Spatial species distribution models to predict liver fluke disease (*Fasciola gigantica*) in cattle: A case study of Sokoto State, Nigeria.

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By

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ABSTRACT

Spatial species distribution models to predict liver fluke disease (*Fasciola gigantica)* in cattle*:* A case study of Sokoto State, Nigeria.

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Species distribution models provide an alternative way of observing the distribution of species rather than the conventional methods such as satellite tracking, aerial photography and ground surveys that are both labour and capital intensive.

This thesis presents the first application of species distribution models using short-term and long-climate average in predicting the suitability of habitats and transmission pattern of *F.gigantica* in a semi-arid part of Nigeria in West Africa. The MaxEnt modelling technique was identified in giving better results than BioClim and Domain models in modelling the geographic range of *F.gigantica* based on six accuracy measures (sensitivity, specificity, Kappa, True Skill Statistics, AUC and Correlation). Also, six scenarios were created with MaxEnt using both Bioclim and non-Bioclim variables, which were validated with independent data obtained during the field work. Finally, Bioclim variables generated from IPCC future climate projections under 'modest' RCP 2.6 and 'aggressive' RCP 8.5 greenhouse gas emission scenarios were utilised in the construction of the MaxEnt model for two time slices 2041-2060 and 2061-2080. Subsequently, soil moisture was found to be the most significant variable and the distributions of *F. gigantica* in the study area were significantly associated with it ($p<0.05$). The predicted area of suitability for the disease prevalence has expanded under both RCP's for the two future time slices.

By combining a species distribution model with satellite based and HadGEM2-es climate projections, risk maps with the aid of GIS were generated indicating which provinces of Sokoto State are predicted to experience an increase in fascioliasis risk in the future. This study validated the short-term model by examining the relationship between the risk indices, and climatic variables with fascioliasis recorded prevalence.

This research also used two questionnares through a cross-sectional survey on slaughtered cattle at the abattoirs of the sampled localities in investigating the influence of biological factors on fascioliasis prevalence.

Gathering the models developed in this study, coupled with the biological risk factors, can improve our understanding of both the present and future risks. That will no doubt promote the ability to design effective control strategies against this parasite that takes a heavy toll on animals' health and productivity.

Dedication

This thesis is dedicated to my parents, my beloved wife (Rukayya), my sons, daughters and all my brothers and sisters.

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List of abbreviations

AIRS	Atmospheric Infrared Sounder
AUC	Area Under the Curve
CDC	Centre for Disease Control
CIAT	International Centre for Tropical Agriculture
CliMond	Climatic '*Mondid'*
CMIP	Couple Model Intercomparison Project
COR	Correlation
CRU	Climate Research Unit
DEM	Digital Elevation Model
DMSP	Defence Meteorological satellite Programme
FEWSNET	Famine Early Warning System Network
FNR	False Negative Rate
FPR	False Positive Rate
GARP	Genetic Algorithm for Rule-set Predictions
GDD	Growing Degree Days
GCM	General Circulation Models
GIS	Geographic Information System
GLDAS	Global Land data Assimilation System
GSFC	Goddard Space Flight Centre
HADGEM2-ES	Hardley Centre Global Environmental Model version 2-Earth System
IPCC	Intergovernmental Panel on Climate Change
LST	Land surface Temperature
MaxEnt	Maximum Entropy
MODIS	Moderate resolution imaging spectrometer

NADIS	National Animal Disease Information Service
NASA	National Aeronautics and Space Administration
NDVI	Normalised Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NPC	National Population Commission
RFE	Rainfall Estimates
SRTM	Shuttle Radar Topographic Mission
TNR	True Negative Rate
TPR	True Positive Rate
TSS	True Skill Statistics
WHO	World Health Organisation
WorldClim	World Climate

Chapter 1

Background

1.1Introduction

This chapter provides background knowledge on the topic of this thesis (species distribution models) and an overview of all chapters in this study. It includes explanations of relevant concepts, terms, and tools that shed more light on the topic and its potential contributions to knowledge.

1.2 Species distribution models

Species distribution models predict the possible or actual range of a species through integrating species recorded presence with measured climatic/environmental characteristics that are believed to be favourable for the survival of the species at the known occurrence location (Pearson, 2007). These modelling techniques start by identifying the presence of a species, and then both biotic and abiotic factors assumed to be favourable for the species. These data can then be used to approximate the spatial dispersion of favourable climatic conditions that suit a species across an area of study (Franklin, 2009). This modelling approach is a branch of biogeography (Box, 1981, Pearson et al., 2007), ecological gradient analysis (Whittaker et al., 1973) and geographic information science (Franklin, 1995). Species distribution modelling is sometimes called environmental niche modelling or habitat distribution modelling or climate envelope modelling (Elith and Leathwick, 2009a). Regarding the scale of the study, ecological relationships can be investigated at any level in species distribution models as 'conceptually there are 'no' restrictions on any 'natural scale' (Levin, 1992). Preferably, the scale is to be determined by study objectives and data availability (Elith and Leathwick, 2009b).

Species distribution models fall under the broad category of correlative models that are preoccupied with establishing the relationship between species occurrence at a site and the environmental variables of the site (Pearson, 2007). These environmental variables encompass both the climatic and non-climatic conditions that are suitable for the physiology and persistence of the species otherwise known as environmental space. This environmental space is based on the theory of ecological niches that has for long been applied in ecological studies (Chase and Leibold, 2003). Grinnell (1917) defines an ecological niche as part of the habitat that maintains a population of species over a long period in environmental space. This definition was supported by Peterson (2003) who added that niche provides the specific limit of a geographic range of a species with suitable ecological conditions. On the other hand, Elton (1927) defines the ecological niche as the predation and prey relationships of a species or the interrelationships of species among themselves, especially in the food web. This definition assumes that species maintain survival based on suitability of the environmental conditions and their ability to withstand competition with other species (Hirzel et al., 2002, Sober´on, 2007)

As modelling species distribution based on the Eltonian definition is always a difficult task since it involves interrelationships between species, thus this study used the expanded definition of a niche in line with Hutchinsonian theory. This theory described a niche as an ‘n-dimensional volume' of species habitat that contains suitable environmental conditions that can support species survival without the need to emigrate (Hutchinson, 1957). This geographic area occupied by the species according to Hutchinson (1957) is referred to as a fundamental or potential niche. This potential niche implies the actual or the full extent of the suitable habitats that can support species survival in environmental space, but some factors such as biotic interactions (competition with other species, predation) or geographic obstacles may impede species from occupying all suitable habitats (Anderson and Mart´ınez-Meyer, 2004). A realised niche is the actual area that species are inhabiting where there is no possibility of exclusion (of the species) due to biotic competition, and hence it is a subset of fundamental niche (Hutchinson 1957). Pearson (2007) further added that due to some constraints on the realised niche in the form of geographic barriers (very high elevation, slope) and biotic factors (competition with the same species or different species) can enforce species to inhabit an area referred to as occupied niche. Nevertheless, it is vital to understand that a species can occupy habitats that are not suitable for their livelihood as a result of moving away from more suitable habitats. This situation explains the theory of source-sink (Pulliam, 2000) where the former as the sink (unsuitable) while the latter as the source (suitable). Furthermore, due to a possibility of adverse conditions at the ‘sink,' it is expected that the species may face extinction.

1.2.1Types of data for species distribution models

The data for species distribution modelling, according to Pearson et al. (2007) are divided into two types: biological data that explains the observed occurrence sites of species and environmental data associated with the landscape where the species is present. The biological data are available from a variety of sources, which include personal collection, land surveys, museum collections, and online resources. Different researchers in species distribution modelling utilise these sources (Fleishman et al., 2001, Araújo et al., 2005, Raxworthy et al., 2003). Moreover, these biological data are in two categories: firstly, sites where the species presence is known (presence-only) and secondly on locations where the species are present and where absent (presence/absence). The use of this latter type of biological data according to Brotons et al. (2004) often leads to better model performance. However, there should be caution in the use of presence/absence records since some sites may be suitable for species survival but during the survey, the species may not be detected thereby leading to the inclusion of 'false absences'(Hirzel et al., 2002). Some notable limitations of biological data for species distribution modelling include species misidentification, the wrong coordinate system of samples and tendency of samples to be collected that are closer to human settlements and access routes (Graham et al., 2004, Pearson 2007). Regarding environmental data, the most common variables in species distribution modelling are climate (temperature, precipitation) altitude or configuration of the landscape (slope, elevation), vegetation and soil type (Franklin, 2009).

1.2.2 Generic species distribution models

In modelling species distribution, 'generic' techniques (Fox, 2012) are available that include statistical methods (logistic regression, generalised linear models, generalised additive models) and machine-learning methods [maximum entropy and artificial neural networks] (Pearson, 2007). Also, the algorithms of some of these methods uses presence/absence or presence-only record of species in modelling the species geographic range (Franklin, 2009). The algorithms of presence/absence techniques differentiates between species presence locations and absence locations in modelling spatial distribution of a species. Examples include generalised linear models (GLMs,), generalised additive models (GAMs), Genetic Algorithm for Rule-set Predictions (GARP) and artificial neural networks (ANNS). In contrast the algorithms of the presence-only techniques distinguishes species present locations and background locations since absent locations are unknown (Graham et al., 2004). These methods include BioClim (Busby, 1991), MaxEnt (Phillips et al., 2006), SPECIES (Pearson et al., 2002) and Domain (Carpenter et al., 1993). All these models apply to any climate-sensitive species given availability of occurrence records and associated environmental characteristics. Chapter 4 of this thesis compared three of these presence-only methods (MaxEnt, BioClim, and Domain) in modelling the geographic range of *F. gigantica* in the present study area

1.2.3 Species-specific species distribution models

Species-specific correlative models were developed specifically on helminthiases with a particular focus on fascioliasis due to the dependence of its life cycle on climate and weather conditions (de Waal et al., 2007). Ollerenshaw and Rowlands (1959) study provided the foundation for building a fascioliasis risk index based on the availability of a ten-year prevalence record that enabled the creation and validation of statistical methods. Another added impetus was awareness and knowledge of the influence of temperature and moisture in the geographic range of fascioliases coupled with the parasite's international distribution. All these factors make fascioliases unique and the ideal parasite for the application of the species-specific correlative model that is currently in use in the early warning system (EWS) in the UK. This technique explains the temporal transmission pattern of fascioliasis as an index of risk that incorporates 'the application of geographic information system (GIS) technology' (Malone et al., 1998b). Finally, chapter 5 applied this method in producing the first short term and long-term fascioliasis risk in Sokoto State, Nigeria.

1.2.4 Limitations of species distribution models

Despite the values of species distribution models (discussed later), some limitations are affecting the efficient performance of these models. Reddy and D´avalos (2003) explained that bias in species distribution modelling could occur owing to the tendency to select species occurrence records that are closer to human settlements, rivers or roads. Many data on species occurrence are opportunistic records and hence their collection is not based on systematic field surveys that can guarantee better fitness for species distribution modelling (Franklin, 2009b). Also, the existing record of species at a site may not be too accurate regarding X and Y Coordinates, or in having the right species of reference or in attaining the optimal number of records needed to produce the best modelling results (Stockwell and Peterson, 2002). Similarly, the climatic variables used in modelling may not be too accurate due to errors associated with the models applied to generate them which even if used in modelling may lead to unreliable results. In addressing the issue of bias in the selection of species occurrence records, Fourcade et al.

(2014) proposed some techniques. Each one of the techniques is expected to reduce bias in species occurrence records thereby increasing the reliability of modelling results.

Another essential pitfall that may affect the efficient performance of species distribution models is that the models were developed using occurrence data based on the realised niche (Guisan and Zimmerman, 2000) instead of the fundamental niche. Thus all the major obstacles that can hinder species from occupying all suitable areas such as very high elevations or biotic interactions (competition with other species, predation) are not considered (Pulliam, 2000, Anderson and Mart´ınez-Meyer, 2004). Some few approaches have incorporated biotic environments in species distribution modelling (Araújo and Luoto, 2007. Heikinnen et al., 2007.)

Finally, another limitation of correlative models as noted by Ortega-huerta and Peterson (2008) and Pearson et al. (2006) is that different species distribution models even though developed with the same inputs often yield different outputs. This result was also confirmed by Loiselle et al. (2003) in their study where different models produced various outcomes. This variation in performance according to Thuiller (2003) can be resolved using the newly available ‘framework' for choosing most scientifically reliable statistical models. In other words, a broad understanding of how the algorithm of different mathematical models work can provide precious information in selecting the best model that suits a specific species or study area. (Elith and Leathwick, 2009b)

1.2.5 Applications of species distribution models

Beyond all these limitations, species distribution models have broad applications in different areas. Studies by Peterson et al. (2006), Kozak and Wiens (2006) and Raxworthy et al. (2007) proved that species distribution models could be advantageous in the identification of high-risk areas for disease outbreaks, species niche studies, and taxonomy. Given that, species distribution models were used in modelling the geographic range of fascioliasis in Greece, Colombia, the UK, Iran, East Africa and Pakistan (Malone et al., 1998a, Kantzoura et al., 2011b, Fox, 2012, Valentia-Lopez et al., 2012, Afshan et al., 2014). Regarding conservation, these models provide an opportunity for exploration of potential areas which the species can inhabit through aiding appropriate planning of field surveys (Fleishman et al., 2002, Guisan et al., 2006). Species distribution models have also been applied in impact evaluation and management of resources, ecological modelling and in investigating the effects of climate change on biodiversity and ecosystems (Franklin, 2009b).

1.3 Climate-sensitive diseases

Climate fluctuations and changes affect both the present and future geographic range, intensity as well as the transmission pattern of animal diseases (Baylis and Githeko, 2006). Thus, any pathogen whose transmission can be decreased or increased by the influence of climate is regarded as a climate-sensitive disease (Grace et al., 2015). These diseases are affected by climatic elements such as temperature, rainfall and heat stress influencing the activities of the pathogens, vectors and their hosts'. Even the ecosystem services relating to disease transmission and animal management are likely to change due to changes in climate. In this light, 65 animal diseases have been recognised as important to livestock keepers in developing countries out of which 58% are classified as climate-sensitive. In addition, these diseases are reported by the World Health Organisation (WHO, 2006) as having a high probability of affecting the health and wellbeing of not only animals but humans in third world countries due to their zoonotic nature. Furthermore, climate-sensitive diseases are more prevalent in developing countries which are characterised by high temperatures and vulnerable populaces. Moreover, fascioliasis is among 13 diseases that are known as important to livestock keepers in sub-Saharan Africa. The majority of livestock (81%) are in developing countries (FAOSTAT, 2013) where they are under threat of these climate-sensitive diseases, demonstrated by the annual mortality of 20% of ruminants (Otte and Chilonda, 2002).

Table 1-1 Significant Livestock diseases to poor and vulnerable livestock keepers in Africa and Asia

Disease/pathogen	Region			
	WA	ECSA	SA	SEA
Salmonellosis	1	1	1	1
Campylobacteriosis	1	1	1	1
Crytosporidiosis	1	1	1	1
Leptospirosis	1	1	1	1
Botulism	1	1	1	1
Endoparasitosis	1	1	1	1
Listeriosis	1	1	1	1
Toxoplasmosis	1	1	1	1
Escherichia coli infection	1	1	1	1
Anthrax	1	1-	1	1
Fascioliasis	1	1	1	1
Trypanosomiasis	1	1	0	0
Ectoparasites	1	1	1-	1

1=an important problem; 1- =a minor problem; 0=not a problem

Regions: WA= West Africa, ECSA= Eastern, Central and Southern Africa, SA= South Asia, SEA= South-East Asia (source: Grace et al., 2015)

1.4 Geographic Information System (GIS) tool in species distribution modelling

A GIS is a digital-based information system that is an essential tool for species distribution modelling. Pearson (2007) explained that all data about environmental and species occurrence must have the capability to be visualised and stored in a GIS-friendly format before any modelling operations. GIS serves as an instrument that assists SDM in the conversion of different environmental variables and biological data to the same geographic reference system. Also, the GIS tool is essential in analysing model outputs for visualisation and further required manipulations (Pearson et al., 2002).

In addition to the functions mentioned above, GIS is an appropriate tool in the study of fascioliasis which possesses some characteristics in endemic localities. According to Yilma and Malone (1998) changes in the incidence of fascioliasis were related to responses to varied climatic conditions in endemic locations. Moreover, GIS can use these climatic conditions in modelling. Another characteristic of fascioliasis which GIS can incorporate in modelling is practices of animal management and their populations.

Fascioliasis prevalence is associated with the presence of snails that maintain a long lifespan and generations in suitable locations, which also adds to its amenability to GIS analysis.

1.5 Thesis Structure

The dissertation consists of seven chapters classified into three sections (Figure 1.1). The introductory chapters presents the essential background information and explanations of some contextual terms, followed by the presentation of the results and discussions of the methods used in the research. The final section, includes the overall discussion, conclusions and the contributions of the research in the control of liver fluke disease in Sokoto State.

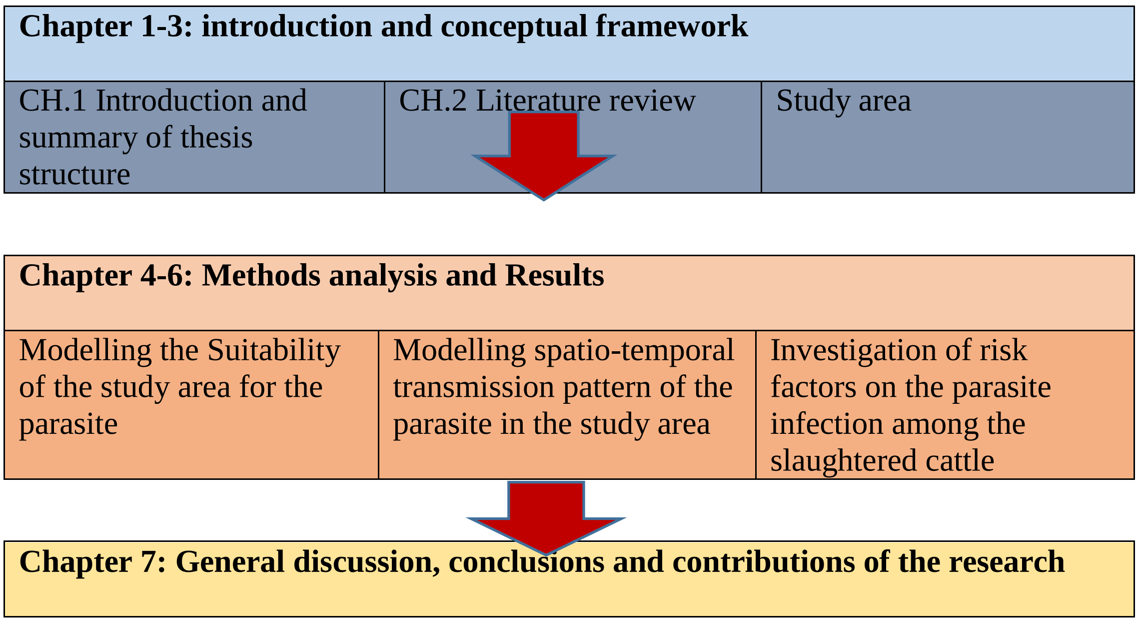

Figure 1-1: Thesis structure

Chapter 1: The chapter explores the main background information on species distribution modelling.

Chapter 2: A related literature review in this chapter started with a description of the lifecycle and essential factors affecting the prevalence of fascioliasis. Also includes a review of some studies on fascioliasis across different parts of the world using species distribution modelling techniques. Presented at the end of the chapter are gaps in the literature, research questions and objectives.

Chapter 3: Highlighted background information about the study area regarding descriptions of its climate, vegetation, agriculture, and hydrology.

Chapter 4: This chapter dealt with modelling of the geographic range of *F.gigantica* in the study area. Different techniques based on presence-only (MaxEnt, BioClim, and Domain) were compared. The chapter also includes the use of BioClim variables from WorldClim and climatic variables from a satellite based on current and future projections in modelling the geographic range of fascioliasis using MaxEnt modelling.

Chapter 5: This chapter presents the use of a species-specific species distribution model in the calculation of climate-based forecast risk of fascioliasis and also in the determination of its spatiotemporal transmission pattern in Sokoto State. The main climatic elements used include rainfall and potential evapotranspiration.

Chapter 6: This provides an investigation into risk determinants (both biological and environmental) for fascioliasis infections among the slaughtered cattle data obtained from fieldwork. It presents the use of binary logistic regression in estimating the likelihood of disease infections due to cattle characteristics, cattle holder socio-economic status, practices of herd/cattle management and environmental variables in the study area.

Chapter 7: This chapter summarises the overall research contributions of this thesis based on the use of spatial distribution models in predicting *F.gigantica* in the study area. It also includes the general discussion and conclusions from chapters 4, 5 and 6. This chapter also presents the main weaknesses of the study and directions for future research.

Chapter 2

Literature Review

2.1 Introduction

Although fascioliasis is among the climate-sensitive diseases, other factors are also important in contributing to its incidence. In this regard, Yatswako and Alhaji (2017) explained that both intrinsic (biological characteristics) and extrinsic (climatic/environmental) factors determine the outbreak and intensity of fascioliasis in domestic animals. According to the Food and Agricultural Organisation report, developing countries keep 81% of the 38 billion livestock population worldwide (FAOSTAT, 2013). However, the health and productivity of this livestock are under severe threats from diseases including fascioliasis (Grace et al., 2012). As reported by Steinfeld et al. (2006) globally the livestock sector accounts for 40% GDP that provides nourishment to humanity and employment of 1.3 billion people. Because of the, 'one health' approach (Conraths et al., 2011) which involves a collaboration of different disciplines in the control of diseases has been recommended.

This chapter, therefore, reviews the literature on the fascioliasis parasite and the factors that affect its geographical distribution. In addition, this chapter reviews applications of species distribution model techniques in the control of fascioliasis across various parts of the world. The essence was to pinpoint research gaps in the study of fascioliasis and as act as a basis for constructing the research questions and objectives for this study.

2.2 Fascioliasis disease

Fascioliasis is a parasitic disease whose life cycle substantially depends on moisture and thermal conditions (Malone et al., 1998a, Mas-Coma et al., 2009, Freitas et al., 2014). This parasitic disease has attracted International attention due to its impacts on animal and public health (Afshan et al., 2014). Furthermore, fascioliasis alongside other helminthic diseases tops the outline of the items in the agenda at the 3rd World Meeting of the Partners for Parasitic Control (PPC) conducted in WHO headquarters, Geneva 2004 (Mas-Coma et al., 2005). In addition, fascioliasis is described as a fatal disease that reduces the productivity of cattle and sheep (Valentia-Lopez et al., 2012, Charlier et al., 2014). Besides, health effects due to fascioliasis constitute substantial economic losses that run into millions of dollars in different parts of the world (Saleha, 1991, Malone et al., 1998a, Fox et al., 2011)

Fascioliasis is caused by two `etiological agents', F.hepatica and *F. gigantica* where the former is more prevalent in temperate areas while the latter is mostly in the tropical regions (Andrews, 1999). Moreover, *F.gigantica* is genetically related to *F.hepatica* but diverged many millions of years ago and then dispersed into various parts of Asia and Africa (Irving et al., 2003). Thus, these two species share common characteristics regarding liver infections of the mammalian host and share the same life cycle. Despite these common attributes, according to Spithill et al. (1999), these two species differ in the amount of moisture needed by their respective intermediate hosts and also in the interactions between the host and the parasite. Differences also exist in the practices of animal management and other development indices between temperate areas where *F.hepatica* thrives and tropical biomes where *F.gigantica* is endemic. Also, *R.natalensis* that transmits *F.gigantica* requires higher temperature and stagnant water bodies whereas *Galba truncatula* needs lower temperature and intermittent water bodies (Mas-Coma, 2004). All these variations account for the epidemiological differences between the two species, which warrants different studies. In Nigeria, only *F.gigantica* thrives, which according to Spithill et al. (1999) reached 60% prevalence rate.

It is essential to note that fascioliasis does not only affect animals but also human beings and hence it is viewed as water or food-borne zoonotic disease owing to its public health effects (Moe, 2004). In that light, it was recognised as foodborne trematodiasis (FBTs) by the World Health Organisation (WHO) as deserving attention since it constitutes a great health burden in many countries of the world. For example, it was reported by Sripa et al. (2010) that human fascioliasis leads to liver and bile duct cancer and is rated number five amongst the ailments noted as possessing the most significant quantity of disability-adjusted life years (DALYs) in 2004.

2.2.1 Lifecycle of fascioliasis

The life cycle of fascioliasis is complicated owing to the presence of both intermediate and definitive hosts couple with favourable environmental factors that are indispensable for the survival of the parasite (Mas-Coma et al., 2014). Tolan (2011) described the developmental stages in the life cycle of fascioliasis as starting with the release of fresh eggs in the bile ducts and faeces of the infected animals and sometimes humans. Under suitable climatic conditions of temperature and moisture, hatching of these eggs in faeces occur and consequently produce miracidia that infect vulnerable lymnaea (natalenses) snails as its intermediate hosts. In addition, the miracidia undergo the reproductive process in the snails and yield sporocyst, rediae and finally cercariae. The snail then discharges the cercariae that later encyst into metacercariae on suitable surfaces such as leaves of grasses and stems (Andrews, 1999, Graczyk and Fried, 1999). Consequently, after ingesting the grass by the grazing animals, the metacercariae excyst in the duodenum and follow through the appropriate intestinal surface into the peritoneal cavity and then finally occupy the liver parenchyma through the biliary ducts for development into adults (Tolan, 2011).

The continuation of the fasciolosis life cycle depends on optimum conditions of climate parameters notably temperature and precipitation (Fox and Hutchings 2013, World Bank 2014). Also, according to Mas-Coma et al. (2009) environmental factors such as latitude and altitude determine the conditions of temperature which may affect the prevalence of fascioliasis (Figure 2.2). *Fasciola gigantica* being a tropical species requires higher minimum temperature than *F.hepatica* that thrives in temperate areas, but the two species overlap in some tropical regions with high altitudes, for example Kenya and Ethiopia (Malone et al., 1998a) and also in Egypt (Soliman, 2008). Extreme hydrological events such as heavy rainfall leads to flooding and accumulation of water under poor drainage, which may provide new habitat for intermediate hosts of fascioliasis (Torgerson and Claxton, 1999). The ecological condition required by the snail *L.A. natalenses* that transmits *F. gigantica* is water that moves sluggishly or collects at a depression, for example in lakes (ponds) or rice fields where irrigation is practiced (Kendall, 1965, Fabiyi, 1987).

Figure 2-2: Associations of risk factors that enhance the emergence of F. gigantica (Togerson and Claxton, 1999 modified).

2.2.2 Intermediate and definitive host of fascioliasis

In the free-living state after emerging from faeces under optimum temperature and moisture, fascioliasis parasite development halts unless accommodated inside the body of another living organism as the vector referred to as the intermediate host (Tolan, 2011). The dominant species of intermediate hosts of *F.gigantica* is *lymnae auricularia sensu lato*. The main subspecies are *L.A. natalenses* and *L.A. refescens* that are found in West Africa and Indian sub continental areas (like Bangladesh and Pakistan) respectively (Spithill et al. 1999).

Figure 2-3: L.a.natelences snails the intermediate hosts of Fasciola gigantica on the leaves of the plant in the study area (fieldwork, 2016).

2.2.3 The global distribution of fascioliasis

Concerning spatial distribution across the globe, Mas-Coma et al. (2009) explained that fascioliasis is the invertebrate-borne disease that has the highest spread across the world including very high altitude areas above the sea level as is the case in Andean countries (Bolivia, Peru, Ecuador, and Venezuela). *Fasciola gigantica* is restricted to areas where ecological conditions permit survival of the intermediate host R.natalensis. As reported by Spithill et al. (1999) the countries of Africa with the highest prevalence of *F.gigantica* are Egypt, Sudan, Tanganyika, Chad, Nigeria, Zambia, Zimbabwe, Uganda, and Ethiopia. In Asia, high prevalence countries include Indonesia, NE Thailand, Philippines, Vietnam, Pakistan, India, Nepal, and Iran.

2.3 Effects of climatic and environmental factors on *Fasciola gigantica* transmission

Climatic elements such as temperature, rainfall and their interactions affect the viability of the parasite in its free-living states (egg and miracidia) and intramolluscan stages [sporocyst, rediae, and cercariae] (Poulin, 2006). Thus, it is vital to comprehend how these elements modulate the activities of the parasites to appreciate the application of climate in the study of the geographic range of fascioliasis. The climatic conditions are required to be within an optimum range for the survival and development of the fascioliasis parasite and its intermediate host snails. This section explained different stages of the life cycle of fascioliasis species under the following subheadings.

2.3.1 Effects of Temperature

The higher the temperature within the optimum range the faster the development of miracidia in eggs of *F.gigantica*, development takes only 10-11 days between 37-38^{O}C whilst the number of days extends to 33 at 17-22^{O}C (Guralp et al., 1964). It was estimated by Grigoryan (1958) that at 24-26^{O}C, 70-80% of eggs would emerge whilst temperature that exceeds 43-44^{O}C will lead to eggs mortality. It was noted by Guralp et al. (1964) that it takes 14 weeks for eggs of *F.gigantica* to start hatching at different batches. In some countries in East Africa such as Kenya, the average temperature was much lower than other parts of the continent and hence the growth of *F. gigantica* eggs was said to be from 52 to 109 days at 10^{O}C and 22^{O}C(Torgerson and Claxton, 1999). They also noted that the level of nourishment and the quantity of parasite the snail contains would encourage and stimulate the ability of the parasite to produce eggs

Temperature is also very significant in influencing the physiology and ability to produce cercariae by snails (Mas-Coma et al., 2009). Dinnik and Dinnik (1963) and (Islam et al., 2014) found that temperature at 26^{O}C stimulates reproductive processes in snails within a few days. Air temperature is therefore very crucial in affecting the prevalence and geographic range of *F.gigantica*. Likewise, infected snails take a minimum of 20 days and maximum of 46-50 days to start shedding of cercariae at 25-27^{O}C (Dinnik and Dinnik, 1963, Sharma et al., 1989). This shedding period is prolonged if the temperature reduces and may take up to 197 days as observed at very high elevations in Kenya (Dinnik and Dinnik 1963).

It was reported by Spithill et al. (1999) that temperature determines the ability of snails to excyst cercariae as metacercariae which anchor suitable objects that are within 6.4cm of the water body. Suhardono and Copeman (2008) reported that metacercariae were more viable in water than outside water environments based on their study in Indonesia. They concluded that the viability of metacercariae was higher at the moderate temperature of 20^{O}C but was reduced as temperature increased to 26, 30 and 35^{O}C. The survival rate of metacercariae outside water environment increases when the air is humid at relatively low temperature. Kimura observed this in Japan where metacercariae survived for 120 days at 12-28^{O}C and relative humidity 30-45% on rice straw.

2.3.2 Effects of Moisture

Moisture is essential for the effective functioning of all activities or processes that support the viability of fascioliasis (Torgerson and Claxton, 1999). In this regard, inadequate moisture or desiccation has been found by Altizer et al. (2006) to be inimical to the survival of fascioliasis and its intermediate host's snails. Rainfall is the primary source of moisture and in situations where rainfall is greater than potential evapotranspiration will provide suitable conditions for transmission of fascioliasis (Mas-Coma et al., 2005). However, during dry seasons in most tropical countries, moisture becomes available at locations that are proximate to water bodies such as irrigation sites, streams or lakes.

At the initial stage of fascioliasis development, moisture is required to disintegrate faecal mass into fluke eggs (Torgerson and Claxton, 1999). Likewise, the intermediate hosts of *F.gigantica* snails *L. a. natalenses* need deep water to survive as they cannot aestivate for a long time during a dry spell or drought. A report by Schillhorn Van Veen et al. (1980) has indicated an increase in the population of snails at the onset of the rainy season in West Africa as the temperature was not limiting throughout the year. Similarly, in Malawi, the period of rainfall around March/April provides ideal conditions for the survival of a large number of snails.

