEP, 1999). Land is a limited national resource but the demands on it continue to increase, which means that the demand projections become out-of-date as time goes on (Airey & Doughty, 2020). Therefore, efforts are not only required to update information needed for land use planning (LUP), but also to improve understanding of the effects of changes in natural phenomenon, society, and technological advancement (Gibson & Timmons, 1976). This research project (in Chapter 3) first considered the uncertainty dimension of spatial planning complexity to ask the question: what might aquaculture look like in Nigeria by 2035? Drivers of aquaculture development in Nigeria were identified using Delphi technique. The main drivers (i.e., those scored very high by stakeholders both on level of importance and level of unpredictability) were availability/cost of aquafeed, land use change, government policy and climate change. These were then characterised and used to describe four possible futures or scenarios of the country's aquaculture sector up to 2035. The four scenarios depict a baseline, favourable, somewhat favourable, and unfavourable situations respectively. For each scenario, future pond aquaculture production was estimated by modelling future changes in land use and pond yield potential. Government estimates suggest a potential of producing 2.5 million metric tonnes (t) of fish annually, but the results suggest that Nigeria is unlikely to reach this estimate by 2035 without interventions. While the scenarios are useful to enhance discussions on potential interventions for improving aquaculture production and sustainability, the quantitative projection associated with a scenario can be used for evaluating these interventions.

Scenarios are used to account for uncertainty, since an experiment is impossible on a future that does not exist and prediction assumes outcomes with a high confidence level (Wright & Goodwin, 2009). A typical example of scenario application to national-scale aquaculture is the Norwegian Salmon industry. While asking if the industry can attain a production of 5 million metric tonnes by 2050, PwC Seafood Barometer (2017) through stakeholders survey, identified the following critical factors: technology innovation, resource usage, environmental sustainability (regulation, lice & climate change issues), that are impacting the industry. The optimistic scenario developed by the PwC Seafood Barometer (2017) assumes that the industry's challenges are solved in a few years and new ones tackled effectively up to 2050. The scenario shows that the Norwegian aquaculture industry can achieve its goal of 5 million tonnes production by 2050 from a baseline of 1.3 million tonnes. This possibility was tied to some growth drivers including increase in the capacity of production systems (particularly Recirculating Aquaculture System - RAS and Closed Containment System - CCS), improved operations in resource use and lice treatment (positive traffic light indicator) as well as increased allowance for new licences. In the present work, even the optimistic scenario showed that Nigeria is unable to achieve its 2.5 million t of estimated aquaculture potential by 2035, with projected production around 450,000 t from a baseline of 250,000 t in 2020. This was based on a future in which the impacts are seen in the aquaculture industry, of improved governance in areas such as land use change, unemployment, importation of raw materials, road construction and research. Specifically, more participation of local communities must be encouraged in creating development plans, while governments at all levels seek to become more accountable (FAO, 2017). Better coordinated research will help boost yield in ponds, tanks, etc., through a more efficient use of resources. Improved road networks will facilitate access to inputs and markets. Proper enforcement of land use laws and regulation will ensure tenure security and encourage increased investments in aquaculture. Ajibo et al. (2021) describes how lack of accountability across economic, social, and environmental spheres in Nigeria has impacted on its quest for sustainable development.