Given the preceding discussion, moisture is indispensable for the dispersal, free-living and intramolluscan stages of fascioliasis (Andrews, 1999). For example even under optimum temperature, desiccation is a severe threat to the viability of metacercariae (Spithill et al., 1999). It is worth emphasising that in semi-arid areas like in Nigeria and elsewhere the transmission of fascioliasis during the dry season is only possible near water bodies (example streams, dams, lakes, and ponds) as sources of moisture since rainfall is only available in wet season. The existence of extensive fadama land (areas liable to flooding) especially in north-western Nigeria and abundant rain in the south and western parts of the country have provided favourable conditions for fascioliasis to thrive which was up to 60% and above (Spithill et al.1999).

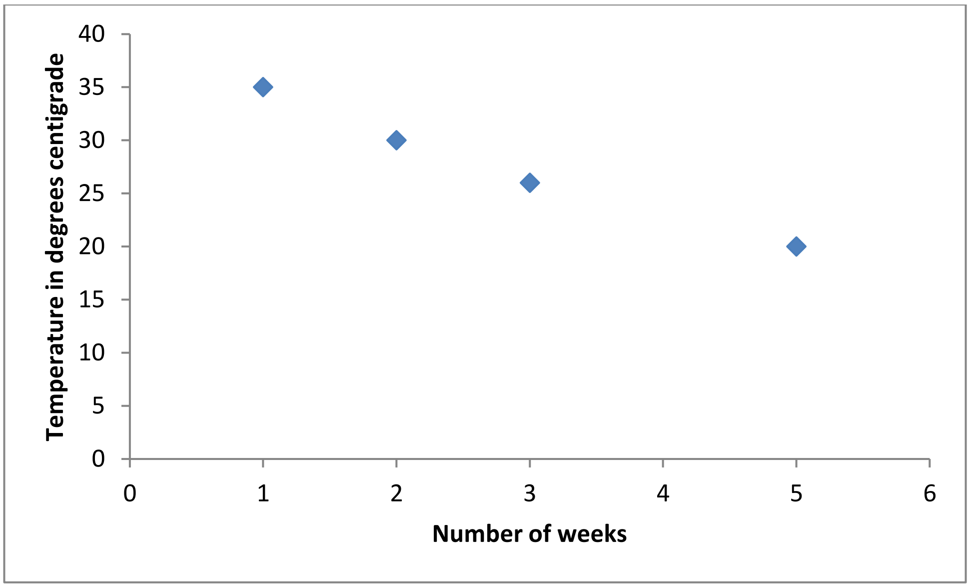

Figure 3-4: Metacercariae weekly survival rate when subjected to desiccation at different temperatures (Spithill et al.1999).

Besides, the productivity of snails decreases during the dry periods due to their habitation of the aquatic environment such as stagnant water (Roberts and Suhadono, 1996). Thus the transmission of fasciolosis will not be active during the desiccation period. However, if the condition of dryness persists, according to Spithill et al. (1999) eggs production in snails continues, but hatching of eggs occurs only if moisture conditions improves. Furthermore, in extreme dry seasons in tropical areas snails can survive for up to six months through hibernation and aestivation (Roberts and Suhadono, 1996, Spithill et al., 1999, Bunza et al., 2008b). Thus dry seasons, especially in the tropics, are invariably not very favourable for growth and development of snails. Moreover, that observation was confirmed by Copeman (2000) based on their research on *F. gigantica* and its intermediate hosts' snails in rice fields in Surade, West Java, Indonesia.

2.3.3. Vegetation

Vegetation is a significant determinant of fascioliasis risk due to its influence in providing habitats to snails and on which metacercariae anchor after emerging from snails. Besides, it serves as nourishment for animals and even humans. These functions, make vegetation a perfect vector for transmission of fascioliasis and is measured by a remote sensing index referred to as Normalised Difference Vegetation Index (NDVI).

NDVI is very useful in epidemiological studies as it represents the amount of moisture in the environment (Malone et al., 2001, Valentia-Lopez et al., 2012). Furthermore, NDVI was described as a composite mixture of various factors of the environment [elevation, precipitation, temperature] (Hay et al., 1997) and hence a good indicator of climate risk. In view of this, NDVI was incorporated as using Geographic Information System (GIS) analysis to show the prediction of climatic risk for the design of control programs against both human and animal fascioliasis in East Africa, Europe and South America (Malone et al., 1998a, Fuentes et al., 2001, Kantzoura et al., 2011, Afshan et al., 2014)

2.4. Effects of biotic (host-parasite) factors on *Fasciola gigantica* transmission

The climatic factors cannot operate in isolation but there are other contributing factors that determine the transmission, intensity and spatial distribution of fascioliasis. These factors are classified into host-parasite and climatic/environmental factors [including definitive hosts management practices] (Yatswako and Alhaji, 2017). The preceding section explained the effects of climatic and environmental factors on fascioliasis prevalence while this section described host-specific factors and their effects on the prevalence of the parasite.

2.4.1 The age of the definitive host

The age of the definitive hosts determines their susceptibility to fascioliasis infection. In this regard, there are two contradictory reports concerning the most vulnerable to infection between the young and old definitive hosts. The first observation was that the young hosts were more susceptible to infection due to low immunity (which increased with age) than the older hosts. It, therefore, means that the more infections the host encounters, the more its immunity develops over time. This observation was supported by Blood (1978) and Noble and Noble (1982) where fascioliasis infections were more predominant among the weaners than the older hosts when compared across different age groups. In contrast to the above observation, Anon (1992) concluded that vulnerability to infection was the same across the old and young host and in some cases even higher among older definitive hosts (Esch, 1977). Similarly, some studies conducted recently shared this view and explained that older hosts were more exposed to the infection than younger ones (Elelu et al., 2016a, Pfukenyi et al., 2006, Pfukenyi and Mukaratirwa, 2004)

2.4.2 The gender of the host

A strong link exists between the sex of the host and fascioliasis infections as a result of the presence of steroid hormones which respond differently to parasitic infection in the definitive host (Esch, 1977). Given this, female hosts were more susceptible to infection than male hosts as concluded in a study by Rahman and Collins (1992). This was because of the observed increase in ‘peri-parturient' (before giving birth) release of parasite's egg that undermined the immunity of lactating female definitive host. These findings were also supported by Berger (1971) that the period of parturition and lactation erodes the acquired immunity against fascioliasis infections and other helminths. Conclusively, the definitive female host were, more vulnerable to infections across a given pasture owing to their tendency to transmit the infection to their calves as ‘adaptive/periodic mechanism' (Briskey, 2004).

2.4.3 Practices of animal management

The type of management system operated by cattle holders can determine their exposure to the risk of fascioliasis infection. Thus, animals reared by a sedentary system of husbandry were less susceptible to infection as reported in a study around Lake Chad by Jean-Richard et al. (2014). In contrast to this, animals reared by pastoralists especially the Fulani's that allow contacts with other herds in mostly snail-infected pasture, were more vulnerable to fascioliasis infections as reported by Elelu et al., (2016a)

2.5 Use of generic models to predict fascioliasis

Presence-only species distribution models have been used extensively in species distribution modelling studies to show the relationship between recorded sites of species occurrence and their estimated climatic conditions [at occurrence sites](Phillips et al., 2006, Franklin, 2009). Maximum entropy (MaxEnt) is one of the most popular presence-only methods introduced in 2006 (Renner and Warton, 2013). The technique has broad applications in modelling the geographic range of various species of plants and animals due to the impacts of climate and environmental factors for different purposes (Gomes et al., 2018, Elith et al., 2011, Welk et al., 2002, Graham and Hijmans, 2006), including the effects of climate changes on species geographic range (Graham and Hijmans, 2006, Echarri and Tambussi, 2009, Cordellier and Pfenninger, 2009). MaxEnt has also been applied in studies involving species dispersal as a function of the relationship between physical and biological factors (Cunningham et al., 2009). However, studies that focused on modelling the geographic ranges of fascioliasis using presence-only techniques are quite a few across the globe, despite being the most widespread pathogen(Mas-Coma et al., 2014) and affecting both animal and human health (Tolan, 2011).

MaxEnt is the presence-only method that was used in northcentral Nigeria by Yaro et al. (2018) in modelling the effect of environmental risk determinants on the prevalence of *Fasciola gigantica* in trade cattle slaughtered in some major abattoirs in Niger state. The study obtained data on fascioliasis prevalence from five municipal abattoirs based on retrospective survey and climatic data were extracted from WorldClim database. The results of the study showed that provinces that lie in the southeastern part of the state that include Katcha, Gbako, Bosso and parts of Rafi and Shiroro were more suitable for the prevalence of the parasite and hence ‘higher risk zones’ than other parts of Niger state. Furthermore, the study indicated that precipitation and mean temperature of the coldest quarter as well as precipitation of the wettest quarter were more influential in modelling the geographic range of *Fasciola gigantica* in the state. The most notable limitations of the study was in the use of core bioclimatic variables (BIO1-19) and hence did not make use of soil moisture based variables (BIO27-35) that are equally significant in modelling the prevalence of fascioliasis in endemic localities.

Another prominent study using MaxEnt was carried out in southeastern Europe by Kantzoura et al. (2011b) in modelling the geographic range for *F. hepatica* genotypes and haplotypes. The results of the studies indicated that both temperature and precipitation had equal weight in model construction for all the genotypes of fascioliasis. However, temperature and precipitation had different effects on the distribution of the three classes of fascioliasis haplotypes (CtCmt1, CtCmt2.1, and CtCmt2.2). In a study in Colombia, by Valentia-Lopez et al. (2012), maps based on climate-based forecast index (CFI) results for the control of *F. hepatica* were developed within a GIS. The index was constructed using growing degree day-water budget concept and the interactions of rainfall and potential evapotranspiration. This CFI risk map was in good agreement with the risk pattern indicated by MaxEnt model that was constructed with environmental variables.

Some of the significant limitations of MaxEnt include the insufficient guide for its use when compared to older methods such as GLM or GAM and the need to refine the use of regularisation in reducing overfitting (Phillips et al., 2006). Also, MaxEnt requires specific software before executing modelling operations. Above all these limitations, MaxEnt needs only the presence of species, and climatic data about the area of study as its algorithm is very deterministic in yielding optimal results. The probability map produced by MaxEnt is uninterrupted in showing variations regarding suitability across the modelled area(Phillips et al., 2006).

Other presence-only techniques such as BioClim and Domain have also been used in species distribution modelling of both plants and animal diseases for different purposes

(Franklin, 2009). In modelling the geographic distribution of fascioliasis across endemic localities of the globe, no any one of these techniques was ever applied individually or in combination with other methods.

2.6 Applications of species-specific models in the studies of fascioliasis

Fascioliasis disease has plagued various parts of the world, and hence it is regarded as one of the most widely spread disease globally (Mas-Coma et al., 2005). Moreover, due to the importance of fascioliasis as a significant threat to animal's health and productivity (Ardo et al., 2014) much research had been conducted to monitor its prevalence and spatial distribution across different parts of the world.

In England, the association between climate and fascioliasis outbreak has been explained by Ollerenshaw and Rowlands since 1959. This study laid the foundation for the development of short-term forecasting using an empirical equation that determines monthly levels of potential evapotranspiration and rainfall. Higher evapotranspiration than rains indicates soil moisture deficit, thereby reducing the risk to a lower stage, while if the reverse is the case, the excess water will accumulate giving rise to greater risk index. The success of this forecast has led to the modification of the index using long-term projection data produced by UKCP09 to create seasonal risk forecast to future (2070). A study by Fox et al. (2011) presents the first long-term forecast of fascioliasis risk in Europe to determine the impact of changes in climate in fascioliasis transmission. Also, the study incorporated the use of immediate past climate provided by UKCIP to assess the changes in the transmission of the parasite as a function of the current climate variables. The result of the study has revealed future variation in transmission intensity across different parts of the UK, with Wales predicted to have the potential of emerging as the highest risk in 2050. The risk has also been shown to vary temporally due to the predicted rise in fascioliasis risk from overwintering larvae.

Moreover, the study simulated that spatially some parts of the UK will experience the lower risk of fascioliasis infection in summer season due to inadequate moisture. Although the study has illustrated the role of long-term changes in climate in influencing fascioliasis risk, there was no utilisation of corresponding prevalence data for model validation. Finally, the study could not determine the effects of climate on fascioliases transmission as this was beyond its scope.

The climate-based model was also applied in the whole of Europe by Caminade et al. (2015) to predict the outbreaks of fascioliasis due to recent climatic changes and future changes in climate. This study adapted the fascioliasis forecasting system developed for Wales by Ollerenshaw and Rowlands (1959) in predicting the incidence of fascioliasis based on the model derived from interactions of temperature and rainfall. The gridded climate data for the period 1959-2013 was extracted from the ground-based stations for all the countries of Europe that were assembled by the work of Haylock et al. (2008). Future climate data were obtained from an ensemble of the climate model developed by Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) for three-time slices beginning from 2011-2030 up to 2071-2090 based on four Representative Concentration Pathways (RCPs 2.6, 4.5, 6 and 8.5). The results of the recent climate-driven risk index have indicated expansion of suitable areas in central and northwestern Europe, which also matched the incidence of fascioliasis infections in animals. Similarly, in the future, the period of fascioliasis transmission was predicted to be longer by four months in northern Europe due to an increase in favourable climatic condition. In southern Europe, the study indicated winter months to experience more risk owing to the predicted increase in moisture and suitable climatic conditions but a decrease in risk in summer months.

A significant limitation of this study is that it used a climate model that was developed specifically for Wales, which limits the applicability of the developed risk model to future projected climate scenarios at the continental scale of Europe (Caminade et al., 2015). In addition, some arid areas in southern Europe that were shown by the model to be of lower risk may not reflect reality as irrigation was not incorporated into the models' construction. Likewise, different types of soils and land use were not considered by the model despite their importance in determining the presence of the fascioliasis parasite. (McCann et al., 2010, Bennema et al., 2009, Charlier et al., 2014).

In Colombia, South America, fascioliasis has undermined the productivity of both cattle and sheep and hence is regarded as important. This led to the development of climate-based risk model by Valentia-Lopez et al. (2012) in order to provide a guide for prevention and control of fascioliasis infection by identifying areas of high risk as well as a temporal transmission pattern. The model was an adaptation of a forecast index applied in East Africa (Malone et al., 1998) based on growing degree days (GDD) and the use of the essential requirements for the parasite's survival notably rainfall and potential evapotranspiration. These variables were used in the calculation of climate-based forecast index (CFI) for Colombia which was converted into a map with the aid of a geographic information system (GIS). The study also developed other techniques for the identification of high-risk areas using elevation, enhanced vegetation index and land surface temperature within the geographic information system and maximum entropy using BioClim variables. Outputs from these methods have indicated spatial relationships in predicted fascioliasis risk pattern with the forecast index grid.

In Asia due to observed prevalence of fascioliasis, climate-based fascioliasis forecast models were developed by Halimi et al. (2015) to predict outbreaks of fascioliasis in Iran. This study made use of a geographical information system and Ollerenshaw's climate-based fascioliasis risk index. A risk map was produced within a GIS that represented the computed index that reflected differences in the climatic conditions of Iran. The country of the study was devided into four classes, with 1st and 4th classes representing lowest and highest risk, reflecting the degree in the availability of suitable climatic conditions that favour fascioliasis transmission. The results of the study showed that a high percentage (91%) of the study area was predicted to be free of fascioliasis outbreaks. This was due to moisture deficit and low thermal regime during the rainy season, especially from December to April. Conversely, areas of high rainfall such as Gilan province, Rasht, Astara, and Bandar Anzaly were found to be high-risk areas, constituting only 3% of Iran.

In East Africa, Malone et al. (1998) adapted the Ollerenshaw climate-driven index of fascioliasis risk using climate data obtained from the Food and Agricultural Organisation (FAO). In the global database, the main essential drivers of fascioliases were rainfall and potential evapotranspiration across all of the area of study. Consequently, the resulting equation for calculating the index was modified to allow the computation of fascioliasis risk either from *F. hepatica* and *F.gigantica* as both species thrived in the study area. Risk index maps were created for each of one of the two species using geographic information system in the study area. The results of the computed risk index indicated spatio-temporal variation in the transmission pattern of both species of fascioliasis. The risk was most significant in areas with the higher amount of soil moisture and very low in arid areas. This should be treated with caution as irrigation practice in these areas may provide suitable habitat for fascioliasis and its hosts.

Furthermore, high altitudes in Ethiopia and Kenya were completely devoid of suitable conditions for the parasite's survival. Regarding validation, the combined risk index was significantly correlated to both ten-year average NDVI data obtained from NOAA and available fasciolosis prevalence record. This study has demonstrated that differences in the seasonal pattern of fascioliasis transmission and spatial variation across regions can be obtained from monthly forecast index. Also, the use of a GIS tool in creating risk index using monthly climate data and computer-based data from agroecological zones was also indicated. Finally, this technique developed in this study was valuable in designing effective methods of control against fascioliasis prevalence in East Africa. Given that, the method was recommended by Mas-Coma et al. (2009) based on the accuracy of its predictions of risk due to fascioliasis in the study area.

A plethora of research was conducted using species-specific models during the last fifty years whilst only a few studies focused on *F. gigantica* with none of these few studies concentrating on any part of West Africa. Few researchers have investigated future projections of climate and their effects on fascioliasis transmission while no study has been applied to any part of Africa.

2.7 Use of regression techniques in modelling the risk of fascioliasis

Regression techniques have been described as relevant to species distribution modelling due to their concern with showing the relationships between the dependent variable, which can be binary, counts or ordinal and the independent or explanatory variables (Franklin, 2009). In the study of fascioliasis regression methods have been used to explain the spatial variation of infections across various areas of study (McCann et al., 2010, Howell et al., 2015, Olsen et al., 2015, Kantzoura et al., 2011a). Some of these studies used binary regression which have the advantages of overcoming the expectations of homogeneity of variances, normality, and linearity over linear regressions (Schuppert, 2009). However, Reed and Wu (2013) explained that some significant limitations of binary regression are limited sample size, restrictions on the number of predictor variables and the evaluation of probability ratio of outcomes (negative or positive). In this section, some reviews of regression methods that were applied to fascioliasis studies and their findings will be discussed.

The distribution range of *F. hepatica* infection in dairy herds at the local spatial unit in England and Wales was explained by McCann et al. (2010) using linear regression models. The independent variables were the climatic, environmental, soil and pasture parameters while the dependent variable was *F. hepatica* infection data in dairy herds obtained from previous research conducted in the winter of 2006/2007. The result of the study showed that the combined influence of climatic and environmental factors described 70-76% of the variation in fluke infection at the level of postcode area. Although various models were created each with both temperature and rainfall as covariates, these two variables remained consistently strong predictors of *F. hepatica* at the smallest spatial units in the area of study. This research has, demonstrated that building spatial models with at least five-year mean of aggregated variables in developing risk maps for fascioliasis can yield better model fitness than using recent individual annual or monthly weather data.

Another related study which was intended to be ‘observational' regarding its assessment of the relationships between exposure to fascioliasis infections in high yielding herds and risk determinants was conducted by Howell et al. (2015) on UK dairy industry. The effect of how farms were managed and associated environmental factors on exposure to fascioliasis infection was examined using multivariable linear regression. The results showed that feeding on wet pasture, the presence of non-dairy cattle on sampled farms, grazing near water bodies such as streams, lakes, and herds that contain few cattle were related positively to exposure to the risk of fascioliasis infection. These factors according to Rapsch et al. (2008) were essential for the survival of *F. hepatica* and its intermediate host snail in temperate areas.

As the knowledge of the prevalence of and risk factors associated with fascioliasis was limited in Denmark, a study was conducted by Olsen et al. (2015) to that effect. The primary source of the data on the prevalence of infection was obtained through meat inspection from 2011 to 2013. Both global and local clustering of infection prevalence were identified using Moran, I technique to find out the underlying environmental factors. In addition, binary logistic regression modelling was applied to the incidence of infection as the dependent variable while the environmental risk factors including cattle management as predictor variables. The result showed an increase in the number of cases across the three years of study while spatial analysis indicated clustering of both positive and negative herds.

Moreover, a meaningful relationship was observed between the environmental parameters such as streams, wetlands pasture and exposure to infection in cattle herds. The primary constraint of this study was that the meat inspection employed has poor sensitivity and as such would not mirror the real prevalence in the population of cattle. In addition, the assessment by the logistic regression model has indicated more possibility of infection in a few areas which was not consistent with the observed prevalence data.

In South America in Espirito Santo state, Brazil Freitas et al. (2014) produced a bioclimatic map to ascertain the proportion of areas in the state that were suitable for the prevalence of *F. hepatica* between 2009 and 2011. The bioclimatic map was generated using 30 years data obtained from 109 weather stations that were situated in the state. The result indicated more than fifty percent of the study area was found suitable for the healthy living of fascioliasis and its intermediate host's snail. The slaughterhouse as the source of information showed that the parasite was more concentrated in three cities such as Atilio vivacqua, Itapemirin, and Anchieta with 28.41%, 25.50%, and 24.95% respectively. The reliability of the information utilised by this research was not objective since slaughterhouses could not give the precise origin of the animals slaughtered. Moreover, no instrument (such as a questionnaire) was used in obtaining relevant data about the slaughtered cattle.

Binary logistic regression technique was applied in Thessaly, Greece to investigate the relationship between risk determinants related to management of pasture and farm, herd and status of the farmer as well as satellite-based environmental data with fascioliasis infection in sheep and goat farms. This study by Kantzoura et al. (2011a) revealed 16.2 % and 78.4% of farms were infected with fascioliasis based on coproantigen and serology respectively. Using coproantigen, all the environmental factors including temperature, rainfall, and elevation were not statistically related to fascioliasis infection. However, based on the serology component, only NDVI variable was statistically related to fascioliasis infection. The study also identified farms that were privately owned with all year round grazing areas, and boggy pastures were highly exposed to the risk of fascioliasis infection in the area of study. The weakness of this research was that the risk map developed could not be a representative for the entire region of Mediterranean due to heterogeneity regarding temperature and rainfall patterns across the region. Also, some area-specific determinants were used by the model which were only applicable to the small spatial unit that was used as the study area thereby making extrapolation to the whole Mediterranean region prohibitive.

2.8 Fascioliasis prevalence studies in West Africa

In West Africa, most of the studies on fascioliasis were based on explaining prevalence at abattoirs and slaughter slabs. However, only a few of these studies incorporated the effects of biological characteristics on fascioliasis infection risk. These characteristics include the breed of the animal, sex, age, socio-economic characteristics of the cattle or animal owner which all affect animal exposure and susceptibility to fascioliasis infections. Some studies have incorporated the use of these non-climatic factors in influencing fascioliasis prevalence across various areas of the world (Tum et al., 2004, Ekwunife and Eneanya, 2006, Ali et al., 2008, Jean-Richard et al., 2014)

In southeastern Chad (a neighbouring country to Nigeria) prevalence of *F.gigantica* infections in slaughtered cattle was investigated by Jean-Richard et al. (2014). The study compared the prevalence of fascioliasis infections between cattle, goats, and sheep through routine meat inspections at three slaughter slabs situated in Grenada, Sidje and Bache Djani. The ethnic background of the animal owner was used as the main risk factor for *F.gigantica* infections. The results suggest that cattle were having the highest infections (68%) while goats were the lowest. Also, animals owned by tribe (Kouri) that were settling close to Lake Chad and other water bodies were having the higher risk of *F.gigantica* infections than that livestock belonging to Gorane, Peul, Arab and Kanembou. The method used in detecting the presence of fascioliasis in the liver of slaughtered animals was defective as only a section of the liver was inspected instead of the whole organ (Jean-Richard et al., 2014). Additionally, other factors such as age, breed, and sex of the animals were not considered in determining risk for fascioliasis infections in this study.

A study was undertaken in Niger republic (that neighbours Nigeria in the north) by Ali et al. (2008) which investigated the presence of fascioliasis in the country. The method applied by this research was the detection of genotype characteristics of the two species of fascioliasis from cattle, sheep, and goats. The result of this study indicated the presence of *F. gigantica* and *F. hepatica* through comparison of internal transcribed spacers (ITS) sequences obtained from samples in the country with gene type of the two species in different endemic localities. This study served as a means of confirming the prevalence of fascioliasis infections and hence more studies are needed for the control of infections in the Niger Republic.

In Nigeria, only a few studies reported the prevalence of fascioliasis based on the influence of biological features or characteristics of slaughtered animals but only one known study by Yaro et al. (2018) incorporated climate variables. A study by Yatswako and Alhaji (2017) investigated the burdens of *F.gigantica* in cattle slaughtered at various abattoirs in North-Central Nigeria. Meat was inspected to identify fascioliasis infection in livers of the slaughtered cattle which is commonly applied in Africa due to its advantage of convenience and affordability over laboratory diagnosis (Phiri, 2006, Yatswako and Alhaji, 2017). The result of the study indicated that breed, age and sex were significant determinants of fascioliasis infections in slaughtered cattle. Studies with similar findings in Nigeria were: in Adamawa (Ardo et al., 2014), in Kano (Danbirni et al., 2015), Imo state (Njoku-Tony and Okoli, 2011) and Ondo state (Afolabi and Olususi, 2016)

Other studies in Nigeria were predominantly the investigation of *F. gigantica* infections among slaughtered animals at abattoirs by veterinary scientists and parasitologist across the various ecological zones of the country. In Western Nigeria, fascioliasis was identified as one of the most harmful diseases in causing damage and condemnations of organs that constitute 20.28% of 641,224 cattle slaughtered at 12 abattoirs in Lagos and Ogun states within 2005-2007(Cadmus and Adesokan, 2009). In Anambra state, investigation of the presence and intensity of *F. gigantica* infections in cattle slaughtered at Onitsha abattoir was carried out by Ekwunife and Eneanya (2006). The method used post-mortem inspection on the slaughtered cattle and discovered levels of *F. gigantica* infection at various abattoirs in the state. In Imo state Njoku-Tony and Okoli (2011) identified the prevalence rate of *F. gigantica* through laboratory analysis of adult fluke eggs of the slaughtered sheep in the major abattoirs of the state. The result showed that 17% of the 367 sheep examined were infected.

In Adamawa state, Nigeria, Ardo et al. (2014) applied a post-mortem examination on the liver of the slaughtered animals and revealed different prevalence rates in the provinces of Yola, Mubi, and Numan. In Kano state, the prevalence of *F. gigantica* on the effect on liver condemnation among the slaughtered cattle was studied by Dan birni et al.,(2015). The result indicated the high cost of the condemned liver due to *F. gigantica* which ran into millions of naira. In Kaduna state, Aliyu et al. (2014) made use of coprology and serology in Zaria to determine the seroprevalence of *F. gigantica* at slaughter slabs and on farms.

In Nigeria, herd-level risk factors and incidence of *F.gigantica* in cattle in Edu, a local government area of Kwara state were investigated by Elelu et al. (2016a). The use of binary logistic regression in the study revealed the influence of age in determining the risk of fascioliasis infections in live cattle. This research was the first attempt at focusing on the risk determinants of live cattle using biological characteristics.

Conclusively, only a few studies on fascioliasis (Elelu et al., 2016a, Yatswako and Alhaji, 2017) in Nigeria, and West Africa applied regression techniques as part of species distribution model methods while the rest was the only description of fascioliasis prevalence from abattoirs. Moreover, none of the studies applies both intrinsic and extrinsic factors in the study of fascioliasis among slaughtered cattle in any part of West Africa.

2.9 Gaps in the literature

In the review of the literature in the preceding sections, the gaps in knowledge that need more focus are:

- To date, the majority of studies on fascioliasis have focused on *F. hepatica* that thrives in data-rich developed countries of the world.
- Even though only a few studies have used species distribution models to investigate the geographic ranges of fascioliasis, to my knowledge, none has applied MaxEnt using IPCC future projections of climate data.
- The use of field survey data in the validation of species distribution models using current climatic variables.
- The necessity to use an approach that compares two or more species distribution models in the study of fascioliasis.
- The studies that focus on the effects of climate and its changes on the spatial species distribution of fascioliasis in the long term or short term are not many, and to date none were applied in any part of West Africa.
- In modelling the distribution of fascioliasis most of the studies used WorldClim data on temperature and precipitation without the use of soil moisture variable from CLIMOND database ((BIO27-35).
- Not known study has investigated both intrinsic and extrinsic risk determinants of *F.gigantica* infections in trade cattle slaughtered at abattoirs.

3.0 Aim, Research Questions, and Objectives

Following the above gaps in the literature, the aim, research questions, and objectives were developed.

3.0.1 Aim

The main aim of the research is to explain and understand species spatial distribution modelling to predict *F.gigantica* in cattle with a focus on Sokoto State, Nigeria.

3.0.2 Research questions

In line with the above aim, the following research questions were formulated

1. How reliably can presence-only species distribution models predict the geographic ranges of *F.gigantica* in Sokoto State?
2. How relevant is a species-specific model in the prediction of spatiotemporal changes in fascioliasis risk in the study area?
3. Are there significant relationships between biological characteristics of animals and climatic/environmental factors with recent fascioliasis infections data among slaughtered cattle?

3.0.3 Objectives of the research

1. To compare the performance of MaxEnt, Domain, and BioClim in modelling the geographic range of fascioliasis.
2. To evaluate MaxEnt in modelling the spatial distribution of fascioliasis based on WorldClim derived climate data (BioClim) and satellite data using independent validation data.
3. To predict the spatial distribution of fascioliasis in the future under scenarios of climate change based on two Representative Concentration Pathways (RCP2.6 and 8.5) for two time periods of 2050 and 2070.
4. To predict spatiotemporal changes in fascioliasis transmission risk through the use of the species-specific model in the study area.
5. To find out the associations between extrinsic and intrinsic factors on recent fascioliasis infections data among slaughtered animals.

Chapter 3

Study Area

3.1Introduction

Sokoto State is one of the northwestern states of Nigeria situated between longitudes 4^o 8′ E and 6^o 54′ E of Greenwich meridian and latitudes 12^o N and 13^o 58′ N of the equator. The state shares boundaries with Kebbi state (southwestern side) and Zamfara state (eastern side) which were carved out from the state in 1991 and 1992 respectively. At the extreme north, Sokoto is the immediate neighbour to Niger republic and occupies 32,000 square kilometres of land area. The state consists of 23 provinces, which include: Tangaza, Binji, Silame, Gudu, Kware, Wamakko, and Sokoto north, Sokoto south, Dange shuni, Tureta, Bodinga, Shagari, Yabo, Tambuwal and Kebbe local governments. The state has a total human population of 3,696,999 million based on a 2006 census (Magaji et al. 2014).

3.2 Climate

The interplay of two opposing air masses is responsible for different climatic conditions in the area. These air masses are tropical maritime air mass and continental air mass that originates from the Atlantic Ocean and Sahara desert respectively. The area or zone where the air masses meet referred to as Intertropical convergence zone (ITCZ) which shifts and fluctuates across the year and as such determines different seasons (Barry & Chorley, 2010). The condition of temperature varies over the year with extreme levels occurring around March to May and the peak in April when it will reach 40^{o}C. Moreover, during November up to February the temperature drops owing to the dry cold wind coming from the Sahara (Abdulrahim et al., 2013). Rainfall begins in April and ceases in the middle or end of September with average values between 500mm and 1,300mm. The state enjoys distinct dry and wet seasons over the year and the main characteristics of the dry season are the hamattan winds blowing from the Sahara desert. The length of the dry season is early October to April and sometimes beyond that and then the wet season commences around May up to September (Magaji et al., 2014).

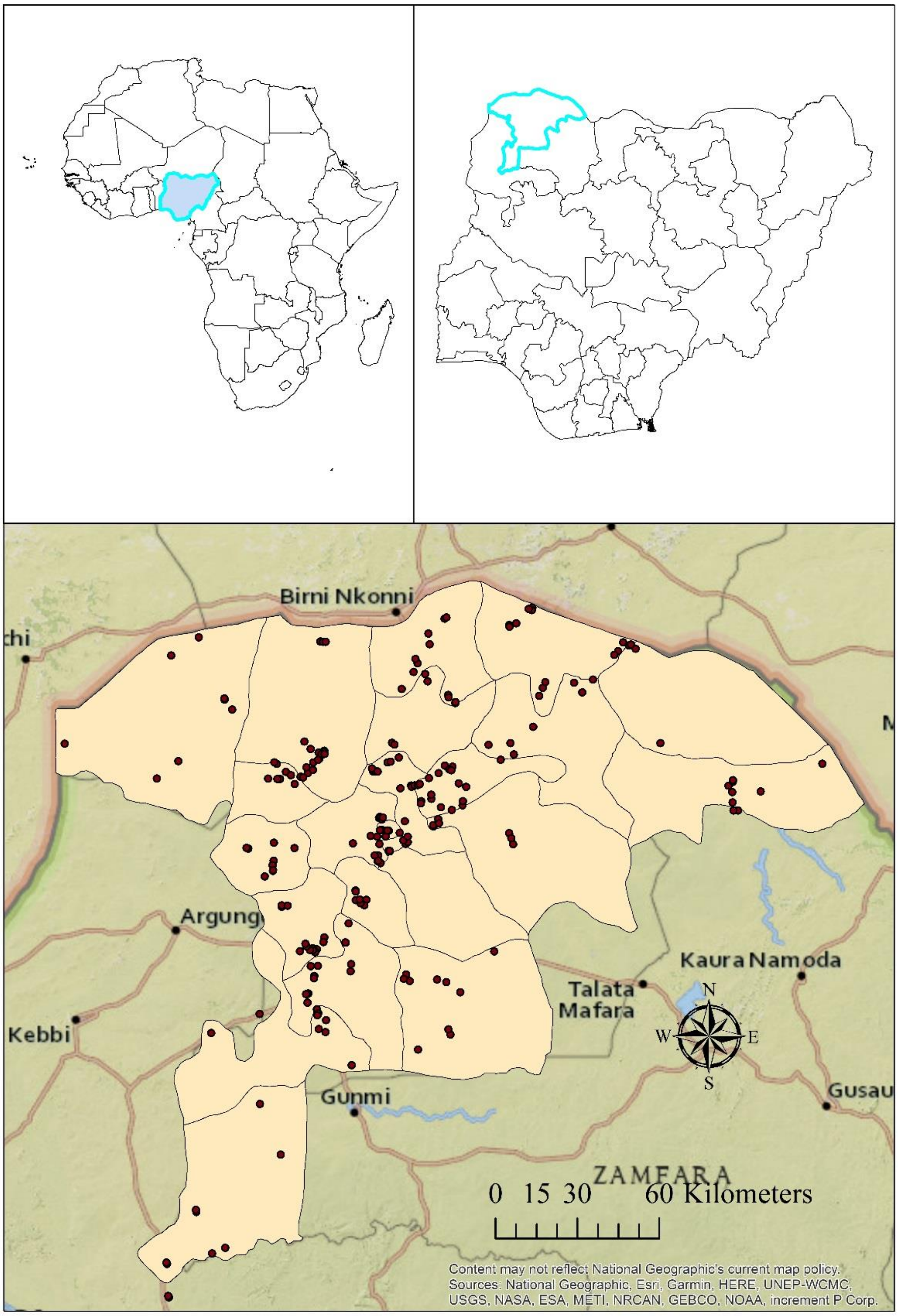

Figure 3-5: The map of the study area.

3.3 Drainage

The presence of a river in a settlement is precious in the provision of drinking water, fishing and irrigation activities. The major river in Sokoto State is called river Rima River that originated from the southeastern parts of Nigeria where it passes through Kano, Katsina and Niger republic. Rima River also cut across the entire Sokoto State and extends to Kebbi and some parts of Zamfara state. Another river of significance is river Sokoto that drains water from Funtua and Dandume in Kastina state. Other notable rivers are river Bunsuru and Gagare which are the two main tributaries that move northwardly and join the main river Rima that invariably provides suitable sites for the survival of different parasitic diseases and their hosts. All the tributaries drain over basement complex rocks characterised by narrow valleys (Abdulrahim et al., 2013).

3.4 Relief

The study area occupies an extensive area in the Illumedan basin which is surrounded by the Precambrian basement complex (Abdulrahim et al., 2013). Regarding geology, the state is underlain by sedimentary rocks, which are supported by basement complex from beneath. Some geological periods such as cretaceous and tertiary era marked the accumulation of sediments in a syncline which became hardened into a rock (Davis, 1982). The different sub groups of sedimentary rocks in Sokoto State are Gundumi formation which constitutes sandstones and clay, associated with water. The second sub group referred to as Rima which constitutes sediments from the sea and divided into Taloka, Dukamaje and Wurno formation. The third group is called Sokoto group originating from the sea and includes Dange (contains clays and shales) and Kalambaina (contains limestone) formations. Sokoto is homogeneously plain with some patches of plateau and sandstone that reached an average height of 300mm (Davis, 1982)

3.5 Vegetation

The vegetation of Sokoto State is described as short grass Sudan savannah and characterised by small grasses and shrubs that do not attain height greater than one meter(Babatunde et al., 2011). Neem trees (Dogon yaro) and Baobao trees constitute forest vegetation in the state. The existence of trees and short grasses of less than one meter covered the entire area of the state. Also, the vegetation consists of not only thorny species with acacia trees but also dump lam around water courses with some patches of seasonal grasses (Abdulrahim et al., 2013).

3.6 Agriculture

Sokoto is predominantly an agrarian state with more than 85% of the population engaged in agricultural practices. Farming practices in the state include crop farming and livestock rearing where the former involves cultivation of crops such as millet, guinea corn, sugar cane, beans and cereals. On the other hand, the state is ranked as the second leading producer of livestock in Nigeriathe where a large proportion of the indigenes are practicing animal husbandry. The yearly average of livestock numbers of the erstwhile Sokoto State (as it was bifurcated into Kebbi state and Zamfara state in 1991 and 1996 respectively) livestock numbers was estimated at 1,772,830 cattle (17,290 density/km^2), 2,466,484 goats (24,055 density/km^2) 2,566,246 sheep (25,028 density/km^2), 43,960 camels (0.429 density/km^2) and 109,484 dogs (1.068 density/km^2)" (Magaji et al., 2014).

Chapter 4

Modelling the geographic range of *Fasciola gigantica* in Sokoto State, Nigeria

4.0 Preface

This chapter explored the first modelling of the geographic range of *F.gigantica* in Sokoto State using presence-only species distribution models.

In this chapter, a paper titled 'Modelling the geographic range of *Fasciola gigantica* in semi-arid West Africa: a case study of Sokoto State, Nigeria', was formed and is under the second stage of review with the International Journal of Geo-Information (ijgi-401307).

4.1Introduction

The ability of a model to predict the geographical distribution of species relies on its 'accuracy' (Liu et al., 2009) which reflects most importantly the model's ability to differentiate between species occurrence locations and non-occurrence locations (Ash & Shwartz, 1999). In the evaluation of the accurate performance of MaxEnt, this study compared it with two other presence-only methods, BioClim (Busby, 1986, Busby, 1991) and Domain (Carpenter et al., 1993), using data on the distribution of *F. gigantica* in Sokoto State, Nigeria. The former technique models the suitability of an area through creating 'bioclimatic envelope' that encloses the extremes of the environmental range of the known occurrence sites of a species (Busby, 1986). The latter model uses a measure of agreement as a metric from a point-to-point based on 'Gower distance' in environmental space to predict any potential site as suitable owing to its closeness to the known occurrence locations(Carpenter et al., 1993). According to Meynecke (2004) and Walther et al. (2004), many studies applied BIOCLIM and Domain models in the predictions of the geographical distribution of taxa in different parts of the continents of Africa, South America and Australia. Phillips et al. (2006) described this approach of comparing performance between different modelling techniques as a research need in species distribution modelling. As noted by Segurado and Araujo (2004) and Elith et al. (2006) a few studies have compared the accuracy of presence-only models. Some of these have compared MaxEnt with GARP (Phillips et al., 2006), MaxEnt with BioClim (Hijmans, 2012), and between BioClim, Domain and other presence-absence methods using only five accuracy measures (Tognelli et al., 2009).

In the study of fascioliasis using eight accuracy measures, this approach is the first attempt to compare MaxEnt with the BioClim and Domain models. In addition, no known study has applied these methods in comparison with MaxEnt in modelling a spatial range of fascioliasis across any part of the globe. Furthermore, this study created six scenarios based on different combinations of Bioclim variables and non-Bioclim or satellite-based variables. The MaxEnt model used the variables in each scenario in determining the spatial distribution of *F. gigantica* in Sokoto State. Also, this study made a comparison between the current and future predictions of suitable areas for *F. gigantica* prevalence using maxEnt model. The essence was to evaluate the dynamics of *F.gigantica* disease transmission in the study area due to future changes in climate.

The Centers for Disease Control and Prevention (CDC, 2010) and the World Health Organisation (WHO, 2006) referred *F. gigantica* as a neglected tropical animal disease and zoonotic respectively. That, therefore, makes the disease pose severe threats to developing countries like Nigeria where funding on public and veterinary services are grossly inadequate (Blackburn et al., 2015). The disease is known to impair the productivity of the infected animals that leads to the loss of millions of dollars worldwide thereby becoming inimical to trade and human wellbeing indirectly (Mas-Coma et al., 2005, Fürst et al., 2012). The effects of the disease on humans even though not yet reported in the study area has been captured in various parts of the world and is regarded as important (Tolan, 2011, Esteban et al., 2003, Mas-Coma & Bargues, 1997). It is essential to model the likelihood of spread of *F.gigantica* using species distribution modelling techniques in order to achieve public health objectives and to contribute to the knowledge of its spatial epidemiology(Levine et al., 2004, Zeilhofer et al., 2007). This study aims to provide novel methods using GIS analysis for the design of appropriate monitoring to control *F. gigantica* infections of domestic animals in Sokoto State, Nigeria.

4.2Materials and Methods

4.2.1*Fasciola gigantica* occurrence data

Data on 210 reported presence locations of *F. gigantica* were obtained from the Ministry of Animal Health in Sokoto State, established in 1965. The second source of the data was from Sokoto State Ministry of Animal and Fisheries development that contained fascioliasis prevalence record for ten years (2005-2014). The data was mainly paper records of the various localities with documented incidences of liver fluke. One major shortcoming of the data from these two sources was that the occurrence localities lacked spatial coordinates. Given that, the coordinates of the locations were collected from the

National Population Commission (NPC), Sokoto State, branch where a gazette of all the localities in the state with their spatial coordinates exists. The use of fascioliasis occurrence data from the mentioned ministries in Sokoto State was due to the availability of only a few (3) records from the Global Biodiversity Information Facility (GBIF) in Nigeria.

The low number of <300 presence records in this study proved to be adequate. Because it was discovered in other studies using GARP alone, and in its comparison with MaxEnt that 50 and 15 records respectively produced acceptable results that were statistically significant (Stockwell & Peterson, 2002, Papes & Baubert, 2007). Also, according to Pearson et al. (2007) as few as five records using MaxEnt alone produced accurate modelling results. That, therefore, adds confidence in the reliability of the results obtained in the present study. However, the use of appropriate scale regarding the spatial extents of the study area and grain of environmental variables can determine 'the performance of species distribution model'(Khosravi et al., 2015). In addition, some other studies by Seo et al. (2009) and Guisan et al. (2007) confirmed that increasing the size of the study area enhanced the model performance while the reverse was the case when the grain size of climatic variables was increased. That is because AUC being one of the most effective measures of accuracy is determined greatly by the scale of the study domain.

4.2.2Data preparation

The most notable sources of occurrence data for species in species distribution modelling are through field survey, gathering from existing records otherwise known as 'opportunistic samples' and thirdly from atlas data which consist of grids(Franklin, 2009a). The data for this study falls into the second category and hence may exhibit clustering and duplication of sample points of *Fasciola gigantica* occurrence. That, therefore, demands 'cleaning' of the sample points (Newbold, 2010, Hijmans, 2011) in order to obtain a complete collection of unduplicated presence records that determine the efficient performance of species distribution models (Elith et al., 2011). Based on this motive, this study applied the use of Nearest Neighbour Index (Clark and Evans 1954) employed in R in ECOSPAT package (Di Cola et al., 2017) in the reduction of clustering and increasing the minimum distance between any two sample points to 1km. That was to conform to the spatial resolution of the environmental variables used in this study. Barbosa et al. (2009) asserted that both the variables and the species' records 'must' have the same spatial resolution in order to obtain accuracy in species distribution modelling. Consequently, that will also promote proper understanding of environmental conditions occupied by the species and the effectiveness of predicting the geographic range of the species across the area of study (Philips et al. 2017). The formula for the calculation of the Nearest Neighbour Index (Evans and Clark, 1954) is as follows:

$$E_{(di)} = \left[\left(0.5 * \sqrt{\frac{A}{N}}\right) + \left(0.0514 + \frac{0.041}{\sqrt{N}}\right) * \frac{B}{N}\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathit{equation}\ 1$$

Where A and B are a record of species and N is the sum of all the species records in the study area.

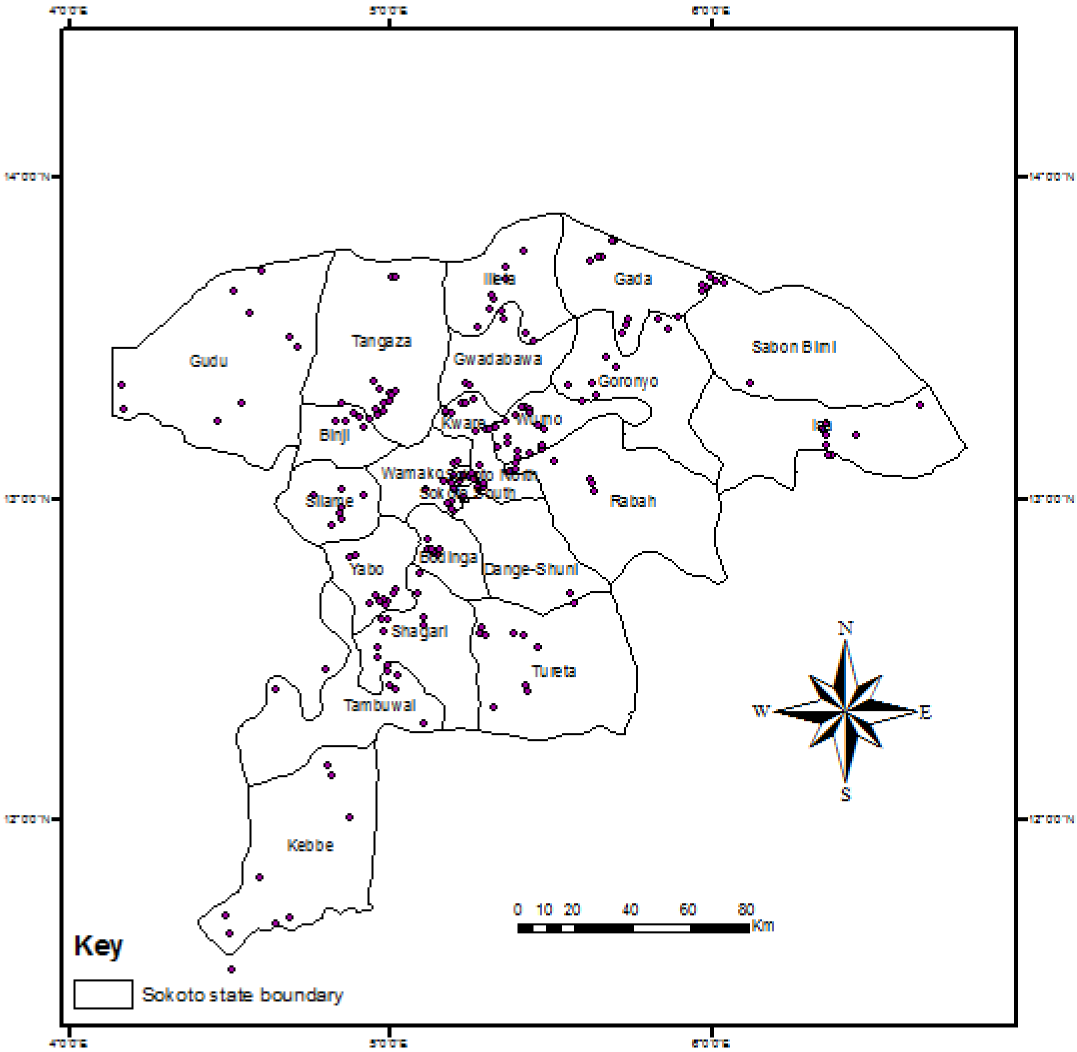

Figure 4-6: Map of Sokoto State showing the occurrence sites for F. gigantica used in species distribution modelling.

4.2.3 Source of climatic and environmental data for species distribution modelling

This research utilised climatic and environmental variables in species distribution modelling of fascioliasis due to their influence in every stage of the parasite's lifecycle (Yilma & Malone, 1998, Spithill et al., 1999a, McCann et al., 2010a, Fox et al., 2011). These variables include temperature, rainfall, elevation and vegetation index (NDVI) obtained from remotely sensed data and ground based stations. This subsection described each variable used in this research as follows:

4.2.3.1BioClim

World climate (WorldClim) data base version 1.4 available at (http://www.worldclim.org) was used in generating Bioclim variables that have been applied extensively in many species distribution modelling of plants and animals (Busby, 1991, Masuoka et al., 2009, Joyner, 2010, Kouam et al., 2010, Kantzoura et al., 2011b). This data base gathered monthly climate data across weather stations from all parts of the world between the period of 1950-2000 (Hijmans et al., 2005). Consequently, the database produced climate surfaces for the entire land surfaces of the World except for Antarctica that includes monthly averages of temperature (maximum, minimum and mean) and precipitation after being subjected to thin-plate smoothing spline interpolation using ANUSPLIN software package (Hutchinson, 2004).

According to Hijmans et al. (2005), the interpolation was used to reduce the original coarse resolution of approximately 111 km to a finer resolution of 1 km. The WorldClim data were later validated using the records of the global weather stations targeted at minimising the uncertainty and errors related to interpolation. For species distribution modelling, the WorldClim developed BioClim variables from the derived averages of precipitation, mean, minimum and maximum temperature with the same resolution and the same temporal range as other climate variables (Hijmans & Elith, 2016). These variables apply to many species distribution models because they exhibit suitability in capturing the long term effects of climatic variables that are more biologically relevant to species of plants and animals worldwide (Nix, 1986, Kumar et al., 2009., Reddy et al., 2015, Kantzoura et al., 2011b). Table 4:3 contained the nineteen Bioclim variables (Bo1-19) and their interpretations.

4.2.3.2 CliMond Bioclim (Soil moisture)

CliMond is a French word Climatic *'mondid'* meaning World climate that provides a collection of climate data, techniques of modelling and Bioclim variables available at (http://www.climond.org/). This database is accessible for free public use in species distribution modelling, climate studies and niche modelling among others (Hutchinson et al., 2009, Kriticos et al., 2012, Kriticos et al., 2014). Also, this CliMond data set used interpolation in the derivations of climate surfaces at 10' and 30' for the entire land surfaces of the World. It was further highlighted by Kriticos et al. (2012) that this data base applied WorldClim and Climate Research Unit (CRU) data sets as a 'baseline climatology' due to their accuracy and broad applications in research.

According to Kriticos et al. (2014), the inadequacy of the core suite of Bioclim variables (BIO1-19) in species distribution modelling of some organisms has led to the development of the soil moisture Bioclim variables (BIO28-35) that are at present only available at CliMond Archive (Hutchinson et al., 2009). That was due to the complexity of creating soil moisture-based variables that require the use of water-balance soil moisture index unlike the core variables developed from temperature and rainfall only through more expedient and straight forward processes (Hijmans et al., 2005, Hutchinson et al., 2009). The processes of creating soil moisture index BioClim variables as described by Kriticos et al. (2012) involved the use of two software programs viz: DYMEX (thoroughly explained by Maywald et al. (2007)) and CLIMEX software that was useful in determining the approximate climatic influence in the distribution of species across different years (Sutherst et al., 2007). These two software packages assisted in the creation of a 'single-bucket' soil moisture model through interpolation of monthly climatic parameters. These climate values were useful in the estimation of weekly dryness and saturation of moisture by using a scale of zero to one respectively. Consequently, CliMond database used the aggregated weekly values into soil moisture index that ranges from BIO28 to BIO35(see table 4:3) available in ASCII grid and ESRI grid format (Kriticos et al., 2012). The CliMond data sets have the advantage over WorldClim and CRU data set of including more variables that are relevant for species distribution modelling (Kriticos et al., 2012).

4.2.3.3 Elevation

The Digital elevation model (DEM) was used in this study and is described as the general characteristics of a landscape quantitatively expressed regarding 'grids, contours or irregular network'(Florinsky, 1998). DEM is a product of the global 1-arc second Shuttle Radar Topographic Mission (SRTM) via the United States Geological Survey's EarthExplorer website (http://earthexplorer.usgs.gov). This elevation data developed from the joint project by NASA, the National Geospatial-Intelligence Agency as well as the German and Italian Space Agencies and hence refered to as most comprehensive (Farr et al., 2007). Acccording to Rodriguez et al. (2006), the Jet Propulsion Laboratory data gathered interferometric radar data for the creation of the elevation data within less than 60^0 latitudes of the World.

The SRTM elevation data has broad applications primarily in the study of geomorphological and hydrological processes in different parts of the World (Blumberg, 2006, Grohman et al., 2007, Ludwig & Schneider, 2006, Zandbergen, 2008). From these processes, several terrain variables emerged that affect movement and availability of rainfall water on the earth surface for applications in species distribution models

(Franklin, 2009b). This study used slope and topographic index as extracts from the DEM using ArcGIS 10.3 spatial analyst due to their relevance in species distribution models (Franklin, 2009b). The topographic index explains the role of slope gradient and topography in the dispersion and generation of surface runoff calculated as follows;

$$WT = In\left(\frac{AT}{T\tan\beta}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\,equation\ 2$$

where T represents soil transmissivity, A is upslope contributing area, and β is slope angle. T is constant with a value of 1 implying homogeneity in soil properties and stable hyrological state (Franklin, 2009b).

In this study, maximum entropy predicted that soil moisture variable had the highest contribution in the geographic distribution of *F. gigantica* in the study area. Given that, the topographic index was incorporated into one of the modelling scenarios as a surrogate to SRTM elevation in order to examine its contribution to the prediction of *F. gigantica* geographic distribution in the study area.

4.2.3.4 Land SurfaceTemperature

Land surface temperature MODIS LST (MOD11C1) for the period of 2005-2014 was available from the National Aeronautic and Space Administration (NASA) Earth Observations website (http://neo.sci.gsfc.nasa.gov/). Many types of research applied this remotely sensed data on LST due to its accuracy across different parts of the world (Mildrexler et al., 2011, Hengl et al., 2012, Guangmeng & Mei, 2004, Julien & Sobrino, 2009, Langer et al., 2010, Hulley & Hook, 2009). The day and night algorithm was used in the creation of a primary source of the data set and its emissivities through the recording of mean temperatures for both day and night in kelvin (Kantzoura et al., 2011a). Wan and Dozier (1996), explained that the split-window algorithm and approximated emissivities from different land cover provided the secondary source of the data set. This latter algorithm has the advantage of correcting for the atmospheric and emissivity effects (Wan, 1999). In order to add quality to the data set all the unusable records of LSTs due to the effect of clouds were rejected through the double-screening method before reprojecting the MOD11C1 (Wan et al., 2002). The database determined the accuracy of the data through the validation to a more advanced stage 1, and the errors were less than 1^{O} across uniform surfaces of grassland vegetation, crops and water (Wan, 2013). The original resolution of the data is 0.05 degrees (approximately 5km), and the temporal resolutions are monthly, eight days and daily. The data set has temporal coverage of March 2000 to January-2007 based on version 004 while version 0041 continued from

January 1, 2007, to present. Wan (1999) described these two versions referred to as C4.1 and C4 as very accurate especially over deserts and semi-arid areas and also consistent. He further stated that the main weaknesses of these two versions were in the inflation of data values in lakes and vegetated areas and also lacked stability regarding emissivity values especially in the atmospheric window channels in bands 31 and 32. The area coverage of the data is global using latitude and longitude grid.

4.2.3.5 Vegetation

The vegetation provides shelter for many pathogen parasites including fascioliasis and hence regarded as an essential determinant of *F.gigantica* risk (Kantzoura et al., 2011b). It is determined by an index referred to as Normalised Difference Vegetation Index (NDVI). This research used this NDVI data set from 2005 to 2014 and is available on the National Aeronautic and Space Administration (NASA) website (http://neo.sci.gsfc.nasa.gov/). Also, the index was the product of Moderate Resolution Imaging Spectroradiometer (MODIS) described by Wiegand et al. (1991) as capable of capturing the variability in vegetation conditions and the calculation of biophysical parameters from arid areas to dense vegetation of rain forest regions. The NDVI index uses an equation that consists of red and near infra-red NIR signals that Huete et al. (1999) described as having responses that 'are radiometrically calibrated, cloud-filtered, atmospherically corrected, spatially and temporally gridded and adjusted for view angle influences to produce the level 3 vegetation index maps. The level 3 products are 16- and 30-day, cloud-free vegetation maps at 250m, 1km and 0.25^0 spatial resolution.' The NDVI has positive values that show bare soil if it is zero or 0.1 and 0.5 values imply sparse vegetation while greater than 0.6 to 1 show dense vegetation. The negative values always show clouds and water surfaces. (Leta et al., 2015)

This MODIS NDVI was a 'continuity index' and more up to date then the existing NOAA-AVHRR NDVI (Prince et al., 1994). Also, the product has been validated and compared with other products such as GIMMS NDVI by Schucknecht et al. (2017) and Fensholt et al. (2012) and was found to be very much related as well as consistent with this product especially in the semi-arid West Africa. MODIS has been recommended for studies on the epidemiology of pathogens especially fascioliasis due to mainly their spatial resolution (Kantzoura et al., 2011a).

4.2.3.6 Rainfall data

This research utilised RFE 2.0 data (http://earlywarning.usgs.gov/fews.), developed to minimise random errors and bias commonly associated with the existing rainfall products in order to enhance the validity of precipitation approximations (Xie & Arkin, 1996). The earlier version RFE1.0 was phased out in 2001 and replaced with current version RFE2.0 (Herman et al., 1997) due to the applications of more recent data sources and methods (NOAACPC, 2001). The earlier version used a satellite based product of Meteosat five integrated with daily rain gauge data obtained from the World Meteorological Organisation's (WMO) Global Telecommunication System data. The latest version RFE2.0 was improved with the utilisation of two most recent instruments that are called Special Sensor Microwave/ Imager (SSM/I) on board the Defence Meteorological Satellite Programme (DMSP) and Advanced Microwave Sounding Unit (AMSU) (Hoscilo et al., 2015).

The necessity for the utility of satellite-based approximations of precipitation in Africa 'arises' due to the presence of very few and unevenly distributed weather stations across the continent (NOAACPC, 2001). Various studies in Africa used RFE v2.0 in comparison with other satellite-based products and or weather stations-based rainfall estimates in order to test the accuracy of the product. Toté et al. (2015) compared two satellite-based rainfall estimates that is Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and TAMSAT African Rainfall Climatology And Time-series (TARCAT) with RFE v2.0 and concluded that the estimates of RFE v2.0 and CHIRPS performed well in their estimation of rainfall for drought and flood monitoring in Mozambique. The performance of FEWSNET rainfall estimates was equated with that of the weather stations mainly in the Sahelian parts of Africa with insufficient gauged data (Symeonakis et al., 2009, Maidment et al., 2013). The study by Symeonakis et al. (2009) also compared two rainfall approximation methods using RFE 1.0 as baseline data with some weather stations-based methods. In the end, they concluded that there were agreements between precipitation approximations by satellite-based FEWSNET and weather-station-based approximations.

Moreover, this manifected itself across areas with rainfall record of 14mm per thirty years as of March 1996 with the low bias of 0.03 and r^2 of 0.6 in South Africa. A perfect relationship with RFE 1.0 product also observed in West Africa and Madagascar. Regarding the comparison of accuracy between the older version RFE1.0 and the new version RFE2.0, there was a disparity between one country and another in Africa. For example, according to Dinku et al. (2008), RFE1.0 gave the best result in Ethiopia than RFE2.0 while in Zimbabwe RFE2.0 was slightly better than RFE1.0.

RFE2.0 is available for the whole of Africa from 2000 to date with a spatial resolution of 8 kilometres at 10-day composites, and this study used the data from 2005-2014. Furthermore, there was resampling of the data to 1km in order to align with the other data sets as an essential requirement for maximum entropy modelling. Although the data was accurate across various locations in Africa, at the original resolution, the database estimated rainfall without incorporating orographic rainfall effects (NOAACPC, 2001) which may cause uncertainty.

4.2.3.7 Soil moisture

In order to obtain a scientifically rigorous soil moisture datasets, this research utilised the Global Land Data Assimilation System (GLDAS-2) produced through the combined efforts of the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), the Goddard Space Flight Centre (GSFC) and the National Centre for Environmental Prediction [NCEP] (Cai et al., 2017). This data set integrated both field data from ground land-surface-based station data as well as satellite measurements. That is to satisfy the objective of obtaining the real condition of landscape and ‘fluxes’ through the application of sophisticated land surface modelling and assimilation methods (Rodell et al., 2004). It also made use of four land-based models, which includes Catchment, Noah, the Community Land model (CLM) and Variable Infiltration Capacity (VIC). Kumar et al., 2006, explained that GLDAS has a unique quality of being driven by many offline models related to the landscape that combined a large number of station data processed at a resolution of 2.5^0 to 1km by Land Information System (LIS).

This version of GLDAS-2 is more ‘climatologically consistent’ than the earlier version GLDAS-1 as the latter caused some artefacts in the trend from 1979 to present due to many ‘switching’ of data sources (Rui & Beaudoing, 2014). The GLDAS-2 consists of 28 parameters of precipitation, temperature and soil moisture which consist of four strata- 0-10cm, 10-40cm, 40-100cm and 100-200 cm depths using kg/m^2 as a unit area of soil water content(Cai et al., 2017). The data set’s accuracy and validity have been tested against existing data from various origins (Zhang et al., 2008, Chen et al., 2013, Cheng et al., 2015). Syed et al. (2008) and Reichle et al. (2007) explained that GLDAS-2 products applied extensively in hydrology and as an input into weather and climate-based models.

The GLDAS-2 version is available at 0.25 spatial resolution in NetCDF format. This study made use of monthly moisture values obtained through the mean of 3-hourly products based on soil depth of between 0-200cm.