There are several studies that have used scenarios to structure problems for MCE (Marttunen et al., 2017), but scarce for spatial MCE. The study in Chapter 4 of this research project is one of the first attempts in aquaculture research to integrate scenarios with SMCE. This is a useful consideration in the Ecosystem Approach to Aquaculture (EAA) discourse since the identification and allocation of suitable areas (or aquaculture zone) is a critical step in the EAA implementation process. The conversion of croplands and other land use/cover for aquaculture expansion is being restricted or even prohibited in some parts of the world due to the spontaneous expansion of aquaculture over the years (Filipski & Belton, 2018; Joffre et al., 2019; Ottinger et al., 2016; Yu et al., 2020). To support strategic allocation of zones, the result in Chapter 4 highlights the importance of a systematic approach to developing site suitability model coupled with decision analysis. Several studies on aquaculture site assessment have developed different methodologies for producing suitability and site selection models (e.g. Aguilar-Manjarrez & Nath, 1998; Asmah et al., 2021; Barillé et al., 2020; Díaz et al., 2017; Falconer et al., 2013). However, many do not go as far as prioritizing areas for the development of sites or zones, instead leaving that open for users to interpret the results themselves. It was considered here that planners and decision makers at a national level need as much clarity as possible when interpreting suitability models. In view of this, more specific and distinct areas were located within the GIS environment. However, at the national level, LUP is more about the establishment of priorities (policies, plan, and programmes) for subnational or state level projects, than the actual allocation of land for different uses (Faludi, 2000; FAO, 1993).

National land use plans are broad, in that they are meant to cover a large area and extend to several communities (Amler et al., 1999). Therefore, the type of information required by decision makers at this level is less detailed compared to the others (state and local) where actual allocation of zone takes place (FAO and UNEP, 1999). For example, while national-level spatial models may involve factors like poverty index per state (as used here in Chapter 4), state-level models can only use such information either in a different form (like average income per local government area) or at a finer resolution. Since the modelling approach developed in Chapter 4 was for identifying at national scale, alternative zones that are suitable for aquaculture, it can be seen in Figure 4.11, how important it is to set clear objectives or strategic priorities. The occurrence of the potential zones in each model corresponded to the respective strategic priorities drawn from the scenario narratives in the preceding chapter. In real life application, this indicates why and how the objectives of aquaculture development plan should inform site suitability modelling, instead of the other way around. Meanwhile, a national scale site suitability model for aquaculture lends itself mostly to estimating potential. Nash (1995) noted that it is common for objectives of aquaculture plans to be guided by political considerations instead of economic and social realities. When objectives are stated in clear terms and prioritised, supported by appropriate policies and investments, then they become targets which facilitate the equitable allocation of natural resources.

Also, in developing countries like Nigeria, long-term aquaculture plans for 15 years or more are expected to be broad. This is because the required data to achieve a detailed plan is lacking, and as mentioned earlier, the conditions that inform the plan become outdated with time. Therefore, in this context, such long-term plans are more suited for formulating strategies, while being supported by medium or short-term plans during implementation (Nash, 1995). Across the different geographical areas of Nigeria, some states are naturally more productive in aquaculture than others, mostly in terms of water availability. This may be one of the major reasons that more fish farms are found in the south of Nigeria, a humid forest zone, than the Sahelian northern parts. However, the starting point for national planning purposes would be to consider that some areas have established aquaculture activities and looking to expand or intensify while others may seek to begin aquaculture development. Consequently, development requirements are likely to vary between and within states. Again, such disparity was captured by setting strategic priorities and subsequent spatial modelling and decision analysis to identify the best alternative among a number of potential zones. In any case, to expand areas known for aquaculture or develop new ones, stakeholders' perspectives, particularly farmers are key (Corner et al., 2020; Sevaly, 2001). The study presented in Chapter 5 explored the views of famers in Nigeria about some important factors to be considered when planning the expansion of aquaculture clusters or the development of new ones.

Cluster farming is shown to be a promising way for supporting aquaculture growth in Asia, primarily because of reduction in production cost and improved access to market (Ha et al., 2013; Hu et al., 2019; Kassam et al., 2011). Clustering of farms is believed to be a good way to promote inclusive growth (UNIDO, 2013). It facilitates interaction between farmers (horizontal coordination) and between farmers and other actors in the aquaculture value chain (vertical coordination) (Ha et al., 2013). In this research project, it was found that most farmers had a positive perception of aquaculture clusters (Figure 5.5). Also, most farmers remained positive about the potential limitations of aquaculture clusters. There is some disagreement among farmers on whether they are happy to have several fish farms in the vicinity of their farms, although majority were positive, and most importantly over 80% of those who are part of an existing cluster are willing to remain. Another interesting result was the identification of 2 key determinants of farmers perception, their main source of advice and where they discharge farm effluents. This is useful information to consider when designing and/or implementing spatial plan for aquaculture. There are several factors that influence perception. Overall farmers attitude to the concept of aquaculture clustering was thought of, in same way as technology adoption. The perception of the benefit and ease of use of a technology are among the most important determinants of technology adoption (Kumar et al., 2018; Meijer et al., 2015).