4.2.3.8 Future BioClim

This future climate dataset was a product of the International Centre for Tropical Agriculture and available online at http://gisweb.ciat.cgiar.org/GCMPage. The database used WorldClim (Hijmans et al., 2005) as its baseline climate. That was due to considering the high resolution and broad applications of WorldClim data by researchers in different fields as well as having more than half a thousand times citations in high quality journals (Ramirez & Jarvis, 2010). The dataset employed a method that involved introducing coarse GCM cells into the computation of climate data from either ground-based stations or interpolated climate surfaces with high resolution referred to as spatial disaggregation (Buytaert et al., 2009). That was meant to maintain standard and consistency in the spatial pattern of the general circulation model (GCM) outputs in the dataset. They added that this method has advantages in reducing uncertainties as well as in retaining the original GCM patterns over time periods than the conventional method of downscaling GCM outputs through interpolation. Given the advantages of spatial disaggregation, according to (Ramirez & Jarvis, 2010), this database applied it on 24 General Circulation Models from the IPCC Fourth Assessment Report (2007) while using climatologies of the WorldClim (Hijmans et al., 2005) as a base. These GCMs were available from the Earth System Grid (ESG) database for three different scenarios of emission of A1B, A2 and B1 and the temporal scale of 30 year average divided into seven slices (Buytaert et al., 2009)

In line with the IPCC Fourth Assessment Report (2007), there was the development of various Coupled Model Intercomparison projects (CMIP) aimed at disseminating and encouraging GCM science associated knowledge. The latest project being CMIP.3 provided GCM outputs for free public use through the online network of the Earth System Grid (ESG). CIAT subsequently downloaded the dataset as reported by Buytaert et al. (2009) for the emission scenarios SRES-A1B, A2 and B1 as well as for seven thirty year averages that covered 2010-2039 and ended 2070-2099. Moreover, the GCM used time series generated by the database for the computation of the 30 year running means for the present day projections as well as seven projections for the future beginning from 2010-2039 up to 2050-2099. Finally, there was a disaggregation of the anomalies which imply the variation between the means of the GCMs products of 1960-1990 and the future projections of specifically precipitation, maximum and minimum temperature (Ramirez & Jarvis, 2010). Consequently, these were added to the baseline climate obtained from WorldClim (Hijmans et al., 2005) by utilising complete 'sum' for temperature and 'relative changes' for precipitation (Ramirez & Jarvis, 2010). In the end, the database computed and obtained a mean temperature from both the maximum and minimum temperatures. From these variables, the database created 19 bioclimatic variables for applications into species distribution modelling due to their association with the species biological mechanisms and their distributions (Busby, 1991).

4.2.4 Multi-collinearity

Multicollinearity implies a correlation between environmental and climatic variables (Kovacs et al., 2005, franklin, 2009). However, due to the sensitivity of most of the modelling techniques to very high levels of correlation among variables, it appears necessary to subject them (variables) to test for multicollinearity (Merow et al., 2013). Aguilera et al., (2006) highlighted that it is impossible to have uncorrelated variables, but it is necessary to keep the level of correlation at certain limits for easy identification of relationships among variables. In this regard, this study utilised the Pearson correlation coefficient, and the maximum degree of correlation (positive and negative) among variables maintained at 0.75.

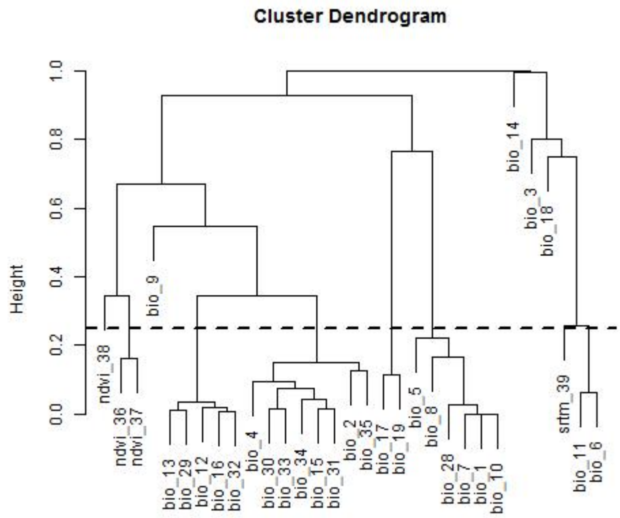

Figure 4-7: Cluster dendrogram showing correlations of Bioclim variables. The dotted line marked the limit of correlation to 0.75. All the branches indicate variables that were highly correlated and hence only one variable was chosen on each branch.

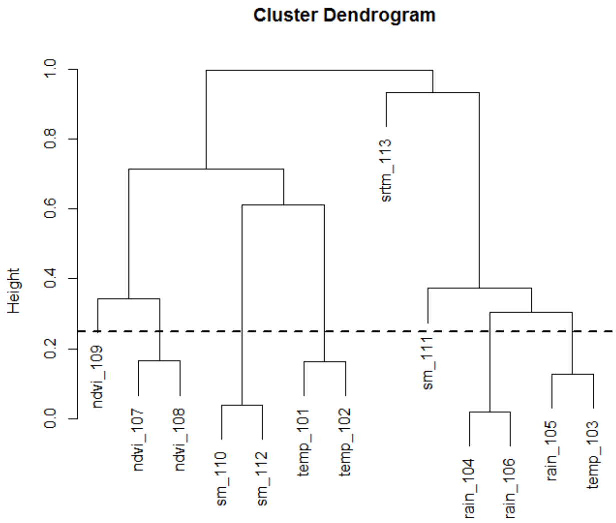

Figure 4-8: Cluster dendrogram showing correlations of non-Bioclim variables. Similar to Figure 4-2, the level of correlation was kept at 0.75 and the dotted line marked the limit of the relationship.

Table 4 -2: Interpretation of the acronym of the remotely sensed dataset based on climate and environment used in the MaxEnt model

Variable	Description
tmp101_ann	Mean annual temperature
tmp102_ann	Minimum annual temperature
tmp103_ann	Maximum annual temperature
rain_104_ann	Maximum annual rainfall
rain_105_ann	Mean annual rainfall
rain_106_ann	Minimum annual rainfall
ndvi_107_ann (NDVI_36)*	Maximum annual NDVI
ndvi_108_ann (NDVI_37)*	Minimum annual NDVI
ndvi_109_ann (NDVI_38)*	Mean annual NDVI
sm_110_ann	Mean annual soil moisture
sm_111_ann	Maximum annual soil moisture
sm_112_ann	Minimum annual soil moisture
srtm_113_ann (SRTM_39)*	Mean elevation

NB: All the metric marked * was the code used when the variable combined with Bioclim variables

Table 4-3: Climatic and environmental dataset used in the research

Data	source	Temporal coverage	Spatial resolution	ID Number	Temporal scale
BIOCLIM	(http://www.worldclim.org).	1950-2000	1km	BIO1-BIO35	
Temperature	http://neo.sci.gsfc.nasa.gov/	2005-2014	0.05º (6km)	MOD11C1	Monthly
Soil moisture	https://giovanni.gsfc.nasa.gov/giovanni/	2005-2014	0.25 Degrees (28km)	GLDAS-2	Monthly
NDVI	http://neo.sci.gsfc.nasa.gov/	2005-2014	1km	MOD13A2	Monthly
Rainfall	Fews Net data (http://earlywarning.usgs.gov/fews.)	2005-2014	8km	FEWSNET RFE 2.0)]	10 days
Elevation	http://earthexplorer.usgs.gov	2000	30m	SRTM	

Table 4-4: List of bioclimatic parameters from WorldClim applied in the Model (Hijmans & Elith, 2016)

Code	Bioclimatic variables
Bio_1	Annual Mean Temperature
Bio_2	Mean Diurnal Range(mean of monthly (max temp-min temp))
Bio_3	Isothermality(P2/P7)*(100)
Bio_4	Temperature Seasonality(standard deviation *100)
Bio_5	The maximum temperature of warmest month
Bio_6	Min Temperature of the coldest month
Bio_7	Temperature Annual Range(P5-P6)
Bio_8	Mean Temperature of the wettest quarter
Bio_9	Mean temperature of driest quarter
Bio_10	Mean temperature of the warmest quarter
Bio_11	Mean Temperature of coldest quarter
Bio_12	Annual precipitation
Bio_13	Precipitation of the wettest month
Bio_14	Precipitation of the driest month
Bio_15	Precipitation of seasonality (Coefficient of variation)
Bio_16	Precipitation of the wettest quarter
Bio_17	Precipitation of the driest quarter
Bio_18	Precipitation of the warmest quarter
Bio_19	Precipitation of the coldest quarter
Bio_28	Annual mean moisture index
Bio_29	Highest weekly moisture index
Bio_30	Lowest weekly moisture index
Bio_31	Moisture index seasonality
Bio_32	Mean moisture index of wettest quarter
Bio_33	Mean moisture index of driest quarter
Bio_34	Mean moisture index of warmest quarter
Bio_35	Mean moisture index of coldest quarter

4.2.5 Maximum entropy modelling

Maximum entropy is a presence-only machine learning technique developed in 2004 (Elith et al., 2010) that makes use of the known presence of a species at a site and the measured climatic variables across the site in order to model the species geographic dispersion (Phillips et al., 2006). That is in contrast with presence-absence methods that use both the presence and absence of a species in modelling the geographical distribution of the species, for example, random forests, boosted regression trees and generalised linear models (Elith et al., 2011). Maximum entropy mainly utilises two data sets that include a known site of species occurrence and the approximated measurement of variables (climatic or environmental) over those sites in order to model the suitability of the habitat (sites) for the species (Franklin, 2009b) in Figure 4:4. The main idea is that the dispersion of the species (which is unknown) should have maximum entropy (in terms of consistency with the data) (Merow et al., 2013) and as such should be uniform across the area of study under the condition of satisfying some constraints (Phillips et al., 2006). These constraints are that the values of these variables predicted should be equivalent to or near to their observed values which reflects the principle of maximum entropy(Elith et al., 2011)

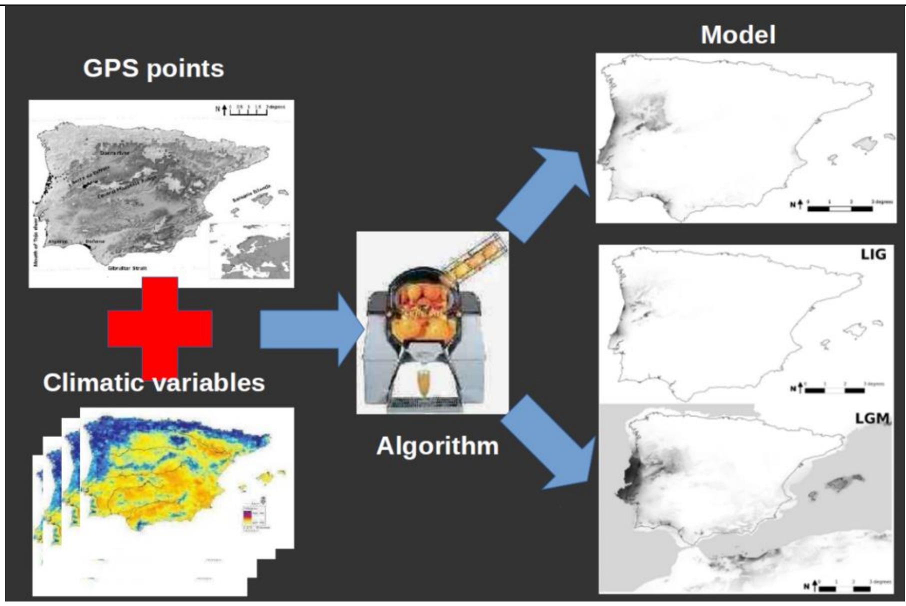

Figure 4-9: This illustrates the data requirements of Maximum entropy modelling method. The GPS points refer to geographic coordinates of a species location, and the climate variables are the values obtained through measurement over the same location. These data were then transformed mathematically by maxEnt algorithm through the use of its features that are linear, quadratic, product, threshold and categorical. The essence is to ensure that expected values of each feature match its observed values. Then probability maps would be produced to indicate areas variability about the suitability for the species.(Source: Neftali 2017).

The relationship between the species and the variables used in fitting the MaxEnt model is described as complex and not a linear (Austin, 2002), which therefore necessitates the latter to be changed or transformed mathematically into features (Elith et al., 2011). These features are divided into five classes viz linear, quadratic, product, threshold and hinge (Dudık et al., 2004) and they serve as constraints on the spatial dispersion of species since they are transformations of the original environmental variables. Linear and quadratic are constraining the mean and variance of the climatic variable so that they should match the observed values respectively. The product features function to ensure that the sum of two climatic variables is constrained to match their empirical values. Likewise, the threshold features ensure that the value of continuous climatic variable beyond a particular threshold is given a value of 1 while below is given a zero score. This feature then ensures that the fraction of the distribution that has values for the variables that attain one threshold would be constrained to match their empirical values. Hinge features are similar to threshold features the only difference is that categorical variables are involved (Phillips et al., 2006)

Maximum entropy is a species distribution modelling technique that has been built with a 'guarantee' to produce accurate modelling of species geographical distribution (Phillips et al., 2004, Phillips et al., 2006, Elith et al., 2011). Maximum entropy algorithm according to Phillips et al. (2006) uses various steps of mathematical and statistical operations that are 'deterministic' and consequently 'converge to the maximum entropy probability distribution'. In the explanation of how MaxEnt works this study relies strongly on the contributions of Phillips et al. (2006), Elith et al. (2011) and Merow et al. (2013). For illustration, in this study, we use k to represent a collection of pixels that constitute the study site that consist of smaller sub units as occurrence sites q within the unknown distribution D. Each of the study sites q would have a positive probability value in the unknown distribution approximated to 1. The unknown distribution D is estimated as likely distribution D̂ whose entropy is interpreted as: $H\left(\widehat{D}\right) = \sum_{D \in K} \widehat{D}(D) In\, \widehat{D}(D)$

Where In is the natural logarithm, H is the entropy, D is unknown distribution, $\widehat{D}$ is the estimate of unknown distribution (Phillips et al., 2006).

The algorithm of maximum entropy is effective (Berger et al., 1996) and is consistent with its principle. This means a homogeneous distribution of the unknown distribution D is expected to be achieved through constraining the mathematical transformation of the environmental features f (Elith et al., 2011) to match the observed values at K the study site. Consequently, each feature in the environmental space allocates a number to every site q in the study area K. The assumption or the averages of each feature f under the unknown distribution D is $\sum_{q \in K} D(q) fj(q)$ which is simplified as D[fj].

On the other hand, the empirical or the observed values average is given as $\frac{1}{m}\sum_{i=1}^{m} fj(qi)\ alternatively\ written\ as\ \widetilde{D}[fj](\widetilde{D}$ is representing a homogeneous distribution in the study area). So in line with the principle of maximum entropy, the unknown probability D is constraining the predicted features fj (D[fj]) to have similar average values with the empirical averages D̂[fj] (Jaynes, 1957) which is given as

$$\widehat{D}(D) = \widetilde{D}[fj] \ldots\ldots\ldots\ldots. for\ each\ feature\ fj \ldots\ldots equation\ 1$$

According to Della Pietra et al. (1997), the above proportionality (as shown in equation 1) in the unknown distribution can be performed by application of the mathematical theory of convex duality. This theory as explained by Phillips et al. (2006) indicates similarity between MaxEnt likelihood distribution and Gibbs distribution (Dudık et al., 2004) and is expressed as

$$q\lambda(D) = \frac{e^{\lambda.f(q)}}{z\lambda} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{equation } 2$$

Equation 2 shows Gibbs distribution with λ indicating a vector of n real-valued coefficient or the transformed environmental variable weights, f indicates the vector of the entire n features while $z\lambda$ has a unique function of adding probability distributions $q\lambda$ to be equal to 1 and hence acts as normalizing constant. It is worth emphasizing that the equality between MaxEnt likelihood distribution D and the Gibbs distribution $q\lambda$ as indicated by convex duality 'maximises' the probability of all the m (sample) sites (Phillips et al., 2006). Similarly, the negative log probability of all the m (sample) sites is minimised.

$$\widetilde{D}[-\mathrm{In}(q\lambda)] \ldots\ldots\ldots\ldots\ldots. \textit{equation } 3$$

$\textit{which is alternatively written as } z\lambda - \frac{1}{m}\sum_{i=1}^{m} \lambda.f(qi)$ and is referred to as "log loss"

MaxEnt has an inherent tendency to overfit the training data. This is because the predicted values could not match the observed or empirical values precisely but can only estimate them. In that light, as explained by Phillips et al. (2006) there is a restriction imposed to constrain the average of the expected values under the unknown distribution to be near the observed values. This led to the constraint relaxation in equation (1) with an addendum (Dudık et al., 2004)

$\widehat{D}(D) = \widetilde{D}[fj] \leq \beta j$ ……………………………… equation 4

for each feature fj and constants βj

Consequently, this leads to e_1-regularization that altered the two characterization in (4) above (Phillips et al., 2006): in (5) below MaxEnt distribution is indicated to be Gibbs distribution that sets the minimum limits (between observed and empirical values)

$$\widetilde{D}[-In(q\lambda)] + \sum_{j} \beta j|\lambda j| \ldots\ldots\ldots\ldots.. \textit{equation } 5$$

Where the 'log loss' is the first segment and the second segment 'penalizes' the utility of higher numbers for the coefficients λj (Phillips et al., 2006). According to Williams (1995) regularization has the advantage of not only reducing overfitting but also in coercing MaxEnt to concentrate on the most significant variables. Furthermore, e_1-regularization greatly decreases variables to a small numbers thereby reducing the possibility of overfitting and is referred to as "lasso" in Generalised Linear Models (GLM) and Generalised Additive Models [GAM] (Guisan et al., 2002).

The MaxEnt procedure described in the preceding discussion n will converge at optimal probability distribution through repetition in changing the coefficients $\lambda = (0\ldots.1)$ in order to minimise regularised log loss (Phillips et al., 2006).

4.2.5.1 Modelling scenarios

In species distribution modelling according to Joyner (2010), it is logical to create various scenarios constituting different environmental and climatic variables in order to evaluate the suitability of each scenario in modelling the species spatial distribution. This research developed six scenarios to investigate the spatial distribution of *F. gigantica*. Scenario 1 consists of precipitation and temperature variables (Bioclim). While scenario 2 and 3 contained Bioclim and non-Bioclim variables respectively that described precipitation, temperature and soil moisture variables. As a convention, MaxEnt used only the first scenario variables to model spatial distribution of *F. hepatica*. The soil moisture has a significant influence on the survival of fascioliasis intermediate host especially in the semi-arid parts of the world (Khanjari et al., 2014). The utilisation of more relevant variables in a model can enhance the model's ability to choose the most significant variable (Baldwin, 2009). In that light, the study included NDVI and SRTM elevation into scenario 4 (Bioclim) and scenario 5 (non-Bioclim). Due to the contribution of the soil moisture in the earlier modelling scenarios, this study added the topographic index and slope generated from SRTM elevation in scenario 6. These variables were a surrogate to elevation since they were influential in the redistribution of water across a landscape and hence affect the spatial distribution of species (Franklin, 2009b).

4.2.5.2 Maxent implementation on modelling scenarios

This study downloaded MaxEnt freely on the World Wide Web at http://www.cs.princeton.edu/~schapire/maxEnt. The specific parameters left at default settings include convergence threshold=10^{-5}, maximum iterations=5000, regularisation value 10^{-4}, the maximum number of background points=10000 and auto features involving linear, quadratic, product and binary features utilised in all the runs. That is because Phillips and Dudík (2008) confirmed that the performance of the MaxEnt model based on default settings does not differ from the modified settings as revealed from 'recent simulations'.

4.2.6 BioClim modelling

BioClim (Busby,1986) is an environmental envelope or climate-envelope model (Booth et al.,2014) that provides a binary classification of suitable and unsuitable habitat through the use of "hyper-box" that encompasses favourable environmental conditions occupied by about 100 percent of species (Franklin, 2009a). The software for computing the model is available in the 'dismo' R package for species distribution models (Hijmans et al., 2011b). The algorithm of this modelling technique computes the values of climatic variables across the entire area of study and then make a comparison with the percentage distribution of the values at the recorded occurrence sites (Beaumont et al., 2005). Consequently, the algorithm then selects the values that are at least fifty percent closer to the values at the known occurrence sites for classification as suitable for the species. Carpenter et al. (1993) highlighted that species could survive at any sites that are within the limits of the climatic envelope or rectilinear volume of the known occurrence sites for the species.

The development of an information system that comprised the most relevant variables for species distribution and climatic data occurred at the same time as the first version of BioClim software (Franklin, 2009b). That led to the generation of bioclimatic variables (BIO1-19) that are very suitable for modelling of species (Hijmans et al., 2005). Recently, new methods have emerged (example DIVA-GIS software; www.divagis.org) of implementing BioClim model application to bioclimatic variables for species distribution models referred to as "BioClim" technique (Franklin, 2009b).

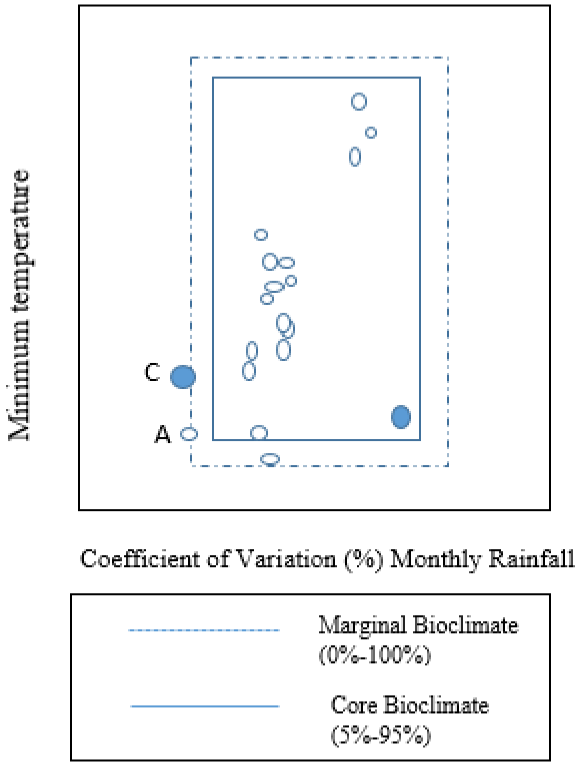

Figure 4-5: BIOCLIM ENVELOP MODEL (Carpenter et al., 1993, modified).This figure shows narrow distribution range of the 5%-95% thereby excluding suitable site 'A' and enclosing unsuitable site 'B' as suitable. Also, the omitted site 'C' was nearest to site 'A' treated by the model as unsuitable

Booth (1990) described the predictions by BioClim models as 'unsound' due to the graphical representation of x and y values of climate and environment as independent of each other. That shortcoming necessitated the need for alternative methods (Walker & Cocks, 1991). It was also noted by Carpenter et al. (1993) that there is a high possibility of exclusion of some known record sites from the 'core bioclimate' which affects the efficient performance of the method. For example, Figure 4:5

4.2.7 Domain modelling

Domain (Carpenter et al., 1993) is a presence-only modelling technique for species distribution that uses 'distance' between environmental parameters at any site and the known occurrence sites for classification into suitable and unsuitable locations for the species (Franklin, 2009b). The software for computing the model is available in the 'dismo' R package of species distribution models (Elith et al., 2011). The distance expressed as 'Gower' distance defined by Legendre and Legendre (1998) as a means of obtaining common attributes through the use of climatic and environmental variables.

The Gower metric measures the common attributes quantitatively in environmental space between two sites X_1 and X_2 (Legendre & Legendre, 1998) as

$$G(X1, X2) = \frac{1}{P}\sum_{j=1}^{P} S12j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; equation\ 11$$

where p is the descriptor of the common attributes or similarities S for each of the descriptors, and j is the distance. The model used the computed values between two locations as the amount of distance in measuring similarity and common attributes in environmental space, and Rj is the maximum distance measured in a set of occurrence locations.

$$s12j = 1 - \frac{[y_1 + y_2\ ]}{R_j} \ldots\ldots\ldots. equation\ 12$$

According to Hijmans et al. (2005), the model can find the distance between the environmental condition at site X_1 and recorded occurrence sites for one climate parameter by computing its mean values across the entire recorded occurrence sites. All the locations within the environmental range as computed in equation 11, the model assigned values between 0 and one while all the omitted locations outside the range got negative values (Carpenter et al., 1993).

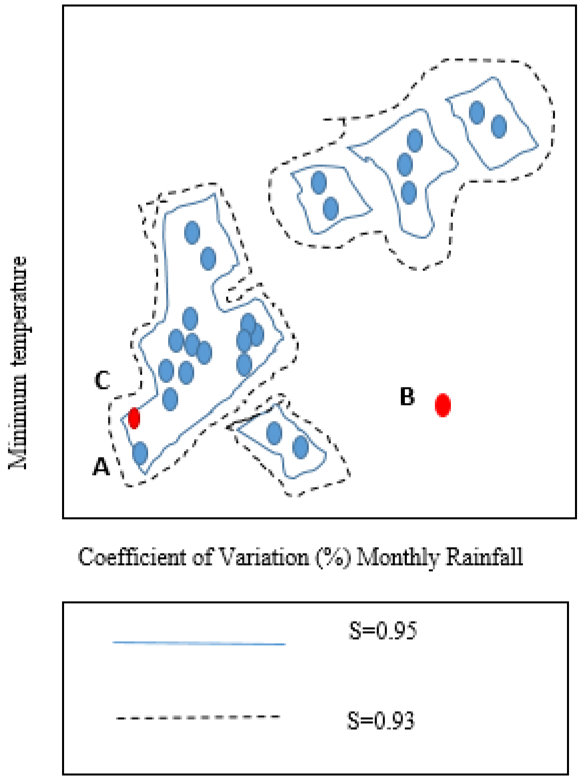

Figure 4-10: Domain model (Carpenter et al., 1993, modified).

The Domain model differs from all other models due to lack of distinct boundary for the environmental envelope (Tsoar et al., 2007) and can generate a map based on common attribute values that may differ continuously across the landscape of interest. Also, the model used a threshold value either based on expert knowledge or subjectively to select sites that may vary in the value of an environmental variable from the recorded occurrence site of not greater than 10% of the range (Carpenter et al., 1993). However, the main criticism of the model was in having the weak predictive ability and performing 'poorly' in detecting climate change effects in species distribution (Elith et al., 2006, Hijmans & Graham, 2006).

4.2.8 Model evaluation

The main essence of evaluating species distribution models is to assess the suitability of an area to a particular species of plants and or animals for habitation through quantification of accurate measures of validity (Franklin, 2009b). In addition, model assessment provides a sound basis for comparison across different models (Segurado & Araujo, 2004, Pearson et al., 2006, Allouche et al., 2006). According to Rykiel (1996), the validity of a model depends on its attainment of certain prescribed standards. These include determining the predictive ability of the model, error percentage and credible nature or acceptance of the model to the global community (Morrison et al., 1998, Franklin, 2009b).

Although, no model is entirely immune from 'errors' since they simplified reality (Franklin, 2009b) but they are still essential for a wide range of applications (Barry & Elith, 2006) as 'errors' could encompass 'variations in the statistical sense'(Goodchild, 1994). Barry and Elith (2006) highlighted that the idea of statistical variation includes both the error and the uncertainty arising not only from the data and model's approximations but also in the unclear or ambivalent interpretation of modelling concepts (Elith & Burgman, 2002, Franklin, 2009b).

This research has followed all the steps described below in evaluating the performance of the models and the modelling scenarios used in this chapter.

4.2.9 Independent evaluation data

Independent evaluation data refers to a new set of data not used in estimating the fitness of the species distribution model (Fielding & Bell, 1997, Barry & Elith, 2006, Franklin, 2009b). It, therefore, gives the 'best' and better method of validating species distribution model than randomly splitting the same data into training and testing (Franklin, 2009b) that often leads to inflation of accuracy measures of the model's performance(Edwards et al., 2006).

This research obtained independent data through a fieldwork approved and funded by the University of Leicester from July to August 2016 and Ministry of Animal health, Sokoto State, through the state Director granted permission for data access and collection. The field survey involved visitation to slaughter houses of fifteen localities of the study area. These localities are Kuchi, Girkua, Shagari, Gidan Abuzai, Silame, Dan Bara, Sokoto north, Gidan Daji, Rabah, Wurno, Goronyo, Gada, Sarkakarwa, Dagoza and Tamaru.

In this study, evaluation of the MaxEnt model was carried out using the collected independent data for 'testing' and another separate data (from a government agency) 'for training' (estimating the fitness) through a technique known as cross-validation(Hijmans, 2012). This method is advantageous as it yields better predictive accuracy through proper assessment of uncertainties (Merow et al., 2013). Hijmans (2012) further highlighted that in species distribution modelling cross-validation has another advantage of not overestimating performance due to the high correlation of variables. That, therefore, is a complete requirement of the conventional goodness of fit statistic both in the evaluation and in a better estimate of ‘predictive power’ of SDM. These reasons make cross-validation the most accurate and reliable measure of evaluating data for species distribution models(Merow et al., 2013).

All the accuracy measures of the model's predictions in this study used the independent test data. That is because all test data if available in species distribution modelling are useful in the evaluation of the model performance (Fielding & Bell, 1997, Liu & Newll, 2011, Hijmans, 2012)

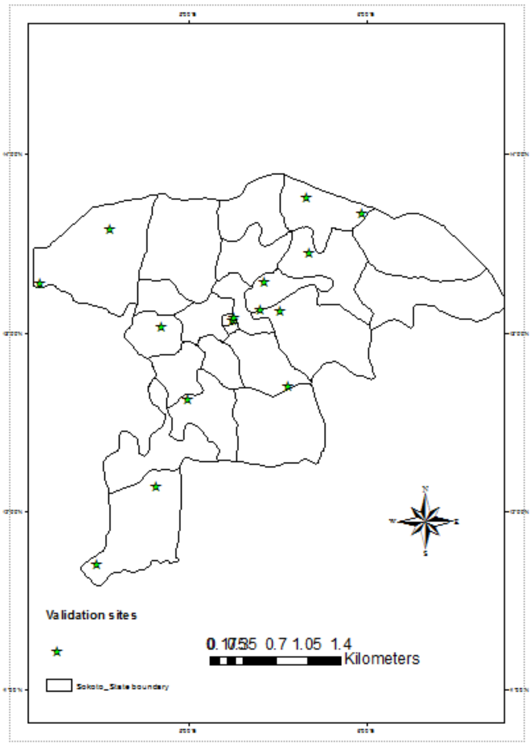

Figure 4-11: Independent evaluation data

4.3.0 Threshold-dependent evaluation

A threshold implies setting a limit for suitability above specific values and unsuitability below those values and is described as a reliable measure of models ability to produce predictive maps for binary (presence and absence) classification (Manel et al., 2001, Liu et al., 2005, Negga, 2007). That would lead to the derivation of a confusion matrix or error matrix (Table 4.4) which consists of observations and predictions of the presence and absence(Fielding & Bell, 1997).

Table 4-5: A Confusion matrix. (a implies true positive rate (TPR), b is the false positive rate (FPR), c is the false negative rate (FNR), and d is true negative rate [TNR](Fielding & Bell, 1997)

		Actual +	Actual -
Predicted	+	a	b
	-	c	d

Several measures of model performance can be generated from the confusion matrix to assess the ability of the model to make accurate classification into presence and absence(Barbosa et al., 2013). For a full description of all the measures see (Fielding & Bell, 1997). Here the study used the following measures: Sensitivity (TPR), specificity (TNR), omission rate (FNR), commission rate (FPR), Kappa and True Skill Statistics (Table 4.5). Sensitivity is the ability of the model to predict presences accurately and therefore indicates omission rate while specificity is the opposite in predicting absences (background) which indicates commission rate (Allouche et al., 2006)

Both false negative rate (FNR) and false positive rates (FPR) imply omission and commission rates respectively (Fielding & Bell, 1997, Barbosa et al., 2013). Omission rates indicate presences that are omitted by the model while commission quantifies the number of absences classified as presences and as hence referred to as 'measures of mismatch'(Barbosa et al., 2013).

The Kappa statistics relies heavily on the number of observations that are correctly and incorrectly predicted (prevalence) in a model in order to give a calculated proportion of specific agreement (Manel et al., 2001). This measure is described as very prominent in species distribution modelling and gives some level of confidence in its prediction of presence and absence (Pearson et al., (2004), Segurado & & Araujo, (2004), Allouche et al., 2006). According to Cohen (1960), the maximum kappa scores are between -1 to +1 with the latter score implying excellent performance while a zero score or less implies a random chance agreement. However, kappa has some short comings for being over reliant on the number of observations (prevalence) which provides some 'misleading information' and inflation of accuracy values referred to as 'statistical artefacts' (Lantz

& Nebenzahl, 1996, Allouche et al., 2006, Zheng & Agresti, 2000, Pontius & Millones, 2011).

Given the criticism surrounding kappa, this research complemented it with an alternative method that proved to be devoid of all its shortcomings that is True Skill Statistics TSS(Somodi et al., 2017). This measure of model performance as described by Allouche et al. (2006) correlates significantly with an area under the curve (AUC) that does not depends on prevalence. The early applications of TSS otherwise known as Hansen-Kuiper's discriminant were in meteorological forecasting in the evaluation of weather forecasts (Accadia et al., 2005). The formula for the calculation of TSS consists of the derived elements from the confusion matrix (Table 4:5). One primary common attribute between kappa and TSS according to Allouche et al. (2006) is that both are accounting for omission and commission errors resulting from random chance. The value scores of TSS ranging between -1 to +1, where zero implies model goodness that is tantamount to random guessing while +1 implies perfection in agreement.

Table 4-6. Indices of evaluating the correct performance of MaxEnt, BioClim and Domain as derived from figure confusion matrix.

Measure	Calculation
Sensitivity	a/(a+c)
Specificity	d/(b+d)
False positive rate	b/(b+d)
False negative rate	c/(a+c)
Kappa	[(a+d) – (((a+c)(a+b) + (b+d)(c+d))/N)]/[N-(((a+c)(a+b)+(b+d)(c+d))/N]
True Skill Statistics	ad-bc/(a+c)(b+d)=Sensitivity+Specificity-1

In order for this study to test whether the MaxEnt model's predictions of the independent validation test localities were significant and not through random chances (Anderson et al., 2002) a one-tail binomial test was used. The null hypothesis expresses that the selection of the model was not by chance from the collection of all other models with the equivalent predicted area that is suitable for the species (Phillips et al., 2006).

All the threshold-dependent measures of evaluation used by this study required a choice of a threshold which has much impact on binary (presence and absence maps) classification (Freeman & Moisen, 2008b). In that light, this study applied a threshold based on the 10th percentile training presence. This threshold according to Jarnevich and Reynolds (2010) depends on the choice of a value which if exceeded classify 90% of the training points as suitable for the species. Morueta-Holme et al. (2010) and Jarnevich and Reynolds (2010) used this threshold in their respective studies where they described it as resulting 'to a more conservative' model than other thresholds criteria that may lead to over-estimate of the model's predictive ability. This study selects this threshold as it gives a correct binary classification of species distribution models that included almost all the known occurrence locations for the prevalence of *F. gigantica* in the study area.

4.3.1Threshold-independent evaluation

Species distribution models are evaluated using threshold-independent measures due to their ability to utilise complete information provided by the model in order to explain the general characteristics of the species distribution(Merow et al., 2013, Fielding & Bell, 1997). These measures assess the performance of a model without relying on any particular threshold (Deleo, 1993, Phillips et al., 2006). Receiver operating characteristic (ROC) has its origin in signal processing and it gives an indication of the models ability in ranking cases (discriminating) into two categories or classes using all possible thresholds (Deleo, 1993, Zweig & Campbell, 1993, Provost & Fawcett, 1997, Elith, 2002, Merow et al., 2013). It uses the area under the curve (AUC) which is a technique of scoring higher percentage to the random chances of choosing presence locations than the background localities anytime random selection is made in the presence-only models(Fielding & Bell, 1997, Merow et al., 2013). The application of AUC was initially in presence/absence models that distinguish presence locations from absence locations example generalised linear models (GLM) and generalised additive models (GAMs) (Ferrier et al., 2002). In the presence-only models, AUC was implemented after adjusting this constraint by differentiating between presence and background or random since there was no truly absence record (Anderson et al., 2003a). In the achievement of this motive, all the pixels in the area of study were labelled x_{random} while the entire pixels that constitute the geographic extent of the known occurrence locations were labelled $x_{presence}$. (Phillips et al., 2006). The species distribution model used the combined pixels from both the presence and random in predicting the entire area of study (Wiley et al., 2003).

In interpreting the values of AUC, the random prediction had a score of 0.5 and described as bad model while a good model has values closer to 1(Freeman & Moisen, 2008a, Swets, 1988). It was further highlighted that a species distribution model with an AUC score of 0.7 is'potentially significant' and possessing a good predictive ability, while models with AUC equal to or greater than 0.8 are excellent and models with equal to or greater than 0.9 are outstanding (Hosmer & Lemeshow, 2000, Elith et al., 2006, Morueta-Holme et al., 2010, Sobek-Swant et al., 2012).

Fourcade et al. (2014) highlighted that AUC provides a robust estimate of model performance that it is not affected by prevalence (Manel et al., 2001) and hence can be a valid means of comparing different models (Cumming, 2000). The only caveats in the use of AUC as it is ranked-based (Merow et al., 2013) is that validity for comparison among models should ensure that all the models constructed should be similar in terms of study area, background samples, species as well as in the utility of validation data set (Elith et al., 2011)

In the evaluation of species distribution models, this study used the AUC score of both the training data and the independent test data. The former assesses the fitness of the model to the data, and the latter appraises the predictive ability and generality of the model (Arau´ jo & Guisan, 2006, Merow et al., 2013)

In addition to AUC, this research applied other measures in the evaluation of the models as recommended by Shabani et al. (2016) who described AUC as 'overoptimistic' s and hence it could not 'tell the whole story' (Austin, 2007, Peterson et al., 2007). Also, Somodi et al. (2017) suggested complementing AUC with other model goodness measures especially TSS.

4.3.2 Jackknife for variable importance

The significance of each variable in modelling was evaluated using Jackknife. It determines the contribution of each variable by serially accomplishing the following three tasks;

1) Involving all variables in running the model
2) Leaving out one variable at a time in running the model again
3) Using the left out variable alone in stage (2) in running the model.

The most significant variable (s) resulting from these Jackknife operation is the one that increases highest training gains when used alone in running the model and likewise decreases the training gain than all other variables when left out or isolated from the model. (For more explanation refer to MaxEnt tutorial on (www.cs.princeton.edu).

4.3.3Biserial correlation

Biserial correlation is another threshold-independent measure of prediction accuracy in species distribution models (Thibaud et al., 2014, Elith & Graham, 2009, Franklin, 2009b). Zheng and Agresti (2000) defined biserial correlation (COR) as the correlation between what a model predicts and the number of observations scaled between 0-1 in the validation data of the presence-absence model which is mostly computed using Pearson correlation coefficient. The presence-only models calculate the correlation between the model probability estimations (predictions) and the observed validation data of presence and background model. That is because all evaluation measures apply to both presence-absence models and presence and background models but with a different interpretation(Franklin, 2009b).

In testing the statistical significance of the relationship between model predictions and observations, this study used the Wilcoxon rank signed test that is equivalent to a paired two-tailed t-test (Phillips et al., 2006). Also, used the paired two-tailed t-test at 95% confidence interval in testing the statistical significance of the differences in performance between MaxEnt and the other two models.

Figure (4-8) shows the flow chart that explained the procedures used in achieving the objectives of this chapter.

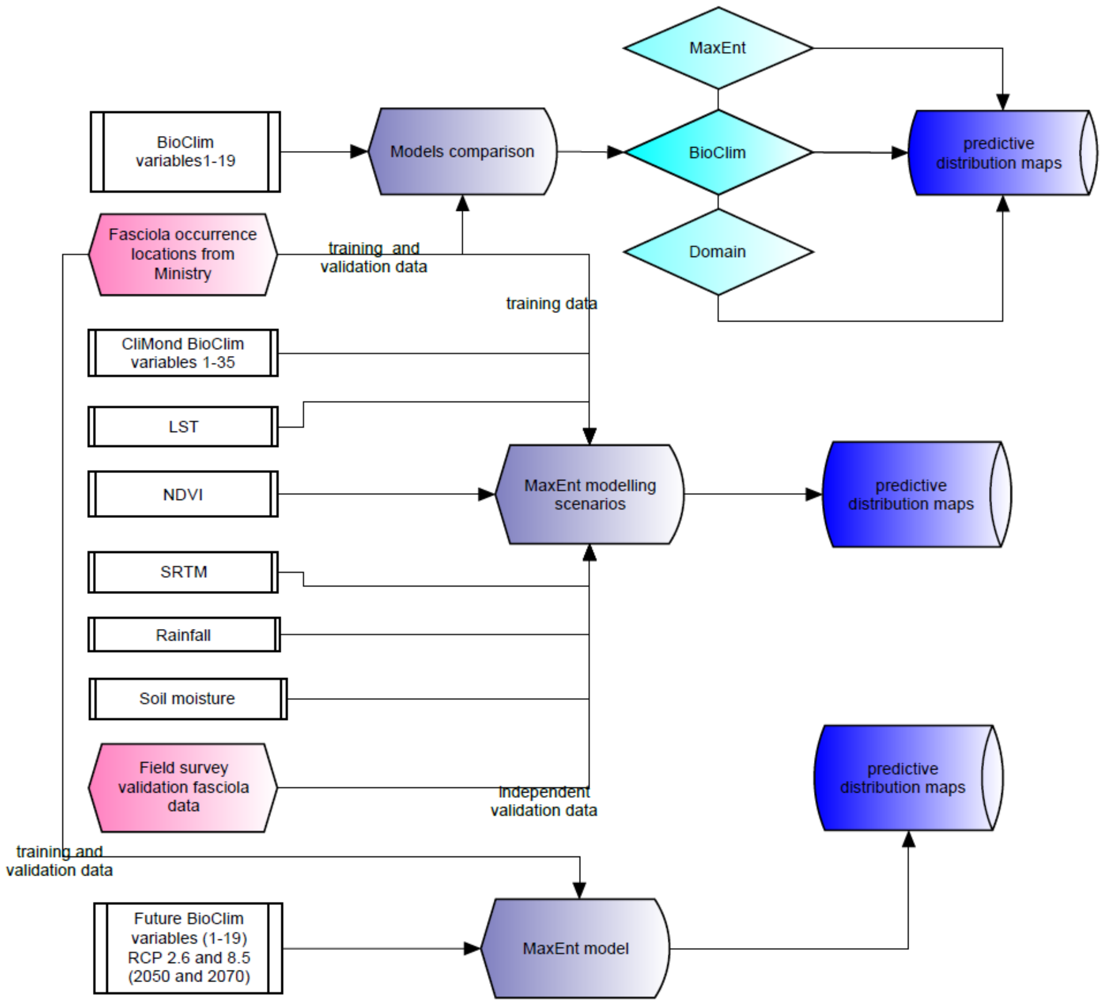

Figure 4-12 Flowchart adopted in this chapter

4.3Results

4.3.1Comparison of MaxEnt with BioClim and Domain models

Figure 4-8 shows the estimates of the six accuracy measures generated from the confusion matrix for the three models using the validation data sets. The performance of MaxEnt being the bench mark model was compared individually with BioClim and then Domain in order to calculate the statistically significant relationships between each pair. MaxEnt has got highest scores regarding sensitivity (TPR), specificity (TNR), Kappa and TSS than BioClim and the differences are statistically significant (t = 4.74, *P*=0.018) at 95% confidence level. Likewise, the scores of MaxEnt are higher than that of Domain model that is also statistically significant (t = 3.90, P=0.030). The Domain model has the highest omission rate (FPR) followed by BioClim model. Similarly, regarding commission rate

(FNR), BioClim has the highest rate followed by Domain and then MaxEnt with the lowest rate.

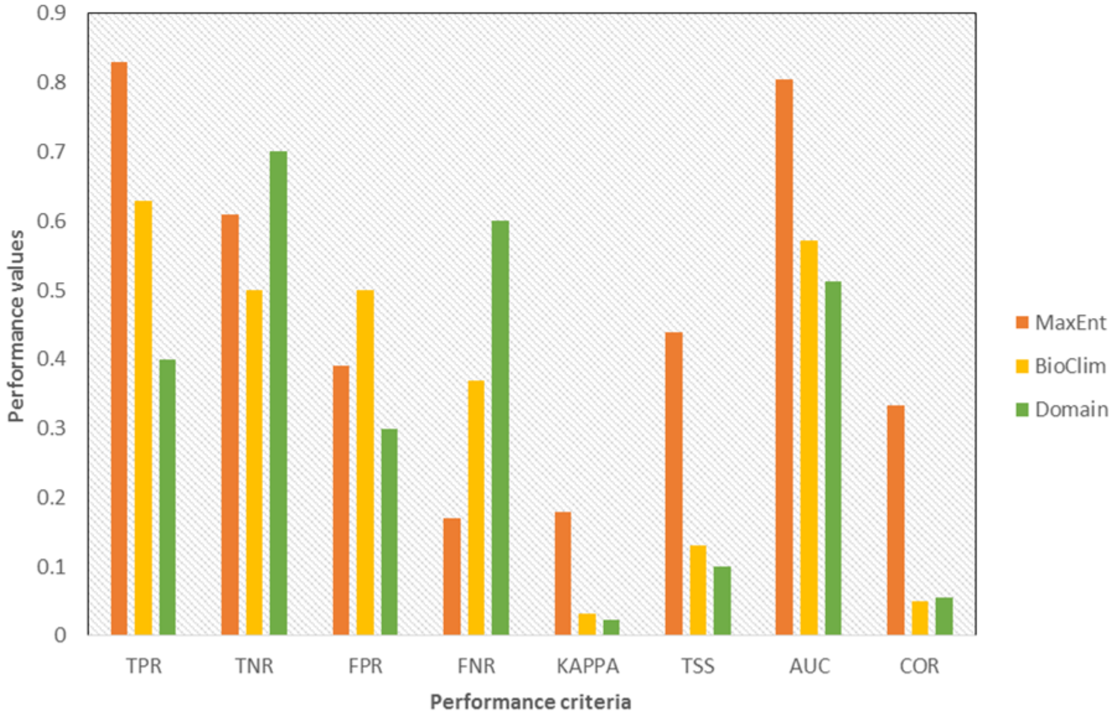

Figure 4-13: Estimates of the six threshold-dependent measures for the three models (MaxEnt, BioClim and Domain) using the validation dataset. In this chart sensitivity and specificity show higher values complemented by omission and commission rates. Barbosa et al. (2013) highlighted that high omission and commission rates do not imply 'a mistake' by a model based on the view that certain circumstances may cause a species not to inhabit all suitable areas or to occupy unsuitable locations. They further added that high omission rates may not indicate the weakness of the model but could be generated from 'errors' resulting from collection and assemblage of the species data. Also, it was explained by Pulliam (1988) that high omission rates might accrue due to the occurrence of the species at unsuitable locations as no data is 'error free' Barbosa et al. (2013). In the same vein, high commission rates may also reflect models ability to detect a species presence at a location that is favourable in terms of environmental conditions but become extinct due to some biological factors (example competition with other species etc.)(Anderson et al., 2003b, Barbosa et al., 2009). According to Barbosa et al. (2013), the result of this study has a high probability of accuracy as it is normal for sensitivity(TPR) values to be higher than specificity (TNR) and likewise for commission rate (FPR) to get higher values than omission rate (FNR).

In the study area, there is spatial variability of the probability of fascioliasis occurrence in the three models (Figure 4-9). The threshold used by the dismo r package (Hijmans et al., 2011a) was equal training sensitivity and logistic specificity threshold used in binary prediction of the three models. The MaxEnt has a threshold value of 0.5353 while BioClim has a value of 0.1101 while Domain model has 0.5856 as its threshold.

The AUC (Table 4-6) and COR (Figure 4-11) values were statistically significant for MaxEnt model based on Wilcoxon signed-rank test (Z = -3.6, P = 0.0001). The values of these indices for both BioClim and Domain were performances that were not better than random and were not significant statistically as revealed by Wilcoxon signed-rank test (Z= -0.8, P =0.189 and Z= -0.8, P = 0.187) respectively. Box plots are shown in Figure 4-10, indicating A, B and C for MaxEnt, BioClim and Domain respectively. The interquartile range for both presence and absence values were higher for MaxEnt than the other two models.

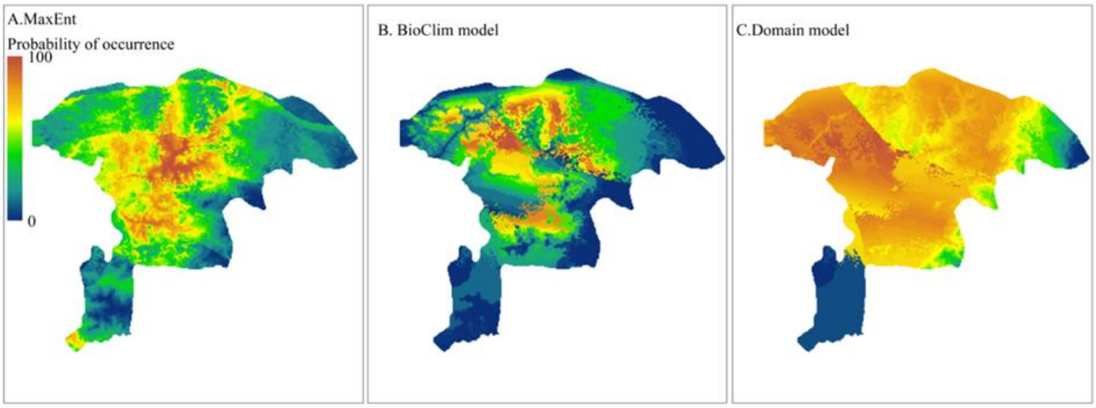

Figure 4-14: Predicted probability of F. gigantica presence from (A) MaxEnt model B) BioClim and C) Domain model. Both models were created using R-dismo package. The training sites constitute 70% while the test samples were 30%. Eight not highly correlated environmental variables based on temperature and precipitation were used. Brownish colour indicated areas of high probability while the dark green showed areas of low probability of occurrence.

Table 4-7: Result of threshold-independent measure of modelling methods

Model	Total Number of records	Total number of records for training	Total number of records for testing	Number of variables used	AUC for training data	AUC for test data	Corre lation	p-value
MaxEnt	177	158	53	8	0.811	0.8047	0.335	P<0.001
BIOCLIM	177	158	53	8	0.6261	0.5723	0.055	0.189
DOMAIN	177	158	53	8	0.5402	0.5126	0.056	0.187

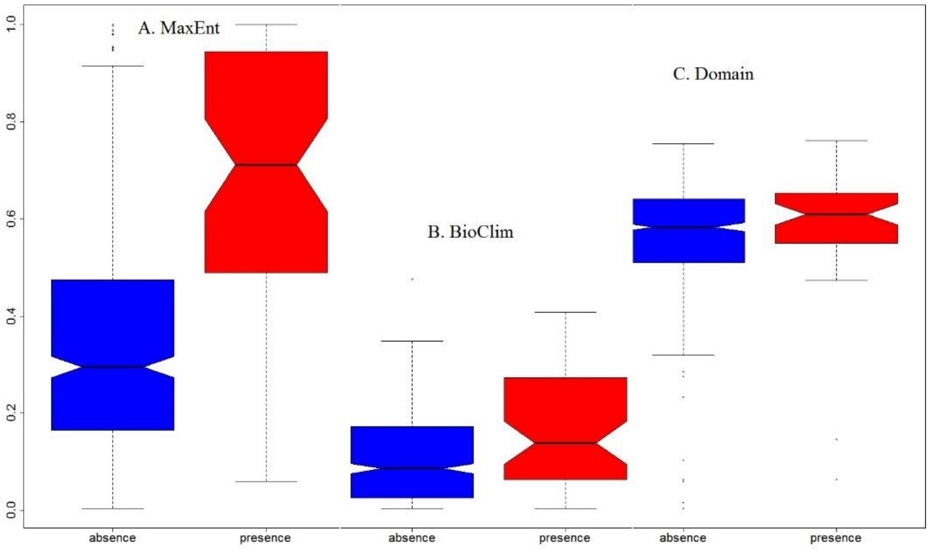

Figure 4-15 : Boxplots of the three models A.MaxEnt, B. BioClim and C. Domain model indicating the probability of predicting both presence and background locations of F.gigantica in the study area.

Table 4-8: Density of livestock population in provinces of Sokoto State in decreasing order of importance

Provinces	Density per km^2
Sokoto south	5585.614
Sokoto north	4634.171
Sabon-Birni	1130.196
Isa	806.3161
Kware	767.073
Bodinga	745.148
Wamakko	584.484
Silame	580
Wurno	471
Dange shuni	451.781
Binji	400.906
Yabo	397.143
Gwadabawa	273.166
Tambuwal	254
Gada	249.698
Shagari	235.931
Goronyo	200.595
Illela	190.628
Kebbe	163.534
Rabah	153.789
Tureta	111.322
Gudu	76.781
Tangaza	57

Source: Ministry of Agriculture/Animal Health and Fisheries Development, Sokoto State

4.3.2 Comparison of MaxEnt modelling based on different scenarios

4.3.2.1Threshold –dependent omission tests

All the six scenarios (Table 8) produced predictions that were better than random. Using the 10th percentile training threshold, the binomial test of omission was significant statistically for all the scenarios (*P* from 0.0027 to 0.034) while their threshold values ranged from 0.2916 to 0.331. Scenario 5 that constitute non-BioClim variables predicted the largest area (0.5106). Regarding the omission rate, scenario 2 ranked highest (20%) while scenario 6 has the lowest omission rate (17%). Similarly, the True Statistics Scores (TSS) for all the scenarios was better than random chance agreement as the values ranged from 0.2964 to 0.4173 and were statistically significant (averaged p=0.014 at the one-tailed test of binomial probabilities).

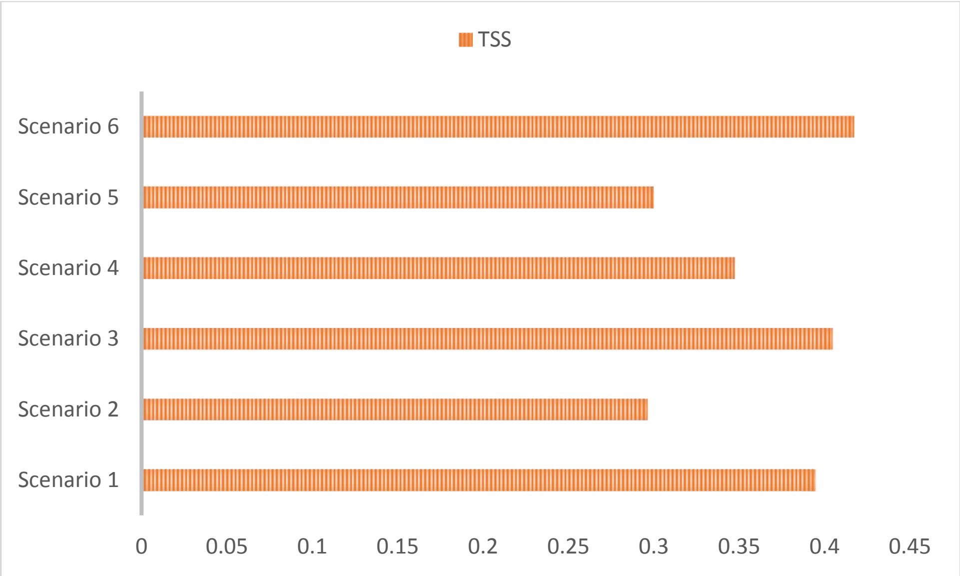

Figure 4-11: Showing the scores of each scenario based on True Skill Statistics generated from the confusion matrix elements using independent test data in maximum entropy modelling of F. gigantica geographical distribution using climatic and environmental variables.

*Table 4-**Error! No text of specified style in document.**-9: Results of the threshold-dependent binomial tests of omission based on 10% percentile training presence*

Scenario	Logistic threshold	Fractional predicted area	Test omission rate	P-value
Scenario 1	0.3144	0.4152	0.1941	0.0113
Scenario 2	0.3089	0.5028	0.205	0.028
Scenario 3	0.2992	0.412	0.18	0.0027
Scenario 4	0.2926	0.4607	0.1983	0.0114
Scenario 5	0.331	0.5106	0.1936	0.034
Scenario 6	0.303	0.5043	0.1713	0.019

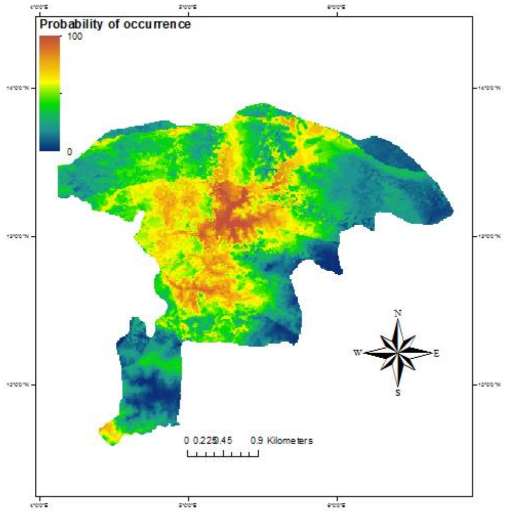

Figure 4-12: Dark brown colour implies a high probability of suitable conditions for F. gigantica, lighter shades of blue implying low predicted the probability of suitable conditions based on scenario 1. That indicates that suitable conditions are predicted to be highly likely through all the four agricultural zones of Sokoto State

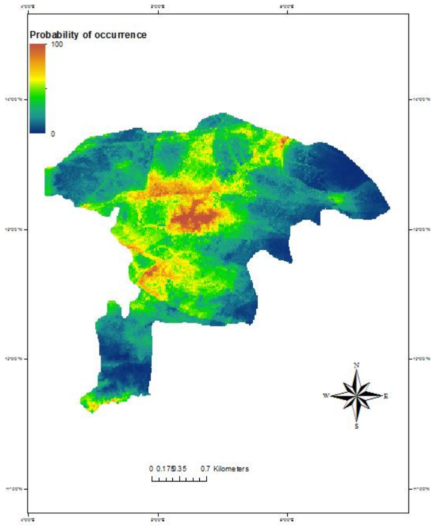

Figure 4-13: Scenario 2 MaxEnt prediction using dark brown colour indicating the probability of suitable conditions and lighter shades of blue implying low predicted the probability of suitable conditions. That prediction is not as extensive as scenario 1 and more concentrated around the centre of the state.

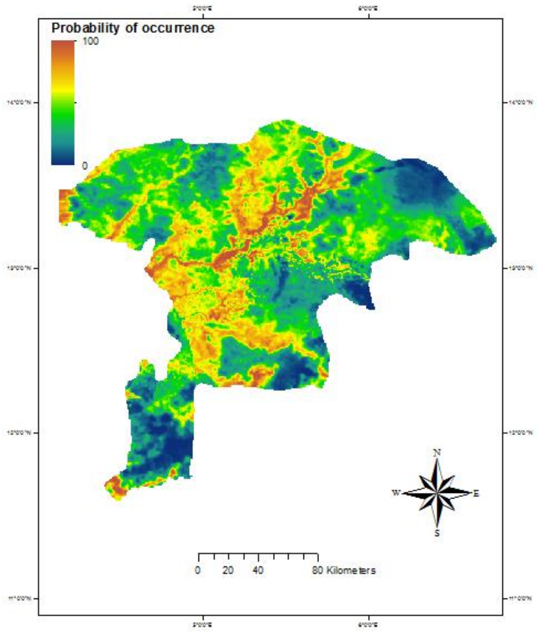

Figure 4-14: Showing wider spread of suitable condition based on Scennario_3 using dark brown colour in implying a high probability of suitable conditions and lighter shades of blue indicating low predicted the probability of suitable conditions for F.gigantica. That gives extensive coverage of Sokoto State.

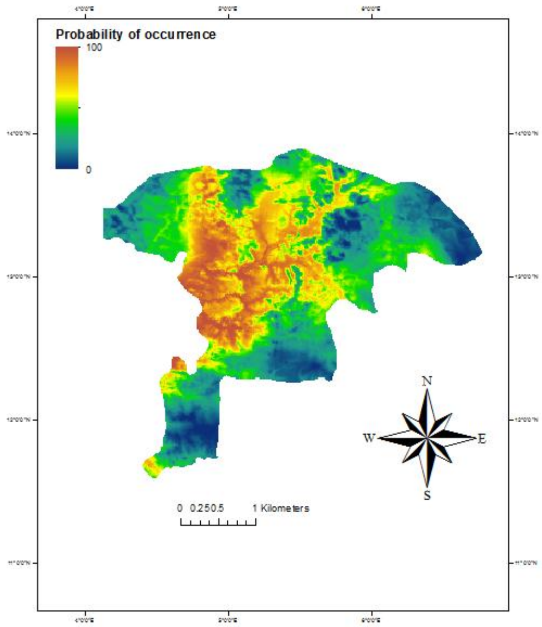

Figure 4-15: This gives slightly uniform coverage of the entire Sokoto state based on scenario_4 using dark brown colour in showing a high probability of suitable conditions and lighter shades of blue implying low predicted the probability of suitable conditions for F.gigantica.

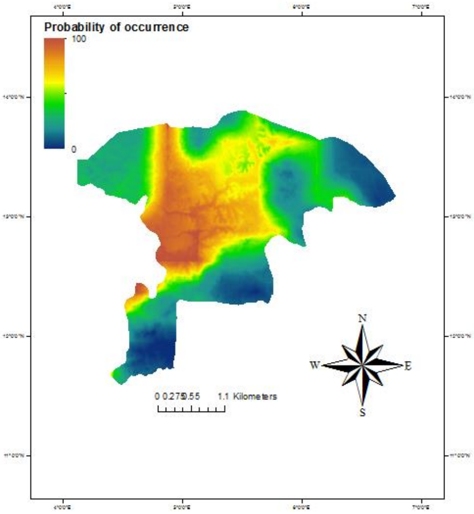

Figure 4-16: Scenario 5 is showing a homogeneous distribution around the centre of Sokoto state using dark brown colour implying a high probability of suitable conditions and lighter shades of blue indicating the low predicted probability of suitable conditions for F.gigantica

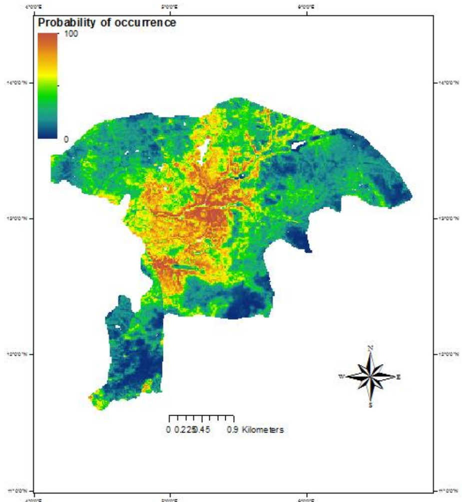

Figure 4-17: The figure shows a geographical distribution that has cut across all parts of Sokoto state based on scenario 6 using dark brown colour in indicating a high probability of suitable conditions and lighter shades of blue implying low predicted the probability of suitable conditions for F.gigantica.

4.4.2.2Threshold-independent tests

For all the scenarios (Table 4-9) using the combination of different climatic and environmental variables, the AUC values based on independent validation data were above 0.5 indicating better than random prediction and were statistically significant (p=0.03 at two-tailed Wilcoxon signed-ranked test). The addition of soil moisture in scenario two did not increase the AUC score, but the inclusion of NDVI and SRTM elevation in scenario 3 raised AUC to 0.7511. In scenario six that contained terrain attributes such as slope and topographic index did not change the AUC value significantly as it remained at 0.744. On the non-Bioclim variables, using all the variables of temperature, precipitation, soil moisture including NDVI and elevation in scenario 4, the AUC value (0.7487) was higher than when the model used only temperature, precipitation and soil moisture variables in scenario 5(0.7082)

On the variable contribution in each scenario, soil moisture consistently had the highest percentage with the minimum value in scenario 6 (30.7) to highest percentage in scenario 5 (79.9). In scenario 1, in the absence of soil moisture, the bio 16 which is precipitation of the wettest quarter, had the most significant effect (24.2%) in the modelling. Other variables that were very influential in the modelling across the whole scenarios that contained them were maximum annual NDVI (NDVI_36), elevation (SRTM_39), precipitation of the warmest quarter (bio_18) and mean temperature of the coldest month (bio_6). Similarly, in the Jackknife AUC, these variables possessed the most valuable data when they were used alone and in combination with all other variables in modelling *F. gigantica* in the study area.