According to the principles of cluster development by the United Nations Industrial Development Organization (UNIDO, 2013), it is possible that cluster-based aquaculture development can leverage on existing clusters to expand aquaculture areas, rather than creating new ones. But farm clusters in Nigeria commonly occur around urban centres (Miller & Atanda, 2011). Given the increasing urban sprawl, it would appear not to be sustainable if attempts are made to expand existing aquaculture clusters in Nigeria rather than creating new ones following comprehensive land use plans. This will ensure that the risk of conflict is minimised, support effective management, and allow room for future expansion. The role of bottom-up process to developing policies and plans in attaining equitable allocation of natural resources is well recognised (UNIDO, 2013), and LUP strongly support such process (FAO, 1993). Another principle of UNIDO that is enabled by proper land use plan implementation is the need to strengthen cluster governance mechanism.

It is important to note that in a comprehensive LUP, the actual allocation of zones for aquaculture would require strategic environmental assessment (SEA) (González Del Campo, 2017) and sustainability assessment (FAO and UNEP, 1999). According to Wood & Dejeddour (1992), SEA may be methodologically feasible but sometimes affected by institutional and political resistance or cost, although it is necessary when the impacts of alternatives is difficult to assess using an Environmental Impact Assessment (EIA) which normally happens at project level. A Strategic Environmental Assessment (SEA) is the process of evaluating the environmental implications of a proposed policy, plan or programme and provides means for looking at cumulative effects and appropriately address them at the earliest stage of decision making (Lee & Walsh, 1992; Schmidt et al., 2005). Unlike EIA, SEA provides recommendations at a strategic level and allows for better evaluation of cumulative effects (Wood & Dejeddour, 1992). There is no single approach to SEA, as it depends on the specific needs. Just like EIA, the main stages of a SEA are screening, scoping and study (Lee & Walsh, 1992). Tetlow & Hanusch (2012) suggest that the largest and most successful area of SEA application is spatial planning due to the requirement for SEA of certain land use plans. To promote sustainable development however, a sustainability assessment is often required. It is expected to assess the extent to which the emerging plan (when judged against reasonable alternatives) will help to achieve relevant environmental, economic, and social objectives (Jackson & Dixon, 2006).

Obviously, a sustainability assessment is important in aquaculture zoning, as with other major land use activities. The components of a LUP are context and location-specific, although most LUP involve the collection of baseline environmental and socioeconomic information; land suitability assessment, prediction of the potential benefits and costs of the plan and addressing them during preparation; identification of strategic alternatives along with their impacts; and monitoring of the actual impacts of the plan during implementation (FAO, 1993; FAO and UNEP, 1999). However, to specifically assess sustainability during LUP, criteria and performance indicators or thresholds must be identified against which the plan will be judged (Boggia et al., 2018; Jackson & Dixon, 2006; Sala et al., 2015; Smyth & Dumanski, 1995). In this research project, it is fair to say that the considerations for sustainable aquaculture development was partial, as they are inclined more to impacts on aquaculture from the environment (physical, social, and economic). This is not surprising since the theme of the research project was on aquaculture site suitability assessment, albeit it considered potential changes in future conditions. Again, this reiterates the complexity of spatial planning because a comprehensive plan will consider also, the beneficial and adverse impacts of aquaculture on the environment.