Table 4-10: Results of the threshold-independent measures of model scenarios

Scenario	Total number of records for training	Independent records for testing	Number of variables used	AUC for training data	AUC for test Test data
Scenario1	176	15	8	0.8347	0.7519
Scenario2	176	15	8	0.8016	0.7281
Scenario3	176	15	11	0.8474	0.7511
Scenario 4	176	15	9	0.8302	0.7487
Scenario 5	176	15	5	0.7722	0.7082
Scenario 6	176	15	12	0.8005	0.743

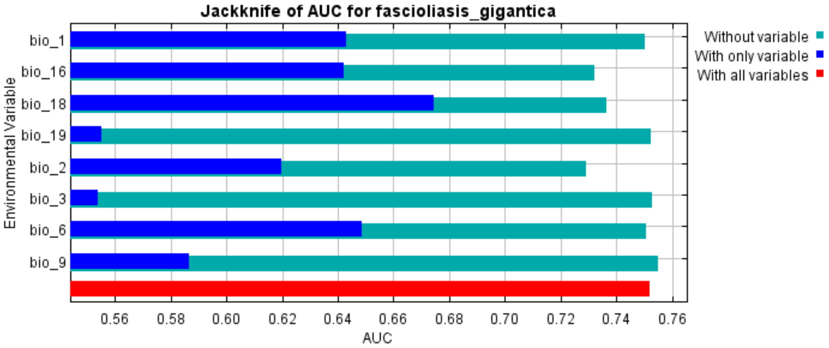

Figure 4-18: Scenario 1 results of the Jackknife test for the MaxEnt model for Sokoto State showing the gain of each variable to the likelihood map model. It uses temperature and precipitation variables (BIO1-19). Precipitation of the wettest quarter (BIO_16) and precipitation of the warmest quarter (BIO_18) have got the highest contribution in modelling the geographical distribution of F. gigantica in Sokoto State in this scenario.

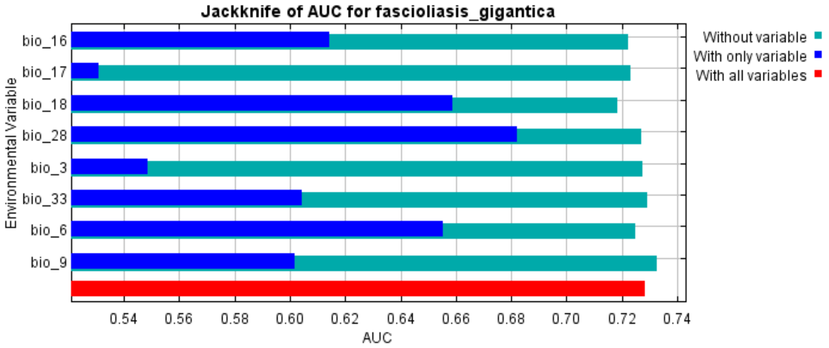

Figure 4-19: Jackknife test for scenario 2 MaxEnt model for Sokoto state showing the gain of each variables in the predicted probability map model. It contained temperature, precipitation and soil moisture variables only. When used alone in running the model annual mean moisture index (BIO_28) and precipitation of the warmest quarter (BIO_18) have got the highest contribution in modelling F. gigantica in Sokoto State in this scenario.

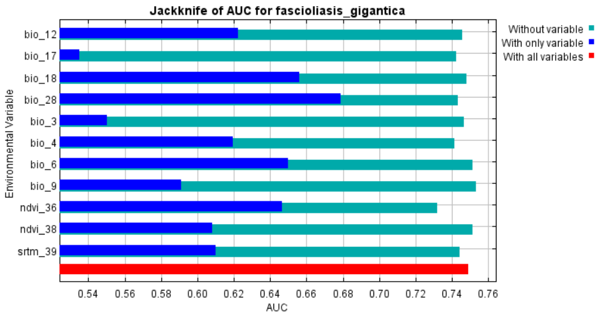

Figure 4-20: Scenario 3 (that contained temperature, precipitation, soil moisture, NDVI and SRTM elevation) results of the Jackknife test for the MaxEnt model for Sokoto state showing the gain of each variable in the predicted probability map model. In this scenario annual mean moisture index (BIO_28) and precipitation of the warmest quarter (BIO_18) were most influential in the modelling the geographical distribution of F. gigantica in Sokoto State

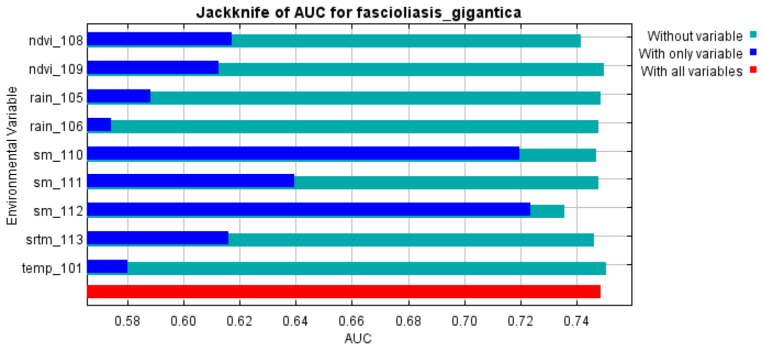

Figure 4-21: This is the non-BioClim scenario four results of the Jackknife test for the MaxEnt model for Sokoto state showing the gain of each variable in the predicted likelihood map model. It contained temperature, rainfall, soil moisture, NDVI and SRTM elevation variables. In this scenario annual mean soil moisture (SM_110) has got the highest contribution in modelling of F. gigantica in Sokoto state. Other important variables include minimum annual NDVI(ndvi_108) and elevation (srtm_113)

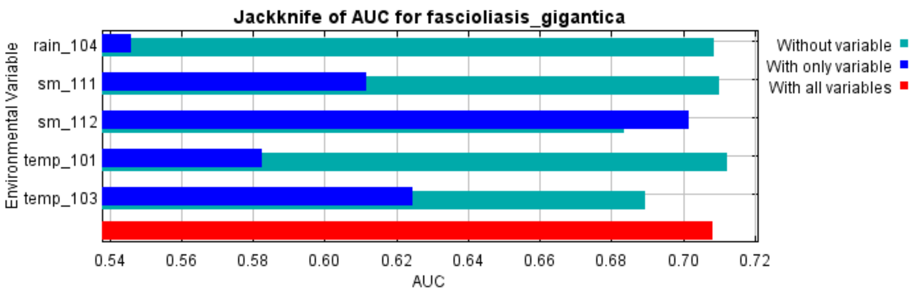

Figure 4-22: This is another non-Bioclim scenario 5 (that consist of temperature, rainfall and soil moisture variables) results of the Jackknife test for the MaxEnt model for Sokoto state showing the gain of each variable in the predicted likelihood map model. In this scenario, minimum annual soil moisture (SM_112) was having the highest contribution in modelling of the disease in the study area.

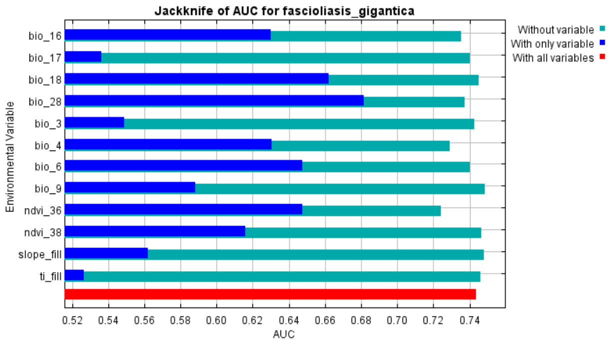

Figure 4-23: This scenario 6 (that contained the combination of Bioclim and non-BioClim variables). In this scenario annual mean moisture index (BIO_28), maximum annual (ndvi_36) and temperature seasonality (bio_4) had greatest effect in modelling the geographic range of F. gigantica in Sokoto State.

Table 4-11: Predictor variable percent Contribution as estimated by Maximum entropy of fascioliasis gigantica in Sokoto state (Non-BioClim)

Variable	Percent contribution	
	Scenario 4	Scenario5
tmp101_ann	0.5	4.3
temp_103		7.8
rain_104		2.2
rain_105	1	
rain_106	2.3	
ndvi_108	11.2	
ndvi109_ann	2	
sm_110	**22.5**	
sm_111	3.5	5.8
sm_112	**46.2**	**79.9**
srtm_113	10.7	

Table 4-12: Predictor variable percent Contribution as estimated by Maximum entropy of fascioliasis gigantica in Sokoto State (BioClim)

Variable	Percent contribution			
	Scenario1	Scenario2	Scenario3	Scenario 6
bio_1	10.8			
bio_2	10.7			
bio_3	1.6	0.3	0.4	0.3
Bio_4			6.8	8
Bio_6	21.4	20.3	8.3	14.1
Bio_9	5.7	5	1.3	1.4
Bio_12			5.8	
Bio_16	**24.2**	5.8		4.1
Bio_17		2.4	4.2	3.3
Bio_18	17.8	9.2	2.3	2.5
Bio_19	7.8			
Bio_28		**49.8**	**36.5**	**30.7**
Bio_33		7.2		
NDVI_36			23.2	22.4
NDVI_38			1.1	2.3
SRTM_39			10.1	
Slope				8.8
Topo_Indx				2.1

4.3.2Forecasting future climate change effects on suitable areas for *Fasciola gigantica* distribution in Sokoto State

The areas (Table 4:12) predicted as suitable for *Fasciola gigantica* distribution in Sokoto State under the RCP's 2.6 and 8.5 for 2050 and 2070 were all statistically significant (p =0.001). The increase in the extent of suitable areas for the parasite was consistent in RCP 8.5 for the two time periods. Conversely, a slight contraction (224.4km) occurred in the earlier period of RCP 2.6 in the year 2050. The MaxEnt model produced the probablity maps based on 10th percentile training presence threshold for each of the future years under RCP's.

Table 4-13: Comparison between current fractional predicted area (13286.4km2) and the future predicted distribution areas for 2050 and 2070 under Representative Concentration Pathways (RCPs) 2.6 and 8.5 that are suitable for F. gigantica prevalence in Sokoto State by maximum entropy modelling

RCP	Future predicted area (km2)		Expansion		Contraction	
	2050	2070	2050	2070	2050	2070
2.6	13062	14307.2	-	1020.8	224.4km	-
8.5	13558.4	13795.2	272	508	-	-

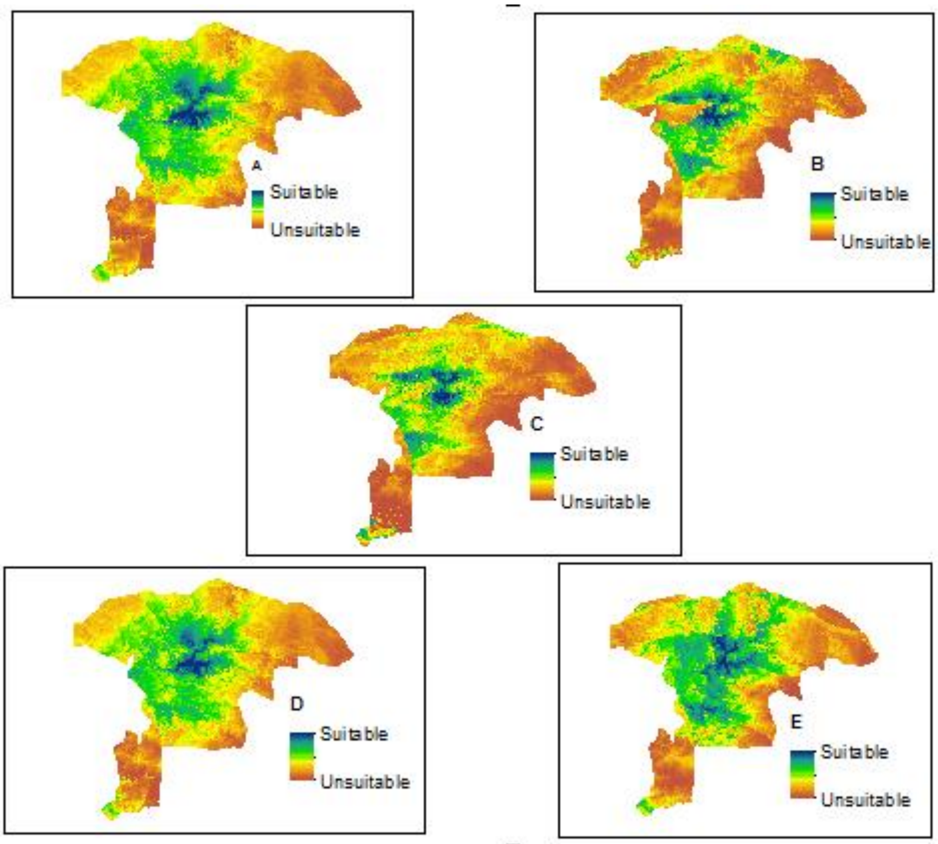

Figure 4-24: A, B, C, D & E: These are the MaxEnt's forecasts of the suitable areas for F. gigantica distribution under RCPs 2.6 and 8.5 for the years 2050 and 2070. The year 2050 under RCP 2.6 was calculated based on a threshold of 0.3069(A) while for 2050 of the same RCP was 0.3401(B). The threshold value used by RCP 8.5 was 0.3257(D) for the year 2050 while 0.3409 (E) was the threshold used for the year 2070 of the same RCP. The dark bluish and green colour is indicating suitability while the reddish colour is indicating unsuitable habitat for fascioliasis distribution in Sokoto State. The middle picture (C) is showing the currently suitable areas as computed by maxEnt using temperature and precipitation variables. These variables were consistent across the RCPs for 2.6 and 8.5 for all the future years under study.

4.3 Discussion and Conclusion

In Nigeria, the prevalence of *F. gigantica* was estimated at 60% (Spithill et al., 1999a) due to favourable prevailing climatic and environmental conditions. Also, there is the availability of extensive areas of low-elevation referred to as floodplains or fadamas that are more common in northern Nigeria that support the existence of water bodies in lakes, ponds and streams (Magaji et al., 2014). Sokoto State is part of northwest Nigeria and is among the leading producers of animals in the country (Mamman, 2005) with a population of over three million people (NPC,2006). The state has an estimated 4 million cattle, sheep and goats (Bala et al., 2014) where the majority of the inhabitants are practicing animal rearing as an alternative to crop farming due to sparse arable land (Magaji et al., 2014). All the known studies on fascioliasis in Nigeria have focused on reporting its prevalence using abattoir records (Bunza et al., 2008b, Magaji et al., 2014, Danbirni et al., 2015, Elelu et al., 2016a). Studies that applied species distribution models to examine the geographic range of fascioliasis in Nigeria or any part of West Africa in response to climatic variables are still elusive. Comparison of Maximum entropy with BioClim and Domain models is a recommended approach in modelling potential distributional range of species (Phillips et al., 2006). Moreover, modelling the geographic range of fascioliasis through GIS analysis was applied in South-Eastern Europe (Kantzoura et al., 2011b), in Northern Europe (McCann et al., 2010a) and East Africa (Yilma & Malone, 1998).

4.4.1Comparison of MaxEnt with BioClim and Domain models

Presence-only techniques apply different algorithms in evaluating the fitness of their test data in species distribution modelling and each of the models according to Pearce and Ferrier (2000) should be rated about their 'function complexity'. Tsoar et al. (2007) confirmed this in their study of comparison between six modelling techniques that variation exists regarding complexity across all the models, which they ranked differently.

Similarly, in this research, considerable differences exist regarding the complexity between the compared three presence-only models. The Domain model applies the 'Gower distance'(Legendre & Legendre, 1998) to the known occurrence locations of species to characterise a location as suitable. The technique has a weakness of not having the ability to classify all the possible locations as suitable that have the same environmental conditions as the occurrence locations (Tsoar et al., 2007). The BioClim model uses a climatic envelope encompassing the suitable environmental conditions occupied by known occurrence locations of the species (Carpenter et al., 1993). Its main limitation is that the method cannot capture the effect of associations between environmental variables on the distribution of species (Tsoar et al., 2007, Franklin, 2009a).

The findings of this study agreed with some previous studies regarding the higher performance of MaxEnt over other modelling techniques (Hernendez et al., 2006, Phillips et al., 2006, Pearson et al., 2007, Tognelli et al., 2009). The main limitation observed from the study by Elith et al. (2006) was that the assessment of their model's predictive ability was with the utility of field observation data of species absences. Moreover, according to them could give unreliable result due to several possible factors like competition with other species or geographic obstacles that limit the distribution of species at potential habitat. Other approaches noted these factors (Tyre et al., 2001, Anderson et al., 2002). Another limitation that applies to all these studies is that there were no projections of the modelling methods to the use of future climate which according to Thuiller (2004) may affect performance across different models. In addition, the modelling techniques compared in these studies did not capture the effects of potential factors that include obstacles due to geographic location or competition with other species that can inhibit species from inhabiting all sites that are favourable for their survival. Few approaches have applied this method (Anderson et al., 2002, Thomas et al., 2004). However, none of these approaches of comparison between models ever applied to modelling the distribution range of fascioliasis in any part of the World despite its threat to public health and global food security.

The results of this study confirmed the versatility of MaxEnt and its 'expressiveness' (Elith et al., 2006) than all the methods compared in this study due to having a very effective and deterministic algorithm that was created with a 'guarantee' to produce best modelling result with the even small number of occurrence localities (Phillips et al., 2006). Hence in this study MaxEnt is consistently outperforming BioClim and Domain in all accuracy measures. Similarly, that agreed with Segurado and Araujo (2004) who stated that both BioClim and Domain models perform less well when subjected to a comparison with other techniques. Also, this further reflects the conclusion by Elith et al. (2006) that predictive accuracy significantly influenced by model complexity. According to Dudık et al. (2004) and Phillips et al. (2006) MaxEnt is currently one of the most efficient and successful modelling technique due to the utility of its regularisation technique that ensures optimal performance with either large or small number of points. Therefore, due to predictive ability and flexibility, this study among the tested methods agrees that MaxEnt is the best choice for the design of control measures against the prevalence of *F.gigantica* in the study area.

It is explicitly clear regarding the visual investigation that MaxEnt algorithm produced a more reasonable prediction of potential distribution for *F. gigantica* than BioClim and Domain. That was because MaxEnt integrates and sums the contributions of all the climatic and environmental variables at each of the pixels that constitute the study area which reflects its advantage of 'additivity'(Phillips et al., 2006) that enabled the production of more continous predictions (see Figure 4-9). MaxEnt also exhibits the capability to show continuity in prediction through differentiating between various levels of probability of species occurrence (Phillips et al., 2006). Given that, it indicated the MaxEnt performance of maintaining higher values regarding AUC, TSS, kappa, sensitivity and specificity than BioClim and Domain models in the present studies.

Sokoto North and South were the core areas of suitability as predicted by MaxEnt probability map in this study that supports a high density of animals (Table 4-7). This result is consistent with the findings by Tum et al. (2004) that applied a geographic information system to create a model for mapping risk of fascioliasis in cattle in Cambodia where cattle density was confirmed to be a risk factor for fascioliasis transmission. Fabiyi and Adeleye (1982) corroborated that fact with a report that in Nigeria the morphology of fascioliasis prevalence is consistent with zones of high animal density among others.

The poor performance of BioClim and Domain models in this study might be due to the small number of occurrence records. However, a study by Beaumont et al. (2005) indicated the optimal performance of BioClim in species distribution modelling was related to the number of sample records of the species. Similarly, Tognelli et al. (2009) reported that small sample size could affect the performance of BioClim model negatively. In contrast, they added that the excellent performance of Domain methods does not rely heavily on sample size. In this study the poor performance of both BioClim and Domain models may be due to the nature of the species, the area of study and the number of samples available for modelling, as was concluded by other studies as a source of variation in performance among modelling techniques (Thuiller et al., 2006, Hernendez et al., 2006, Segurado & Araujo, 2004, Tsoar et al., 2007). It is, therefore, necessary to compare MaxEnt with other presence-only methods (Environmental Niche Factor Analysis ENFA) or presence-absence methods (Genetic Algorithm for Rule-set Prediction GARP, Random forests, boosted regression trees) in the study of fascioliasis in the semi-arid as such studies are beyond the scope of this research.

4.3.2 Comparison of MaxEnt modelling scenarios

MaxEnt algorithm in all the six scenarios performed better than random predictions that were statistically significant. The threshold-dependent binomial test (Table 4-8) indicated independent test sites omission rates and fractional predicted area test that were statistically significant for all the six scenarios. Similarly, the AUC being the threshold-independent measure indicated better than random scores for all the scenarios. The

Bioclim based scenarios (scenario 1, 2, 3 and 6) performed better than non-Bioclim scenarios. That reflected the suitability of Bioclim variables to the biological mechanism of different species of animals and plants (Ramirez & Jarvis, 2010). In addition, the predictions of the potential distribution of *F. gigantica* by all the scenarios were reasonable as they all indicated almost the same 'core' areas of suitability. These probability maps, therefore, show the location of most of the most suitable areas around the central part of Sokoto State, in the provinces of Sokoto north and south extending to Goronyo, Wamakko, Shagari, Silame, Binji, Tangaza and Gwadabawa. These core areas of suitability are cut across by river Rima with large expanse of 'Fadama' which is a Hausa name that denotes area liable to flooding or 'floodplains' that can support irrigation due to being 'low-lying and underlined by shallow aquifers' mostly found adjacent to significant Rivers in Nigeria (Dan-Azumi, 2010).

These Fadama lands or floodplains support the growth of vegetation as they are susceptible to annual flooding due to being lower land surfaces that are located close to rivers that tend to overflow their banks during rainy seasons (Lockaby et al., 2008). A notable flooding event in Sokoto State was in 2010 as reported by Etuonovbe (2011) along the valley of river Rima that has submerged an extensive Fadama land. Subsequently, that might affect snail movement into new areas thereby aiding the prevalence of *F. gigantica* into these new areas (Bunza et al., 2008b). Also according to Dan-Azumi (2010), these fadama lands are used for crop farming throughout the year for the production of vegetables like onions, lettuce, tomatoes and also for animal grazing. Bunza et al. (2008) report that fadama lands are risky areas for fascioliasis prevalence due to the availability of grasses for animals to graze throughout the year as well as water in ponds and lakes that provide habitat for aquatic snails, the intermediate hosts of *F. gigantica*.

Figure 4-25: This is a fadama or floodplain in Goronyo province in Sokoto State. It shows water in lakes where animals including cattle, sheep and donkeys are drinking. At the same time, the animals graze on the vegetation. Moreover, if the animals are infected, their faeces will contain the cercariae which under optimum condition of temperature will aid the transmission of fascioliasis gigantica *(Source: Field work,2016)*

4.3.3 Future prediction of suitable areas for *Fasciola gigantica*

All the models constructed under RCP 2.6 and 8.5 for 2050 and 2070 got AUC scores greater than random at identifying suitable environments for *F. gigantica* in Sokoto State. The only caveat is that future predictions are 'speculative' and full of 'uncertainty' (Joyner, 2010) but never the less there was good agreement between the current distribution and future distribution of *F. gigantica* across the study area. That indicates that *F. gigantica* has established natural ecology over the central part of Sokoto State in the provinces of Sokoto north and south, Kware, Wamakko and Silame. In this study, the suitable areas have expanded between the current distribution and future years except for the early part of 2050 of RCP 2.6. Under RCP 8.5 the expansion was consistent in both 2050 and 2070 indicating the effects of climate change on disease dynamics in the developing world due to urbanisation and possibly lack of climate policy (van Vuuren et al., 2011). However, the use of species distribution models when complemented with interactions between species can provide the best estimates of the distribution of species under climate change (Davis et al., 1998). Parra-Olea et al. (2005) further report that due to lack of alternatives, species distribution models provide the most current applicable method for forecasting the impact of climate change on the spatial dispersal of species of either plants or animals. Similar to the findings in this study MaxEnt has been used in modelling the potential geographical distribution of human parasitic disease in Africa using current and future climatic projections by Slater and Michael (2012). They found out that that the disease has expanded in its distribution due to climate change based on projections under two scenarios A2a and B2a by HADCM3 and CCCMA models for the year 2050.

Conclusion

In this study, we have shown an approach to compare the accuracy of presence-only methods of species distribution models by modelling the geographic range of *F. gigantica* using MaxEnt, BioClim and Domain models. The findings revealed that the differences in the complexity of the modelling algorithms affected their accuracy performance. However, it is very significant to highlight that by modelling the geographic range of *F. gigantica* in Sokoto State in Nigeria in the present study; it does not indicate the precise limits of *F. gigantica* distribution in the whole of Nigeria. Instead, the modelling techniques applied have identified provinces that share the same climatic conditions with the known occurrence sites of *F. gigantica*. These modelling results can support biogeographic information and regard as a first effort to estimate the geographic range of *F. gigantica* in Nigeria.

Our results suggest that future research should focus on increasing the extent of the study area as well as the spatial resolution of the environmental variables which may affect the predictive abilities of different modelling techniques (Karl et al., 2000, Hernandez et al., 2006). This study based on species distribution modelling cannot be a perfect match to actual field survey (Hernendez et al., 2006, Tognelli et al., 2009) but can provide a necessary guide in the planning of appropriate target areas for the control of *F. gigantica* prevalence. In addition, this study identified BioClim variables as more suitable for modelling species distributions than non-BioClim satellite-based aggregated variables. Regarding variable contributions, soil moisture was the most significant determinant of fascioliasis risk in Sokoto State as revealed by MaxEnt based on both BioClim and non-BioClim variables. In the study area, the modelling result showed that all the localities with extensive fadama land and high density of animal population coincided with the most suitable sites for fascioliasis prevalence. In the future, the model predicted the expansion of fascioliasis incidence to new areas due to increased rainfall and temperature in some locations.

Moreover, all the models in our study made use of climatic variables only without integrating other factors that affect livestock management in the study area. These factors according to Kantzoura et al. (2011a) also affect the modelling of a geographic range of fascioliasis. However, using this approach, the models of species distribution can be evaluated and MaxEnt being the best model can be more confidently applied by animal and public health planners in the design of the field survey for the control of *F. gigantica* prevalence or any parasitic pathogens with a similar pattern of transmission in the study area.

CHAPTER 5

Forecasting the incidence of *Fasciola gigantica* risk using the species-specific model in Sokoto state

5.1 Preface

Chapter 4, demonstrated the use of generic species distribution models in modelling the geographic range of *F.gigantica* in the study area. The approach used presence-only techniques due to the availability of fascioliasis occurrence record at government department in Sokoto State. Maximum entropy was the best performing model that indicated the suitability of the study area for fascioliasis prevalence. However, the modelling technique did not indicate a spatio-temporal pattern of *F.gigantica* transmission, which is essential in designing control strategies against fascioliasis prevalence in the study area.

Given that, this study in this chapter used the species-specific model in determining the transmission pattern of *F.gigantica* risk using the essential drivers - temperature and available moisture.

Short term and long term simulation models for fascioliasis are not new in the UK (Ollerenshaw & Rowlands, 1959, Fox et al., 2011, Gettinby et al., 1974), in east Africa (Malone & Yilma, 1999, Yilma & Malone, 1998), in Switzerland (Rapsch et al., 2008) in Iran (Halimi et al., 2015). However, application of species specific models in either short term or long term in any part of West Africa remains rare.

5.2 Introduction

The essential climatic variables that effect the population of both the fascioliasis parasite and its intermediate host snail at each stage of development are air temperature, rainfall and potential evapotranspiration (Mas-Coma et al., 2009). Hence it is important to understand the role of these variables in the transmission of *F. gigantica* in order to 'appreciate' how changes in these variables due to changes in climate may affect fascioliasis risk (Fox et al., 2011). According to Dinnik and Dinnik (1963) temperature within the range of 24^{O}C-26^{O}C support efficient growth of miracidia which develops from *F. gigantica* eggs in faeces while the temperature in excess of 43^{O}C can lead to the eggs mortality. Furthermore, they added that temperature of above 16^{O}C accelerates the growth of *F. gigantica* parasite larvae in the intermediate host. In addition, if the infection of the snail with *F. gigantica* parasite lasts for 46-50 days then the shedding of cercariae commences within a temperature range of 25^{O}C-27^{O}C (Asanji 1988). In the free-living stage of the parasite after ejection from snail according to Suhardono and Copeman (2008) metacercariae is the new form of encysted cercariae that remains viable under an optimum temperature of $26^{O}C$ and soil moisture that resulted primarily from rainfall (Mochankana & Robertson, 2018). It has also been emphasised by Mas-Coma et al. (2009) that the levels of rainfall and evapotranspiration play an important role in influencing the suitability of a habitat for snails being the intermediate host of *F. gigantica.*

In Nigeria the prevalence of fascioliasis has been reported from all the ecological zones: in the North-west; (Danbirni et al., 2015, Bunza et al., 2008b), North-east (Karshima et al., 2016), in South-east (Opara et al., 2005), South-West; (Afolabi & Olususi, 2016) north-Central (Elelu et al., 2016a). The disease was first detected in 1939 in Northern Nigeria impacting the mortality of goats as reported by Burke (Danbirni et al., 2015). Despite the period of over seventy years since the first incidence report and the economic aspect of the losses due to fascioliasis in Nigeria, only a few species-specific distribution models have been developed to guide the control against *F.gigantica* infections.

Given the understanding of the influence of climate in the outbreak of *F.gigantica*, short-term climate models have been developed to forecast the incidence of fascioliasis in different parts of the world. These forecasts according to McCann et al. (2010b) and Halimi et al. (2015) are very valuable in simulating and predicting the outbreaks and seasonal pattern of fascioliasis transmission for the design of effective methods of control. In England and Wales, the fascioliasis forecast system was initiated by Ollerenshaw and Rowlands (1959) using the climate data obtained from weather stations across the island of Anglesey as well as fascioliasis prevalence data for ten years (1948-1957). The values of potential evapotranspiration were computed using the Penman technique. The equation they applied to compute the risk index was Mt = n (R-PE+5), where n indicates the days with rain, R indicates rainfall and PE is potential evapotranspiration. The significant limitations of this fascioliasis forecast indices were in demand for various datasets in the calculation of potential evapotranspiration and lack of distinguishing the specific requirements of the two species of fascioliasis in the equation (Malone & Yilma, 1999). In addition, the index did not use the growing degree days (GDD) which indicate the number of days with tolerable limits of temperature for the parasite's survival. However, the application of the climate-based forecast continued in different parts of the world with some modifications to accommodate other relevant variables that contribute to the outbreaks of fascioliasis including growing degree day (GDD) and Thorntwaite water budget (Ruselle et al., 1984a, Malone & Yilma, 1999). This index created by Ollerenshaw is currently the basis for prediction of fasciolosis in the short-term for the farmers and other stakeholders in the UK by National Animal Disease Information Service (NADIS, 2016).

Fasciola gigantica is a tropical species that is endemic in different parts of Africa including Kenya, Malawi, Tanzania, Zambia, Zimbabwe, Mali, East Africa, Egypt, Botswana, Nigeria and some parts of Asia including Indonesia, Cambodia, Philippines, Iran, India, Pakistan, Burma, Nepal (Spithill et al., 1999b, Mochankana & Robertson, 2018). In Africa, the application of the fascioliasis forecast system was first modified and adapted in East Africa recently where both species of fascioliasis thrived by Malone et al. (1998a). Although the incidence shows that fascioliasis occurs in other regions especially Africa, (Pfukenyi et al., 2006), no study has applied climate-based forecast models to predict *F.gigantica* incidence.

All the known previous forecast systems including short-term and long-term predictions of fascioliasis occurred within the temperate biomes. However, these predictions can be useful in in determining spatio-temporal variability in the prevalence of fascioliasis in some countries of the world especially in West Africa where such studies are elusive. Also, these models can assist the farming community in formulating effective control strategies. The availability of HADGEM2-ES with simulations of fine scale climate parameters provides the means of making a robust long term future projections. This study used the climate data obtained from HADGEM2-ES and from current climate data in combination with modified Yilma and Malone index that was itself a modification of Ollerenshaw and Rowlands (1959). That is to stimulating how short-term and long-term changes in climate will alter *F.gigantica* risk in the future up to 2070 under changes in climate based on two extremes of representative concentration pathways(i.e. RCP2.6 and 8.5). Risk maps based on short-term (2005-2014), immediate past climate (1971-2000) and future climate RCP 2.6 2050, RCP 8.5 2050 and RCP 2.6 2070 to RCP 8.5 2070 were created to show the kind of influence that climate has on the risk of *F.gigantica* in Sokoto State, Nigeria.

5.3 Materials and Methods

5.3.1 AIRS Data

This research used near surface air temperature Atmospheric Infra-Red Sounder (AIRS ,AIRX3STM) of monthly time series downloaded from AIRS/Aqua level 3 Standard Physical Retrieval version 6 (AIRS + AMSU) with a spatial resolution of 1^o by 1^o from 2005 to 2014 (https://disc.gsfc.nasa.gov/SSW/#keywords=AIRX3STM%2006). As reported by Chahine et al. (2006) in May 2002, on the NASA platform three microwave instruments that include AIRS, the Advanced Microwave Sounding Unit (AMSU) and the Humidity Sounder for Brazil began operation on board the Earth Observing System (EOS) Aqua spacecraft. The AIRS instrument captures infrared within the atmospheric spectrum in 2378 bands of frequencies (channels) with a nominal resolving power of about 1200 extending to 'over 95% of the global surface and returning about 3 million spectra daily'(Tobin et al., 2006). The AIRS products have wide applications including improvement in weather simulation as well as hydrological and energy cycle studies (Le Marshall et al., 2005, Tian et al., 2006). In order to improve the accuracy of AIRS products, a 'cloud clearing' of AIRS radiances were carried out using physical retrieval algorithm [PRA] (Chahine et al., 2006) in all the participating AMSU footprints and for the capturing of temperature and water vapour as explained by Susskind et al. (2003).

In terms of validation, the temperature and precipitation products of AIRS correlated highly with the values retrieved by the global operational radiosonde network and radiosondes at dual Atmospheric Radiation Measurement locations (Southern Great Plains(SGP) and Tropical Western Pacific [TWP]) (Divakarla et al., 2006, Tobin et al., 2006). The derivation of these results according to Chahine et al. (2006) were at the National Oceanic and Atmospheric Administration (NOAA)/National Environmental Satellite Data and Information Service (NESDIS).

The AIRS monthly temporal resolution used in this study has the advantage of having 'lowest possible systematic errors'(Tian et al., 2013) and were available for 100% of the period of interest 2005-2014 without any gores(cells with no data).

5.3.2 Rainfall

Refer to section 4.2.3.6 in chapter 4 for the description of the rainfall dataset used in the present chapter

5.3.3 NDVI

The description of NDVI dataset used in this chapter refer to section 4.2.3.5 in chapter 4

5.3.4 Soil moisture

The soil moisture variable used in this chapter was described in chapter 4 section 4.2.3.7

5.3.5 Past climate

The study in this chapter obtained past climate from WorldClim described in section 4.2.3.1 of chapter 4

5.3 .4 Future climate scenarios

For simulating future *F. gigantica* risk, this study utilised future WorldClim data from the Hardley Centre Global Environmental Model version 2- Earth system (HadGEM2-es). Collins et al. (2011), described the model as consisting of two components which are atmospheric and oceanic. HadGEM2-es is preceded by HadGEM1 (Johns et al., 2006) with more flexibility in 'allowing' the computation of climate change impacts on global biogeochemical systems which can have both negative and positive feedbacks (Charlson et al., 1987, Cox et al., 2000, Jones et al., 2009). These feedbacks as noted by Collins et al. (2011) affect the development of a global future climate system.

HadGEM2-ES future projection of climate was among the model outputs used for the elucidation of the fifth phase of the Coupled Model Intercomparison Project five (CMIP5) as well as being one of the model's offshoots from Intergovernmental Panel on Climate Change (IPCC) fifth Assessment Report (AR5). The performance of the model regarding the prediction of yearly cycles of temperature and precipitation was significantly correlated to the ground-based stations over different parts of Africa and Nigeria (Dike et al., 2015).

This study utilised monthly climate change average data at a 1km spatial resolution for two 20-year time periods: 2041-2060, 2061-2080. These two time periods referred to as 2050 and 2070 respectively. The emissions scenarios for each of these two time periods were based on Representative Concentration Pathways (RCPs) reflecting climate forcing from greenhouse gases in the atmosphere in 2100 for RCP8.5 (similar to IPCC: A1F1 and B1 SRES) and RCP2.6 (below IPCC: SRES B1). The climate parameters used include monthly mean Temperature (^{O}C), maximum minimum and mean temperature (^{O}C) and total monthly precipitation (mm/month).

5.4 Forecast parametrisation

This study adapted a fascioliasis forecast index system modified from Ollerenshaw and Rowlands (1959) and applied in East Africa by Malone et al. (1998a). The index referred to as a water-based system (Afshan et al., 2014) was based on thermal and soil moisture requirements of *F. gigantica*. The index was calculated using an empirical equation that incorporated the use of GDD, rainfall and evapotranspiration in determining the level of risk for fascioliasis transmission:

$$\text{Index 1} = (\text{GDD} \times \text{Z}) \times \frac{\text{Rain} - \text{PET}}{25}, \text{If Rain} - \text{PET} > 0, \quad \text{equation 1}$$

where Z implies days with excess rain and 25 is correction factor to reduce the surplus water to 2.5cm

$$Index\ 2 = GDD\ \times Days\ in\ month, if\ (R - PET \times 0.8) > 0 \ldots\ldots\ldots\ldots\ldots equation\ 2$$

where GDD = Growing degree days

R= Rainfall (mm/month)

PET= Potential evapotranspiration (mm/month).

GDD assumed that the developmental stages of a living organism occur within some favourable limits of temperature. At the extremes of these limits, the survival of the organism would be threatened (Ruselle et al., 1984b). GDD was computed as the monthly mean temperature minus the base development temperature (Valencia-López et al., 2012) for the *F. gigantica* which is 16^0C (Dinnik & Dinnik, 1963). The mean monthly temperature was calculated by obtaining the average of the maximum and minimum temperature as follows (Valencia-López et al., 2012)

$$\text{MnT} = \text{Maximum temperature } + \text{ minimum temperature}/2\,.\text{equation 3}$$

$$\text{GDD} = (\text{MnT} - 16^{O}\text{C}) \times \text{ days of month equation 4}$$

For the computation of potential evapotranspiration, the study used the Hargreaves equation (equation 5) where Ra is extra-terrestrial radiation (MJ, m^{-2} day^{-1}) (Droogers & Allen, 2002) T_{max} indicates the mean monthly values of the maximum daily air temperature (^{0}C) while T_{min} is the minimum mean monthly values of daily air temperature (^{0}C), λ is the latent heat of vaporisation, T_a is the average monthly air temperature (Najmaddin, 2017).

$$PE = 0.0023(T_{max} - T_{min})^{0.5}(T_a + 17.8)^{\frac{R_a}{\lambda}} \quad \ldots\ldots\ldots..equation\ 5$$

By entering the formula (equation 2) into Microsoft Excel 2013, this study calculated the fascioliasis forecast index. Moreover, through the use of Excel, the study prepared Coma delimited (CSV) files for use in Geographic Information System (GIS) analysis. The interpretation of the index is 600= no risk, 601-1,500= low risk; 1500-3000=moderate and above 3000 high risks.

In equation 1, subtracting the value of potential evapotranspiration multiplied by 0.8 (PET× 0.8) from rainfall if greater than zero indicates availability of soil moisture storage at the surface of 2.5cm of soil based on a Water Budget model (Malone et al., 1998b, Yilma & Malone, 1998, Valencia-López et al., 2012). In the present study only index 2 was used as applied by Valencia-López et al. (2012) due to its relevance in accounting for soil water availability in the top 2.5cm that suits *F. gigantica* life cycle (Yilma & Malone, 1998). Also, both indexes are similar (Fuentes et al., 2016) but differ in the accumulation of surplus water from the index 1 that is consistent with the life cycle requirements of the intermediate hosts of *F. hepatica* (Yilma & Malone, 1998).

5.5 Proposed Modification to the forecast indices for semi-arid ecological zones

This study investigated the use of soil moisture instead of rainfall in the calculation of fascioliasis index. Although in the semi-arid the presence of moisture is the most crucial determinant that is constraining ‘ecosystem processes’ (Lu et al., 2011), there were some months with more available soil moisture than potential evapotranspiration as identified by this research. Consequently, the presence of soil moisture is always critical for the completion of fascioliasis lifecycle and the activities of its intermediate host's snails (Malone et al., 1998a, Spithill et al., 1999a, Mas-Coma et al., 2009). In addition, in the previous chapter maximum entropy modelling has revealed the role of soil moisture as having the highest contribution in the prevalence of *F. gigantica* in the study area. Despite its simplicity, the proposed index can be valuable since it provides an alternative to the use of rainfall variable that lasts for only a few months especially in the semi-arid parts of west Africa (Barbé et al., 2002).

The index was calculated monthly based on ten-year averages climate data from the satellite in line with a new formula that is equally proposed for semi-arid in tropical areas as follows:

$$Index\ 3 = GDD\ \times Days\ in\ month, if\ (SM - PET) > 0 \ldots\ldots\ldots\ldots\ldots equation\ 6$$

where

SM= soil moisture (mm/month)

PET = potential evapotranspiration (mm/month)

5.6 The study design

For each of the 23 provinces in Sokoto State, a monthly *F. gigantica* climate-based forecast index was computed using the constructed monthly climate forecast model based on the knowledge of life cycle needs of fascioliasis. These provinces constitute the four agricultural zones in Sokoto State as shown in Figure 5-2. The study utilised long-term climate data from WorldClim (1970-2000) being the base line climate, the short-term climate data from satellite 2005-2014 and then the future projection of the long-term years (2050 and 2070) based on Representative Concentration Pathways (2.6 and 8.5) in examining the seasonal transmission pattern.

5.7 Statistical validation of climate variables and forecast Index

In order to validate the use of future climate variables in the simulation of the forecast indices, this study compared quantitatively the WorldClim baseline (1970-2000) climate data with six ground-based stations in the Northwest ecological zone of Nigeria. The climate data within this temporal range was well 'refined' and are an expansion of the first version (Fick & Hijmans, 2017) that were used as the basis for projection of future climate by various earth models (Hijmans et al., 2005). These stations and their spatial coordinates are: in Sokoto State (12.55^{O}N, 5.12^{O}E) Kano state (12.3^{O}N, 8.32^{O}E), Kaduna state (10.42^{O}N, 7.19^{O}E), Katsina state (13.05^{O}N, 7.41^{O}E) Zamfara (12.1^{O}N6.42^{O}E) and Kebbi state (10.53^{O}N, 4.45^{O}E) as shown in Figure 5-1. Furthermore, this study obtained climate data based on daily maximum temperature, minimum temperature and rainfall for 1970-2000 for these stations. The correlation coefficient (equation 7) was used in assessing the level of agreement between baseline climate and each of the weather stations in Northwest Nigeria in respect of these variables. The appropriateness of this technique employed was evident in the validation of satellite data by Dike et al. (2015) through comparison with ground based stations in Africa and across the whole of Nigeria. Also, root-mean-square-error (RMSE) (equation 8) was also used as a means of calculating the differences between the predicted (WorldClim data) and observed (stations data) as employed by Fick and Hijmans (2017) in their production of WorldClim baseline data.

Correlation coefficient denoted as r calculated as;

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{(n\sum x^2) - (\sum x)^2}\sqrt{(n\sum y^2) - (\sum y)^2}} \quad \ldots\ldots\ldots equation\ 7$$

where x and y are the observed climate value and the estimated value respectively, and n is the number of records

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(PW - OS)^2}{N}} \quad \ldots\ldots\ldots\ldots\ldots.. equation\ 8$$

$$BIAS = \frac{\sum_{i=1}^{N}(PW - OS)}{\sum_{i=1}^{N} OS} \quad \ldots\ldots\ldots\ldots\ldots\ldots. equation\ 9$$

where PW stands for the predicted WorldClim data and OS indicates observed stationed data while N implies the total number of records.

A statistical test was also implemented to determine the significance of the correlation between the observed and the simulated values using the p-value (Harris & Jarvis, 2014). In this study, a paired t-test was used to calculate the statistical significance of the relationships between the means of the two data sets at 95% confidence level. The null hypothesis that was tested using Minitab 17 statistical software based on the statement that the difference between the means is zero (with 95% confidence).

Fascioliasis infection prevalence data for each of the 23 provinces in Sokoto State was collected from government documents at the Ministry of Animal Health, Sokoto State. This data was divided into agricultural zones (Table 1). Only the data from Sokoto zone was generated from abattoir while the rest were through slaughter slabs. The validation was done also using correlation coefficient tests (Afshan et al., 2014) to evaluate the relationship between the forecast indices and some significant predictor variables obtained from satellites which include annual averages of rainfall, potential evapotranspiration, soil moisture and NDVI.

Table 5-14: Summary of F. gigantica prevalence reported in the four agricultural zones of Sokoto State.

Agricultural zone	Number of units	Prevalence mean Standard Error	Method of detection
Gwadabawa zone	7	62(SE 9.83)	SS
Isa	5	66.3(SE 11.7)	SS
Sokoto	7	77.08(SE 6.79)	AS
Tambuwal	4	106.57(SE 5.3)	SS

AS= Abattoir survey, SS=Slaughter slab

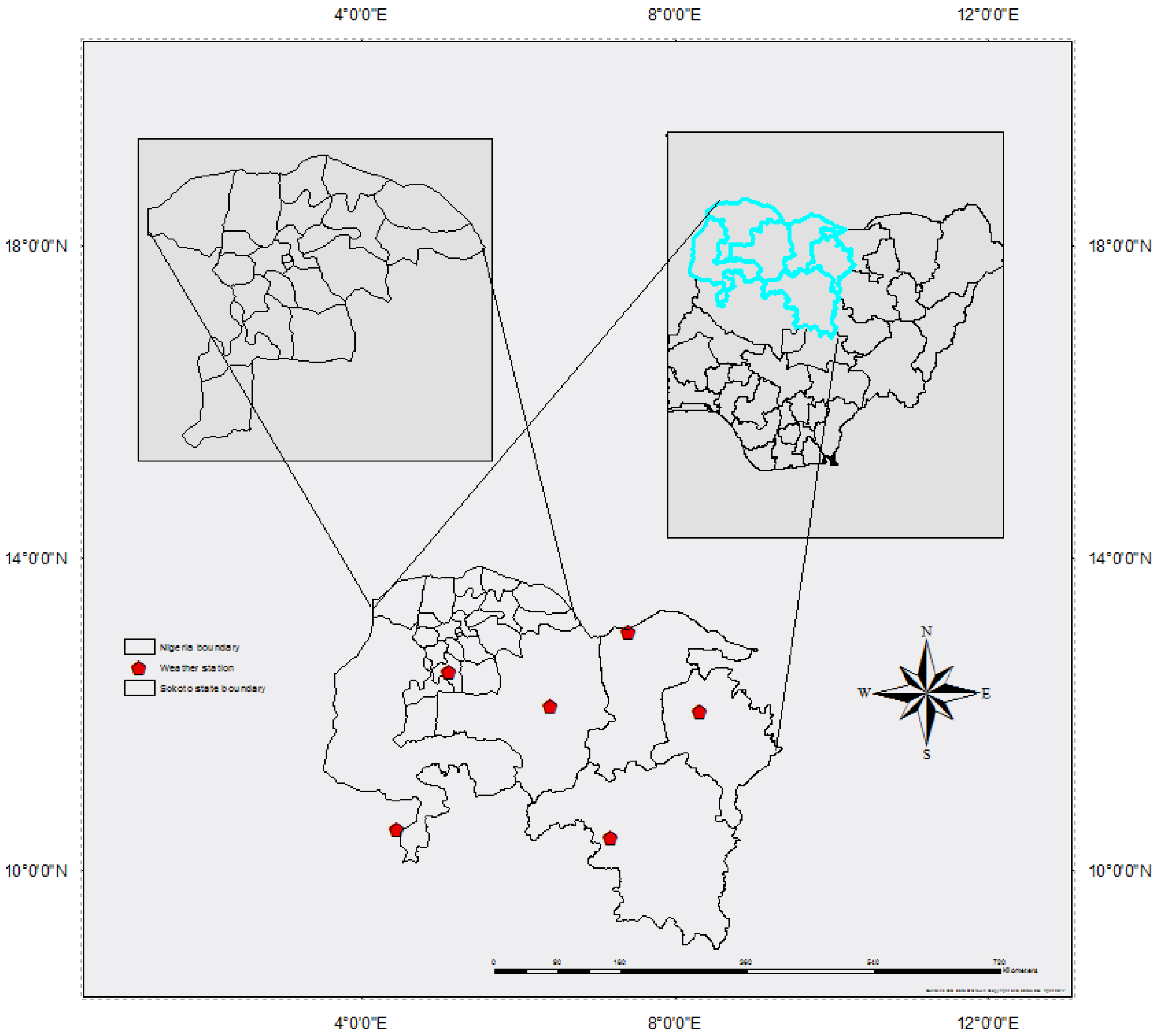

Figure 5-16: weather stations in north western Nigeria

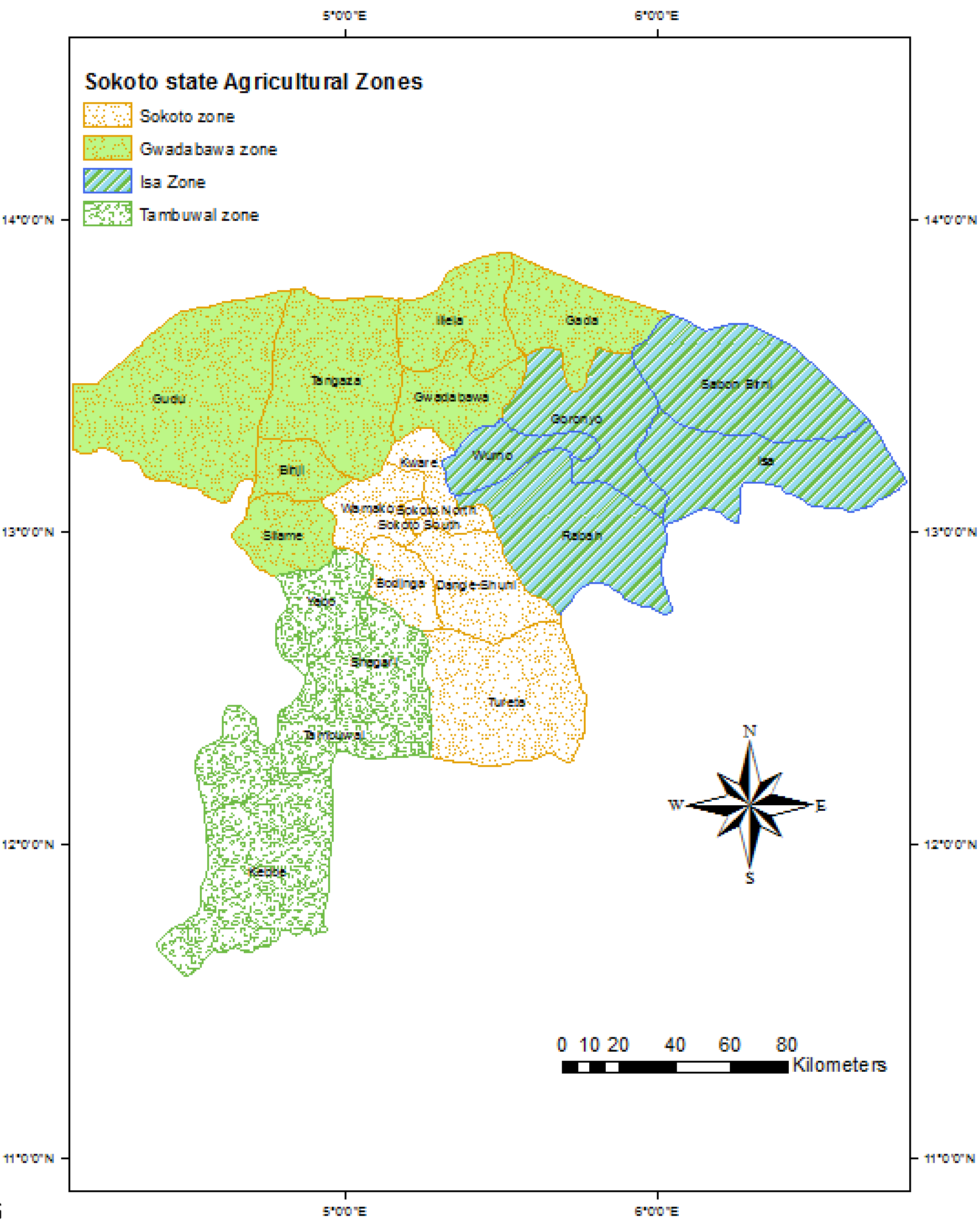

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Figure 5-17: Map of Sokoto state showing the four agricultural zones

Figure (5-3) shows the technique (flowchart) employed in achieving the objectives of this chapter.

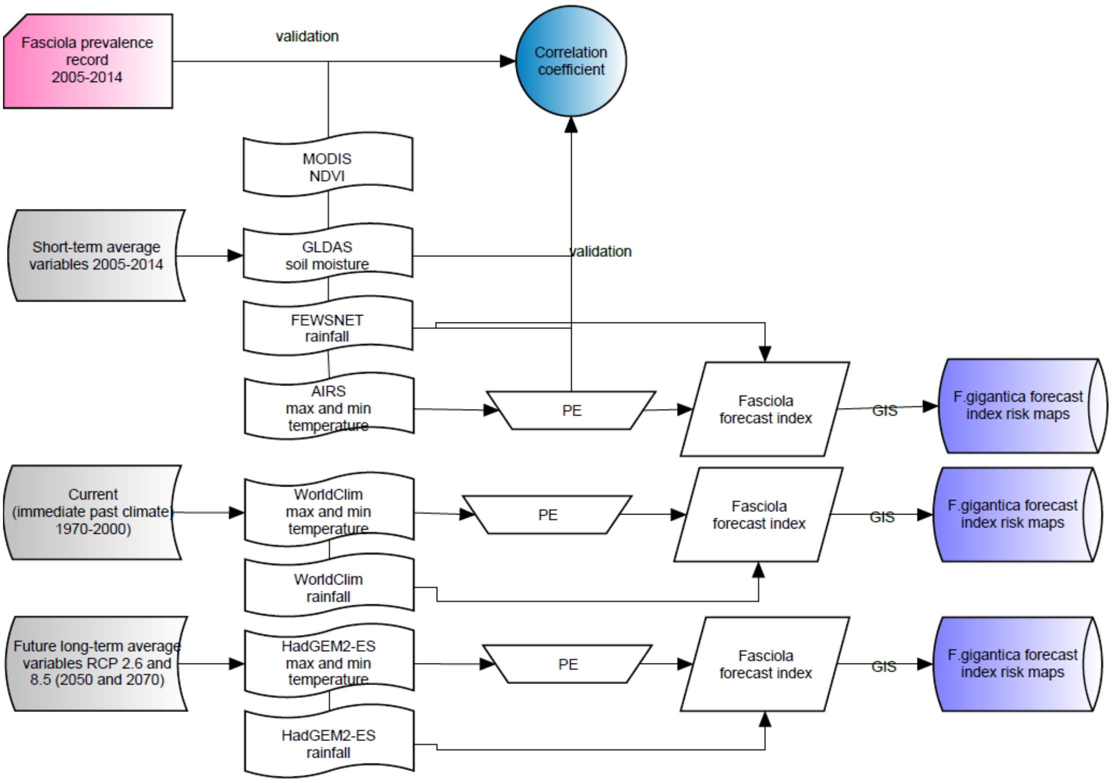


Figure 5-18 Figure shows the flowchart adopted in this chapter

5.8 Results

5.8.1Comparison between baseline climatic data estimated from WorldClim with ground-based stations.

Figure 5-3 shows the baseline monthly average climate data on precipitation from WorldClim and the six ground-based stations. The summary of the correlation coefficient statistics (Table 5-2) indicate that the r value between the baseline (past) precipitation data and all the six stations were high ($r>0.9$) and statistically significant at the 95% confidence level (see appendix). The lowest RMSE for monthly precipitation recorded at Sokoto station (14.24mm, bias=5.3) and highest at Kaduna station (67.2 mm, bias=44.79) with underestimation of Katsina station (24.23mm, bias=-10.75). For monthly maximum temperature, the level of correlations was high for all the stations (Figure 5-4) except for Yelwa (bias=-0.09) and Kaduna (bias=-2.88) but were all statistically significant ($p<0.05$) Table 5-3. For monthly maximum temperature, the RMSE ranged from 1.33 ^{O}C to 3.84 ^{O}C with a tendency towards underestimating the ground based stations except for Sokoto station. The relationship measured between the baseline monthly minimum temperature and the ground based measurements (Figure 5-5) were all high $r > 0.7$ (Table

4) and were all statistically significant ($p<0.05$). The RMSE were between 2.44 and 3.41 with all negative bias except in Sokoto and Yelwa stations.

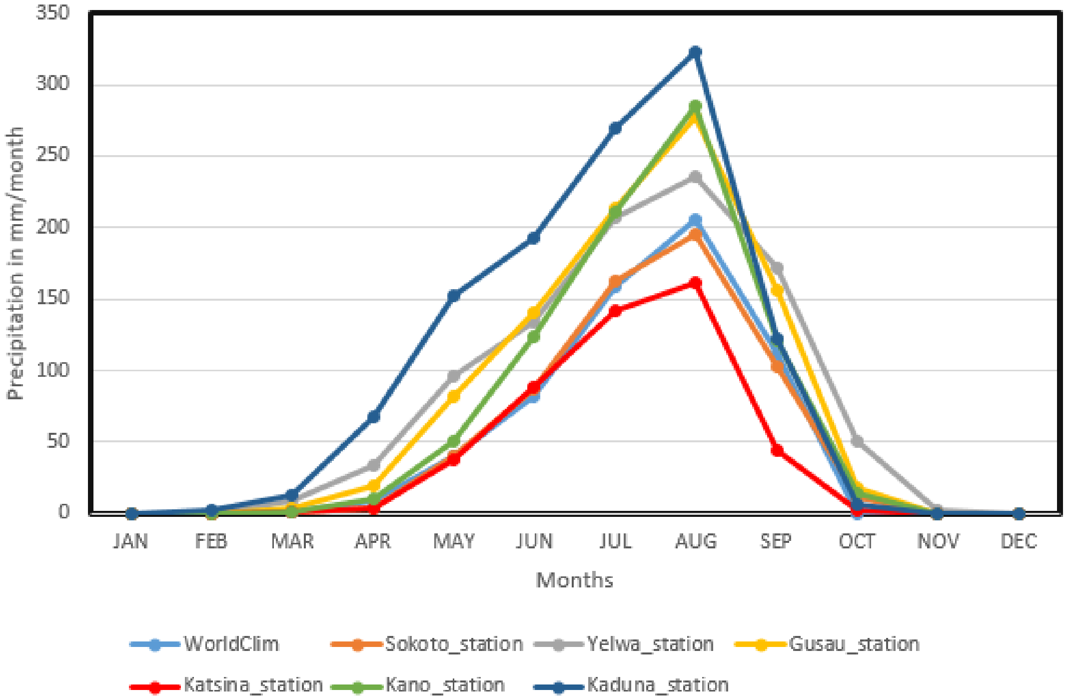


Figure 5-19: Annual mean cycle of precipitation (mm/month) for the north-west ecological region of Nigeria from six ground-based stations quantitatively compared with WorldClim data using Katsina station. The results indicate relationships that were statistically significant (p=001) at 95% confidence level

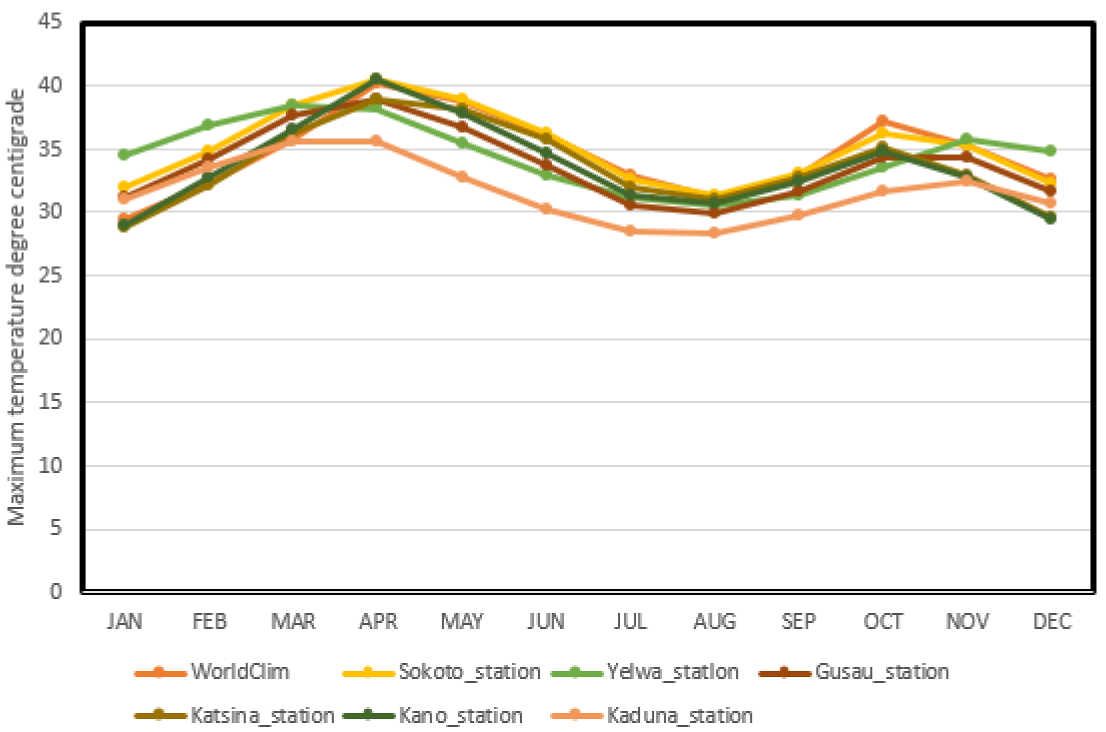


Figure 5-20: Annual mean cycle of maximum temperature (^{O}C) across the northwestern ecological region of Nigeria from six ground-based stations quantitatively compared with WorldClim data using correlation coefficient.