Data and information needs will vary between conflict-motivated LUP and that perceived by the need for change/development (FAO, 1993). Accordingly, the analyses and thresholds of suitability factors must correspond to each situation. Mapping land suitability for different activities is a key step in LUP (FAO and UNEP, 1999). However, detailed appraisal of such suitability maps will be required to help develop a land use plan that is not only based on present environmental and socioeconomic factors but look at potential future changes. Because land use change is driven by the changes and nature of interactions of these factors, the ability to link aquaculture activity to land use change in a given location can provide evidence for others that are planning new development of aquaculture. In addition to informing the feasibility of the new development and pointing out sustainability criteria, it can guide the implementation stage including the evaluation of performance.

The evaluation of spatial/land use plan performance is also a very important step in LUP. One of the ways to carry out an evaluation is to compare the rate of land use change before and after implementation (Abrantes et al., 2016). This research project demonstrates the significance (in chapter 4 and 6) of exploring the past changes in land use and other factors considered in suitability assessment for aquaculture during LUP, in addition to the common practice of gathering only present information. This is because understanding past events could give insights into potential future risks and given that aquaculture is less flexible than many land uses in terms of suitable space, further supports the usefulness of such time series analysis. A time series analysis using spectral indexes was conducted in Chapter 6 to compare land use changes that are occurring between a potential zone and a given area with high concentration of aquaculture ponds. A threshold can be set using the reference site findings (i.e. how aquaculture ponds are expanding relative to other land use) and used to assess the sustainability potential at the potential zone.

How to locate and assess land for aquaculture zoning is central to this research project. As pointed earlier, moves to capitalise on existing areas for expansion might be counterproductive due to urban sprawl. Abrantes et al. (2016) found that zoning did not work as was intended in Lisbon metropolitan region in Portugal between 1990 and 2007 because the conversion of agricultural fields and protected areas continued. This type of finding is expected in developing areas like Nigeria. Therefore, rather than expect LUP to halt unwanted changes in land use, the aim should be to achieve what authors such as (Faludi, 2000; Feitelson et al., 2017; Rudolf & Grădinaru, 2019) described as 'planning-as-learning'. In essence, instead of measuring performance based on the extent to which allocation and development of aquaculture zone conform to the land use plan, it should be measured as the degree to which the plan was used, including how they improve the understanding of decision makers of the present spatial issues and potential ones in the future. Nigeria is a large and highly diverse country. With the rapid growth in the country's population, pressure on natural resources will increase and land use pattern may change across geographic locations. National aquaculture strategy and plans for improved spatial and production management must rely on the best available scientific information to ensure a sustainable future for the sector.

Considering the limitations of this research project highlighted above, further studies may focus on the following: 1) understanding what difference a participatory scenario planning makes in aquaculture scenario generation, compared to that enabled by literature survey/expert opinions. 2) constructing spatial and temporal criteria to better evaluate alternative locations for strategic planning of aquaculture. 3) Evaluating the actual benefits and limitations experienced by farmers in aquaculture clusters in Nigeria and/or the perspectives of other stakeholders about aquaculture clusters. 4) Create land use models to include aquaculture ponds so that the intensity and pattern of expansion can be investigated in different aquaculture areas. 5) Developing subnational or local-level spatial planning tools for aquaculture, which includes not only the impacts of the surrounding on aquaculture but also the other way around.

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APPENDIX A

Survey Questionnaires (Delphi method)

Introduction

This survey is part of a PhD project on ‘Decision support tools for aquaculture planning in Nigeria’, which was designed to engage some relevant experts using the Delphi method. The Delphi method is used for congregating expert opinion through a series of iterative questionnaires, with a goal of coming to a group consensus. It is a useful research methodology where there is no true or knowable answer, such as decision-making, policy, or long-range forecasting.

Participation in this study is voluntary and you are free to withdraw at any time, should you change your mind (email: s.o.yakubu1@stir.ac.uk). You will be assigned a code so your responses are anonymized, and your name/email address will be held confidential only for the purpose of this study.

The study aims to gain insights into the future of aquaculture in Nigeria, to enable the creation of strategic tools for research and development. To this end, it is hoped that 3 or 4 rounds of exercise will be conducted, which should take up to 20 minutes each.

Consent

Your rights include but not limited to the following: right to withdraw, right to information on the outcome, right to rectification and only the research team will have access to your data.

1. Name

2. Email:

3. Affiliation:

Delphi 1: Factor identification questionnaire

1. In your opinion, what are the requisites for Nigeria to realize its estimated potential of 2.5 million metric tonnes (MT) of aquaculture fish production? *Please type in the box below*

2. On a scale of 0 - 5 (0=not at all, 5=high), to what extent do you agree with each factor in the list below as an important driver of change for pond aquaculture in Nigeria?

ID	Factor	Scale
1	Population growth	
2	Poverty and Inequality	
3	Climate change	
4	Availability/cost of inputs	
5	Land use & land cover change	
6	Inflation rate	
7	Unemployment rate	
8	Geopolitical change	
9	Research-Industry relationship	
10	Land tenure system	
11	State of technology	

3. Please state additional factors that you feel are missing from the above list. *Please type in the box below*

Delphi 2: Factor uncertainties and trends questionnaire

1. Below is a shortlist of factors suggested by all the experts; in your judgement, please rank in order of importance and uncertainty for pond aquaculture development in Nigeria.

Factor ID	Factor	Rank	
		Importance	Uncertainty*
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			

**Uncertainty refers to the extent to which a factor is out of the industry's control and the likelihood that any change in the factor will impact aquaculture.*

2. Looking at the current state of factors, what trends do you expect to continue in the long term (10 – 20yrs)? *Please type in the box below*

APPENDIX B

Online questionnaire: Criteria weighting for ranking of the alternative zones

Task: Score the 3 criteria below based on your opinion of their importance.

Instruction: This questionnaire contains four parts (one per page). You should first identify the most important criterion and give it a score of 100, then score the remaining 2 criteria relative to 100 (i.e., each criterion score must be less than 100 but both criteria can have the same score).

Criterion 1 (C1): *An area with good water availability/quality that is consistent throughout the year*

Criterion 2 (C2): *An area where the land use/local market potential to support pond fish farming remained high after it was identified 10-15 years ago*

Criterion 3 (C3): *An area that is less likely to compete with rice farming*

PART 1: To select a suitable zone for pond aquaculture in a country 'X' based on the 3 criteria above, follow the instruction to score the criteria.

Criterion	C1	C2	C3
Score			

PART 2: Now, imagine the following scenario and see if you want to reconsider your scoring.

In country 'X', land use regulation and tax regimes are weak, such that extensive land around peri urban areas is easily converted from one use to another. It is not clear how much progress has been achieved in the use of local feed materials and brood stock development due to lack of reliable data for evaluation. The impacts of changes in temperature, rainfall pattern and desertification on pond farms across geographical regions are not understood.

Criterion	C1	C2	C3
Score			

PART 3: Again, imagine the following scenario and see if it changes anything.

In country 'X', the water use legislation is in force, so measures are becoming stricter for conserving ground & surface waters along with aquatic resources. Other challenges include the growing competition for land between large-scale pond and rice farmers in some states. Allocation decision requires local knowledge, but there is insufficient data on both resource use efficiency and household economies. More erratic rainfall and reduced stream flow is being experienced, even in the southern region, known for high amount of rainfall.

Criterion	C1	C2	C3
Score			

PART 4: Finally, imagine the following scenario and see if it changes anything.

In country 'X', built-up areas are more compact in the supposed peri urban areas as population density increases. Many local authorities do not have legal restrictions on land conversion, and aquaculture widely remains a peri urban affair. Due to aquafeed price fluctuations, many small-scale fish farmers are cutting down on production cost by using waste food materials, including from slaughterhouses. Some have resorted to seasonal farming following the availability of these materials. Others do so in response to seasonal variation in temperature and rainfall.

Criterion	C1	C2	C3
Score			

APPENDIX C

Questionnaire used for data collection on drivers of famers' perception of aquaculture clusters

Section 1: Farm characteristics

1. Consent page
2. What is the area of your farm? …………………………………………….. ft^2 ☐ m^2 ☐
3. Which of these facilities is used on your farm for grow-out fish production? *please tick all that is applicable*

Concrete tank ☐ Earthen Pond ☐ Fibreglass/wooden trough ☐ Collapsible tank ☐ Other: ………………

4. What is the area of the biggest facility for grow-out fish production? ………………………… ft^2 ☐ m^2 ☐
5. How many fingerlings is usually stocked in the facility specified in Question 4? …………………………………………
6. Is your farm a part of any of the following?

Cooperative ☐ Cluster ☐ Group ☐ Association ☐ Not applicable ☐

Name if applicable: ……………………………………………………………………………………………………

7. What is the main source of water on your farm?

Well ☐ Borehole ☐ River/Lake ☐ Rainfall ☐ Other: …………………

Section 2: Resource use and farming practice

8. How many times do you sort/grade fish in a production cycle? 0 ☐ 1-2 ☐ more than 2 ☐ Don't know ☐
9. How do you determine the amount of feed for grow-out fish?

Feed company chart ☐ Feed to satiation ☐ % Body weight calculation ☐ Randomly ☐

Other: ……………………..

10. Which of these water management methods is practiced on your farm? *please tick all that is applicable*

Flow-through ☐ Recirculating ☐ Manual exchange ☐ Biofloc technology ☐

Other: …………………………………..

11. Where do you discharge effluent water from pond/tank?

Ditch on the farm ☐ Surrounding gutter ☐ Agricultural land ☐ Bare land ☐

Other: ………………………………….

12. Why did you select this site for your fish farm?

Farm is part of my inheritance ☐ Area is well-known for fish farming ☐ Only piece of land available to me ☐ Bought as already established farm ☐ Other:

…………………………………………………

13. Where do you get advice on how to solve problems such as fish disease or poor growth? *please tick all that is applicable*

Neighbouring farmers ☐ Extension agents ☐ Personal materials/experience ☐ Online ☐

Other: …………………….

Section 3: Perception of cluster farming

14. To what extent do you agree or disagree with the following statements?

Statement	Strongly agree	Agree	Undecided	Disagree	Strongly disagree
I am/would be comfortable having several fish farms around my farm	☐	☐	☐	☐	☐
More than 70% of fish farmers around me adopt the same farming practices, e.g. feeding method	☐	☐	☐	☐	☐
I worry about pollution from neighbouring fish farms	☐	☐	☐	☐	☐
I worry about pollution from agricultural land	☐	☐	☐	☐	☐
Fish farmers in a cluster have better access to inputs (e.g. feed) than farmers that are not	☐	☐	☐	☐	☐
Fish farmers in a cluster have better access to information (e.g. training opportunities) than farmers that are not	☐	☐	☐	☐	☐
Fish farmers in a cluster have better access to government support than farmers that are not	☐	☐	☐	☐	☐
Fish farms in a cluster are more exposed to theft than farms that are not	☐	☐	☐	☐	☐

Section 4: Farmers' attributes

15. Highest education: Below secondary ☐ Secondary ☐ Above secondary ☐

16. Years of fish farming experience: Below 2 years ☐ 2-5 years ☐ Above 5 years ☐

17. Email address (Optional):

………………………………………………………………………………………………………...

18. Name of farm (Optional):

………………………………………………………………………………………………………..

19. Name of local government and state where farm is located:

……………………………………………………….

20. Please name a primary or secondary school or other educational institution in the area where farm is located:

……
………………….

APPENDIX D

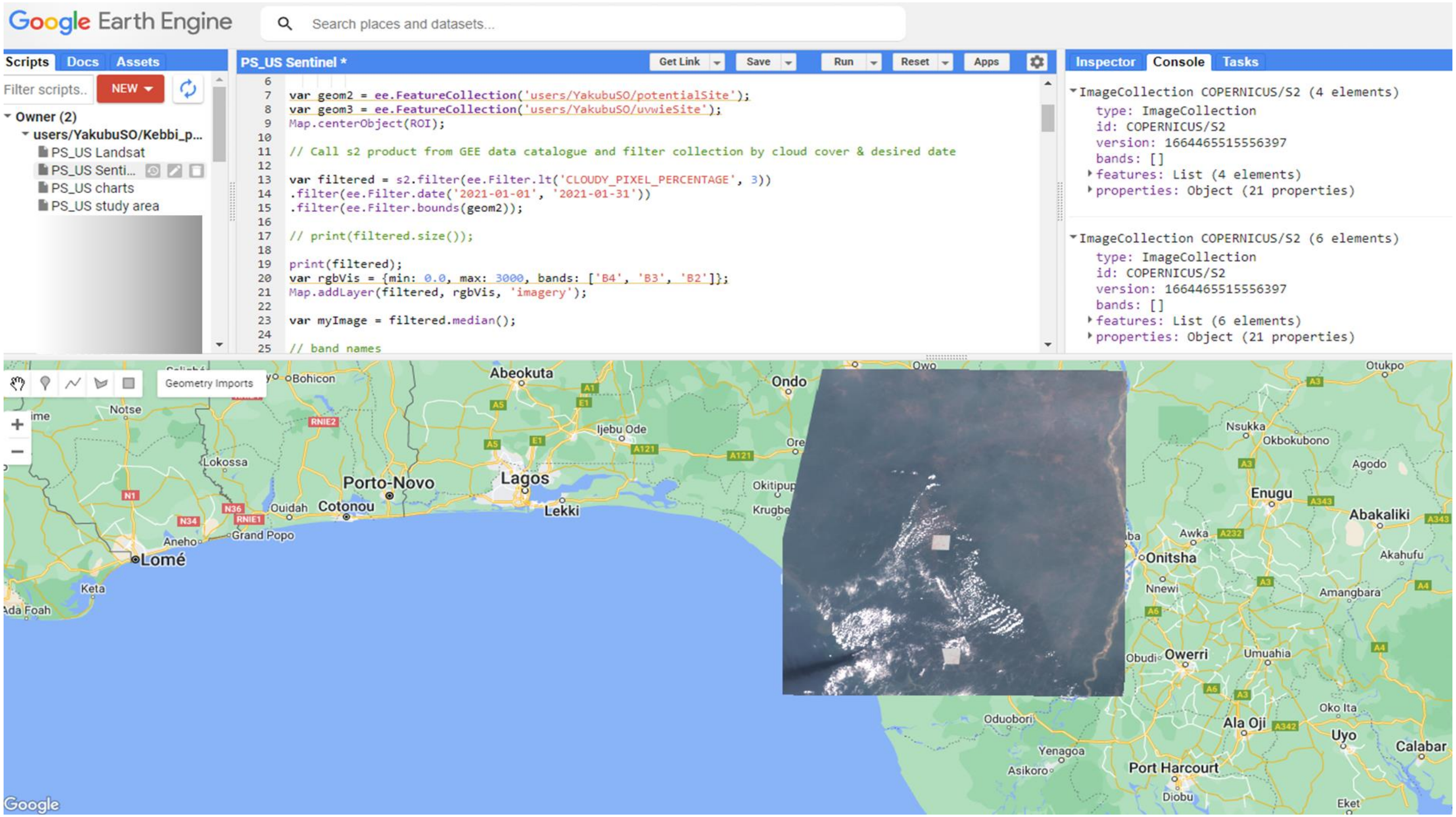

Figure D.1: A screenshot of Google Earth Engine code editor showing the footprint of Sentinel-2 dataset used