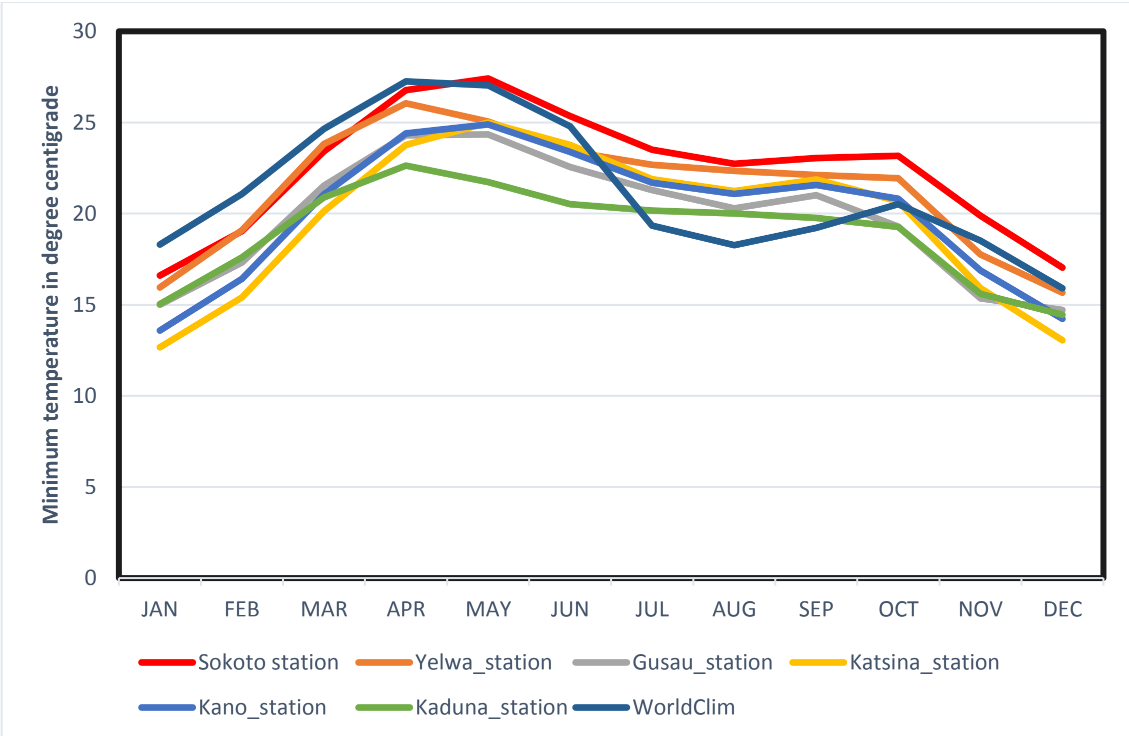


Figure 5-21: Annual mean cycle of minimum temperature (^{O}C) across the northwestern ecological region of Nigeria from six ground-based stations quantitatively compared with WorldClim data using correlation coefficient.

Table 5: 2: Correlation coefficient between mean monthly precipitation WorldClim and weather stations in northwestern Nigeria 1970-2000.

	WorldClim	Sokoto	Yelwa	Gusau	Katsina	Kano	Kaduna
WorldClim	1						
Sokoto	0.99	1					
Yelwa	0.97	0.97	1				
Gusau	0.99	0.99	0.98	1			
Katsina	0.96	0.97	0.93	0.96	1		
Kano	0.99	0.99	0.96	0.99	0.98	1	
Kaduna	0.94	0.95	0.94	0.96	0.97	0.95	1

Table 5-3: Correlation coefficient between maximum monthly temperature from WorldClim and weather stations in northwestern Nigeria 1970-2000

	WorldClim	Sokoto	Yelwa	Gusau	Katsina	Kano	Kaduna
WorldClim	1						
Sokoto	0.92	1					
Yelwa	0.47	0.71	1				
Gusau	0.84	0.97	0.83	1			
Katsina	0.94	0.94	0.45	0.86	1		
Kano	0.93	0.96	0.56	0.91	0.98	1	
Kaduna	0.58	0.81	0.96	0.91	0.60	0.70	1

Table 5-4: Correlation coefficient between minimum monthly temperature from WorldClim and weather stations in north-western Nigeria 1970-2000

	WorldClim	Sokoto	Yelwa	Gusau	Katsina	Kano	Kaduna
WorldClim	1						
Sokoto	0.80	1					
Yelwa	0.80	0.97	1				
Gusau	0.81	0.96	0.98	1			
Katsina	0.70	0.98	0.95	0.96	1		
Kano	0.75	0.99	0.97	0.97	0.99	1	
Kaduna	0.79	0.95	0.99	0.98	0.94	0.96	1

In summary, the WorldClim temperature and precipitation data show high correlations with station data. That, therefore, indicate the reliability of using WorldClim data in modelling the spatial pattern of fascioliaisis transmission in this study.

5.8.2 Comparison of forecast indices with known areas of fascioliasis prevalence in Sokoto State

The fascioliasis risk model showed that the distribution of *F. gigantica* risk was not homogeneous across the four agricultural zones of the country. Table 1 shows infection prevalence spreading across all the four agricultural zones in Sokoto State that are approximately of equal elevation (between 238m-334m see Table 5-6). Based on short-term average rainfall (Figure 5-9) and soil moisture (Figure 5.10) the highest risk areas were localised in the Sokoto and Tambuwal zones. However, forecast index based on soil moisture indicated additional areas of risk in both Gwadabawa and Isa zones. Furthermore, forecast indices based on the long-term average of the past years (Figure 5.11) showed higher risk in the same zones as the short-term with some few foci in Gwadabawa zones while Isa zone was left as reduced risk of fascioliasis infection.

Similarly, in the year 2050, the forecast indices indicated similar areas of higher risk areas in both RCP 2.6 (Figure 5.12) and RCP 8.5 (Figure 5.13). The only difference is that in the former RCP the risk areas extended into more provinces in Isa zone than in Gwadabawa while in the latter RCP both Isa and Gwadabawa zones were having almost the same number of high-risk areas. Tambuwal and Sokoto zones maintained their status as higher risk zones in the year 2070, based on RCP 2.6 (Figure 5.14) and 8.5 (Figure 5.15). In addition, these two RCPs showed almost similar risk pattern with Isa having more risk areas than Gwadabawa zone.

Regarding validation, both positive and inverse relationships were observed (Table 5-7) based on spatial correlation coefficient statistics between the reported prevalence, forecast indices and the relevant climatic and environmental variables using short-term average in the study area. Spatial correlations (Figures 5.7 and 5.8) between forecast indices using rainfall variable ($r=0.67$) and soil moisture ($r=0.37$) respectively with recorded infections prevalence distribution of *F. gigantica* in 23 provinces of Sokoto State. The correlations between monthly averaged fascioliasis infections prevalence were significant with monthly averaged NDVI and rainfall ($P<0.01$), likewise monthly averaged soil moisture ($p<0.05$). However, a significant inverse relationships were observed between infections prevalence and mean monthly temperature ($p<0.01$) and potential evapotranspiration ($p< 0.05$).

Table 5-5: Descriptive statistics of the short-term climatic and environmental variables

Variable	Period	Number of provinces	Mean	SD	SE
Rainfall	2005-2014	23	763.86	62.8	13.09
Soil moisture	2005-2014	23	220.45	12.78	2.66
NDVI	2005-2014	23	0.33	0.06	0.013
Mean Temperature	2005-2014	23	30.36	0.22	0.04
Potential evapotranspiration	2005-2014	23	207.13	2.88	0.60

At 95% confidence level

Table 5-6: Area, average temperature and mean altitude of the 23 provinces that constitute the four agricultural zones of Sokoto state, Nigeria.

Agricultural zone	Province	Area(km2)	Mean temperature(^{O}C)	Altitude (m)
Gwadabawa	Binji	557	33	238
	Gada	1314	32	300
	Gudu	3463	31	279
	Gwadabawa	989	28	278
	Illela	1244	31	277
	Silame	787	32	248
	Tangaza	2470	30	268
Isa	Goronyo	1703	31	300
	Isa	2161	30	322
	Rabah	2431	32	279
	Sabon Birni	2357	31	334
	Wurno	683	30	300
Sokoto	Bodinga	562	30	289
	Dange Shuni	1208	31	311
	Kware	553	32	268
	Sokoto N	51	31	289
	Tureta	2381	30	300
	Wamakko	695	31	268
Tambuwal zone	Kebbe	2609	30	300
	Shagari	1329	30	300
	Tambuwal	1712	30	289
	Yabo	787	31	279

Table 5-7: Correlation coefficient between the reported Fasciola gigantica prevalence monthly aggregated across each of the 23 provinces in Sokoto State and the climatic variables. All the values are significant by student's t-test at 99%.

	F.prevalence	Forecast Index	NDVI	Mean Temp	PE T	Rainfall	Soil moisture
F.prevalence	1						
Forecast Index	0.7	1					
NDVI	0.6	0.6	1				
Mean Temp.	-0.5	-0.4	-0.6	1			
PET	-0.4	-0.5	-0.4	0.8	1		
Rainfall	0.8	0.6	0.7	-0.6	-0.3	1	
Soil moisture	0.4	0.3	0.4	-0.1	-0.2	0.5	1

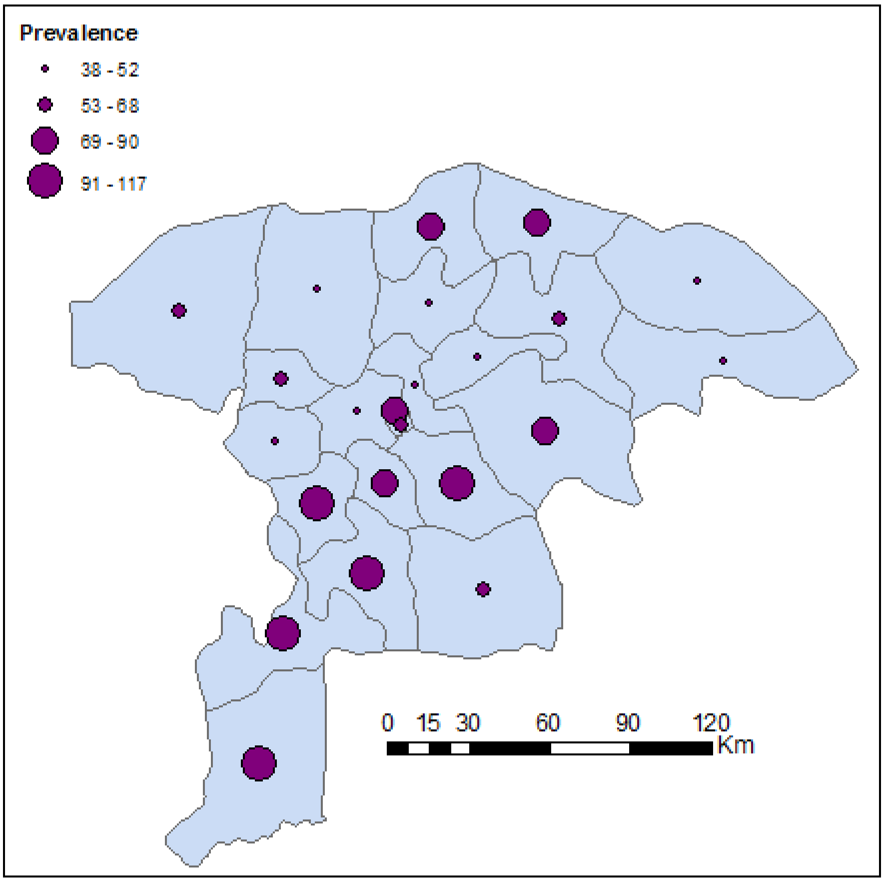


Figure 5-22: This indicates 10-year average (2005-2014) of Fascioliasis prevalence in Sokoto State as obtained from Ministry of Animal Health, Sokoto. The areas with high prevalence were more concentrated around the southern parts of the state that includes Kebbe, Shagari, Tambuwal, Yabo, and Sokoto north.

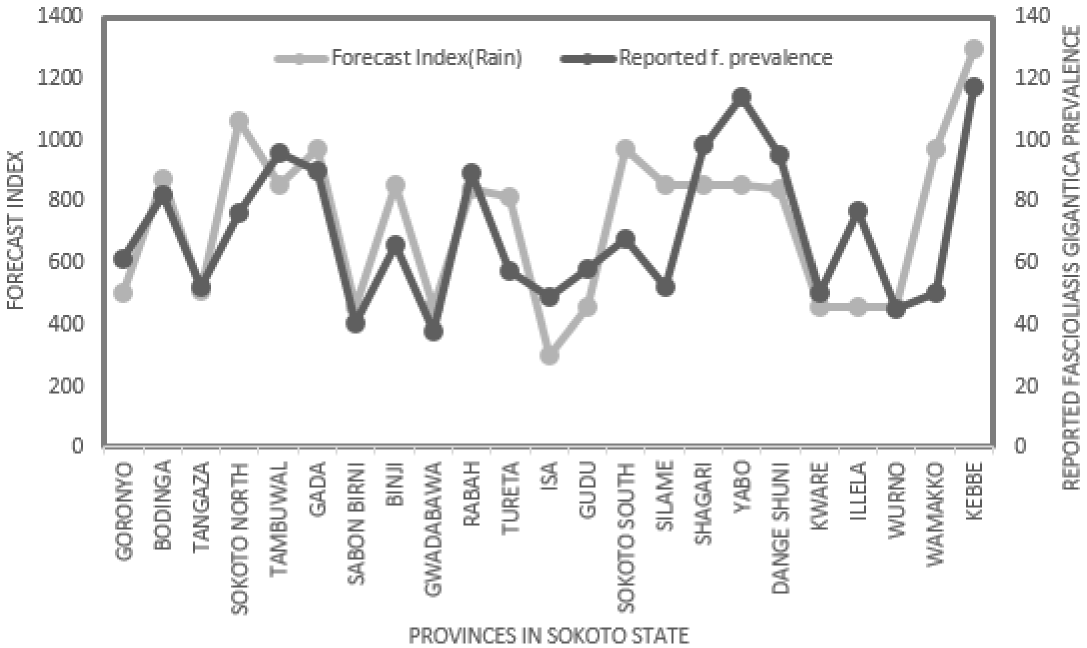


Figure 5-23: Comparison of forecast index using rainfall and potential evapotranspiration with reported F. gigantica prevalence in all the 23 provinces of Sokoto State, Nigeria. A high level of agreement is shown to exist between the reported F. gigantica prevalence in the study area and the forecast indices in respect of each province

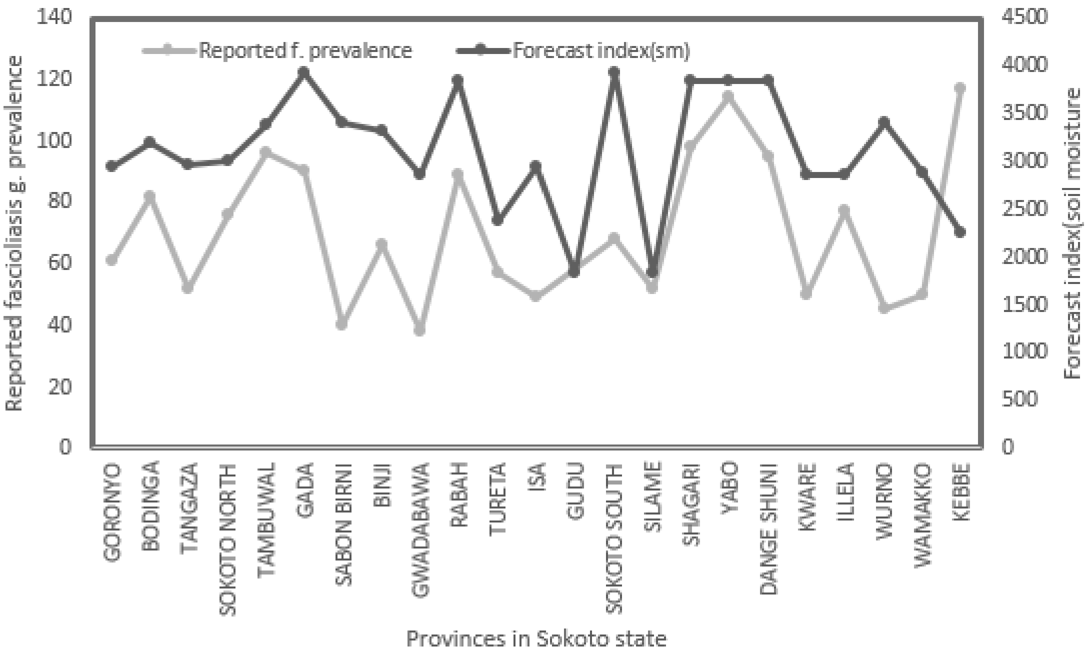


Figure 5-24: Comparison of forecast index using soil moisture and potential evapotranspiration with reported F. gigantica prevalence in all the 23 provinces of Sokoto State, Nigeria. That indicates some level of agreement between available soil moisture in each province and the risk of infection with F.gigantica in the study area.

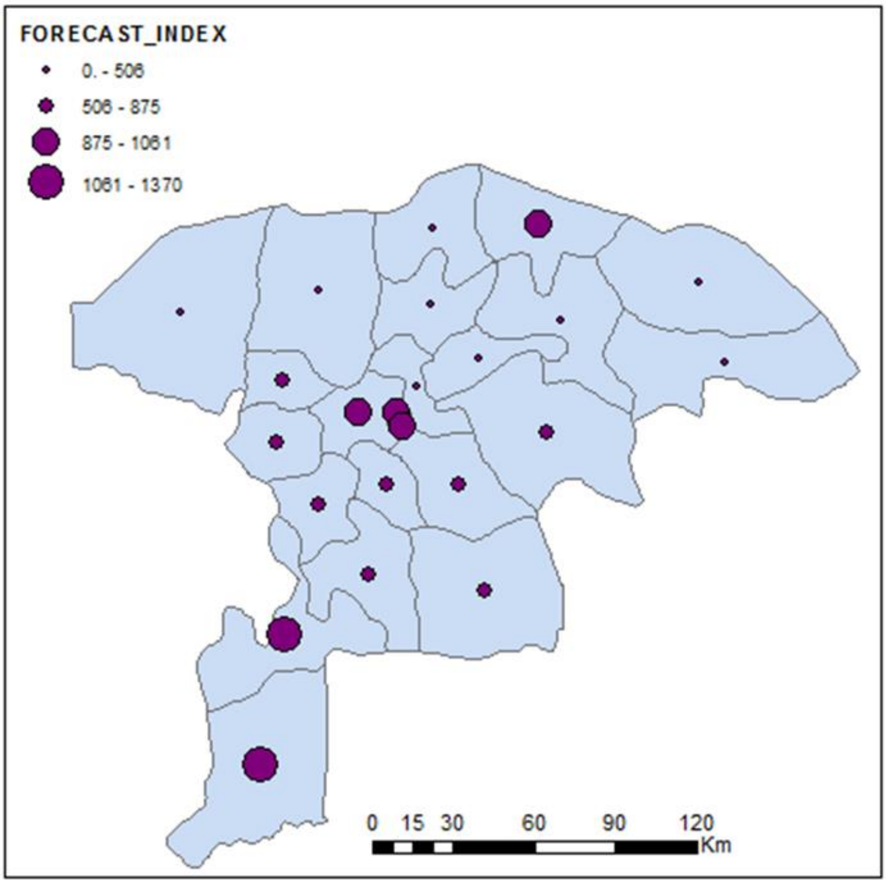


Figure 5-25: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate and remotely sensed database on current climate (2005-2014). The lowest limit of temperature used for the development of F.gigantica was 16^{O}C.

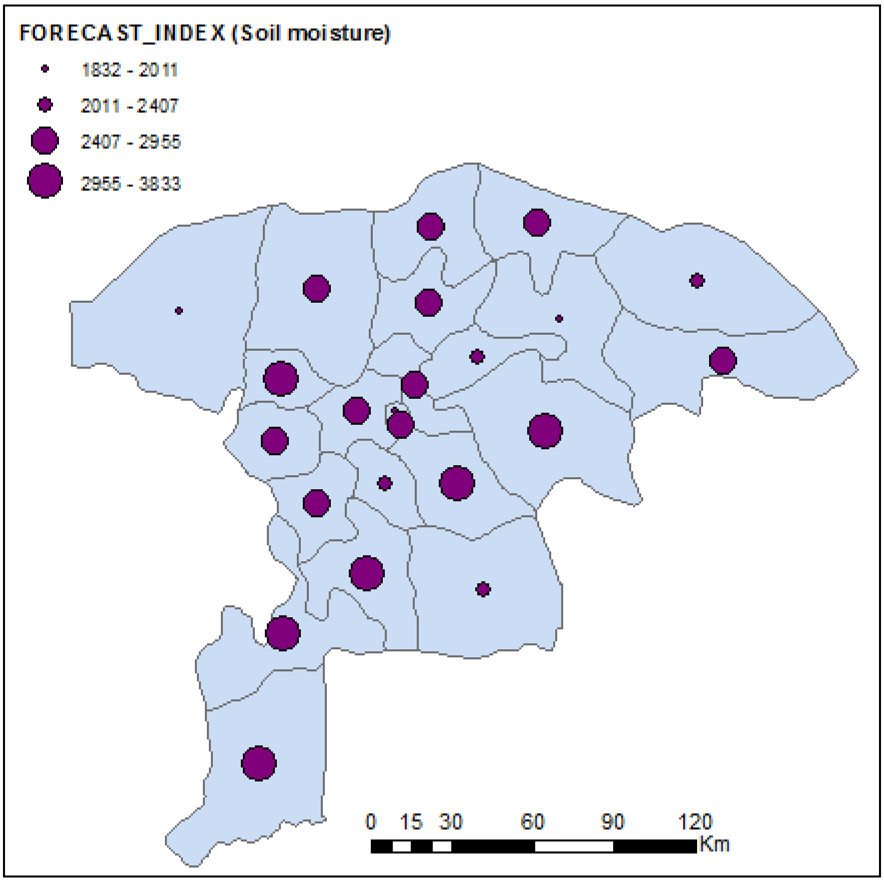


Figure 5-26: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate and remotely sensed database on GLDAS soil moisture (2005-2014). The lowest limit of temperature used for the development of F.gigantica was 16^{O}C.

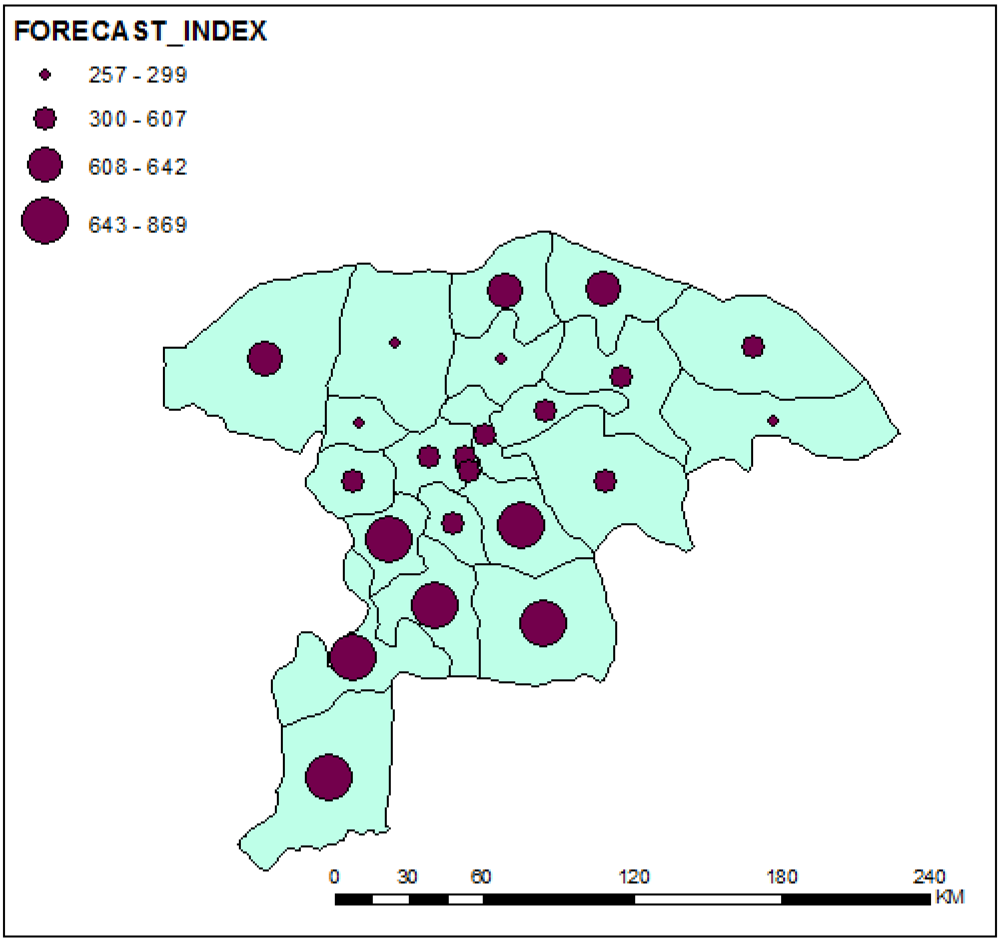


Figure 5-27: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate and WorldClim database on past climate (1970-2000). The lowest limit of temperature used for the development of F.gigantica was 16^{O}C.

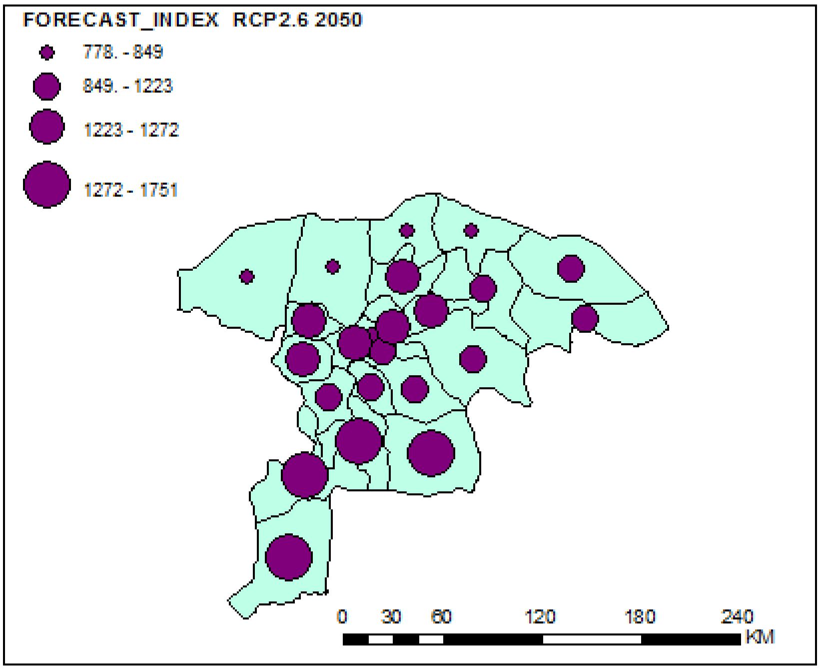


Figure 5-28: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate from HADGEM2-ES model based on RCP2.6 of 2050. The lowest limit of temperature used for the development of F.gigantica was 16^{O}C. The high-risk areas spread from southern part of the state towards the centre leaving only a few areas with low risk.

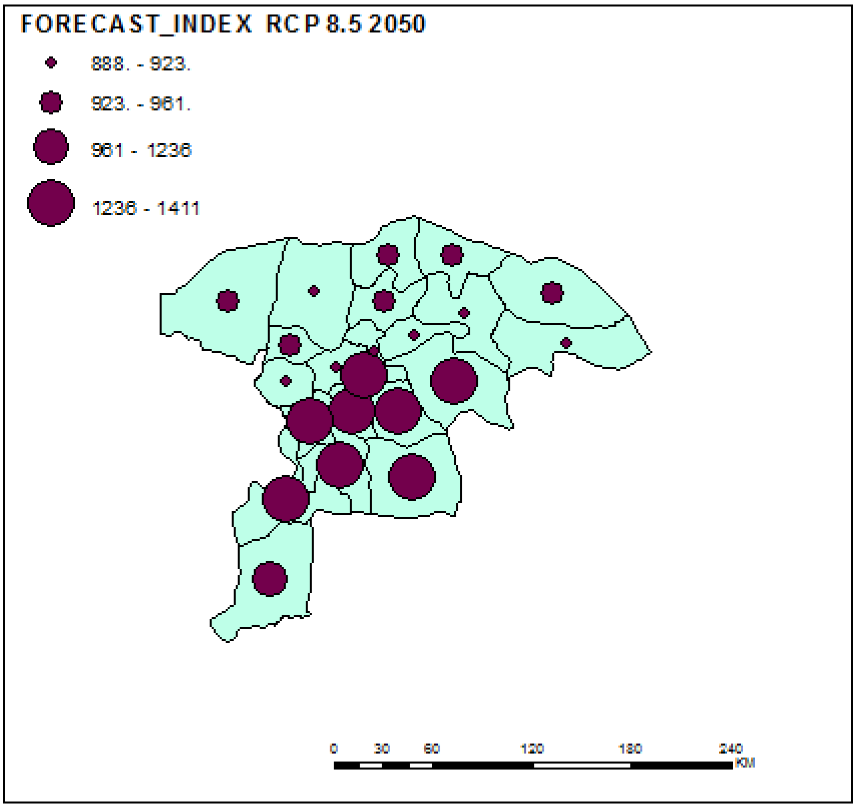


Figure 5-29: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate from HADGEM2-ES model based on RCP8.5 of 2050. The lowest limit of temperature used for the development of F.gigantica was 16^{O}C. The high-risk areas spread from southern part of the state towards the centre leaving more areas than (Figure 5-12) with low risk especially at the northern border.

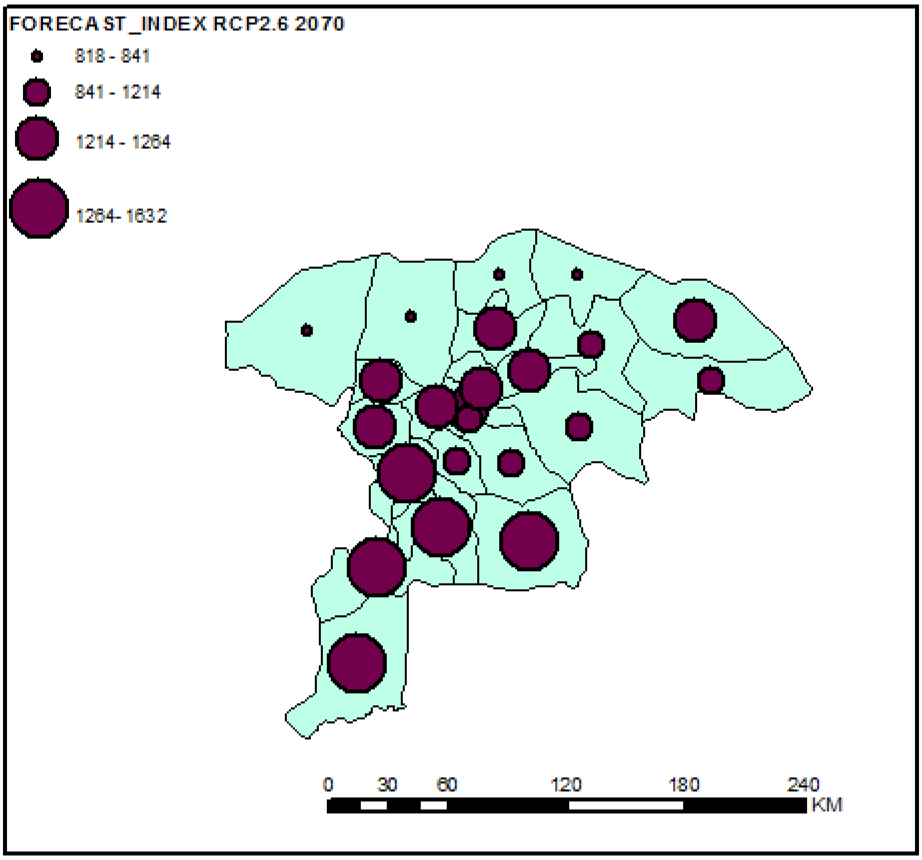


Figure 5-30: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate from HADGEM2-ES model based on RCP2.6 of 2070. The lowest limit of temperature used for the development of F.gigantica was 16^{O}C. The high-risk areas spread from southern part of the state towards the centre leaving only a few areas with low risk.

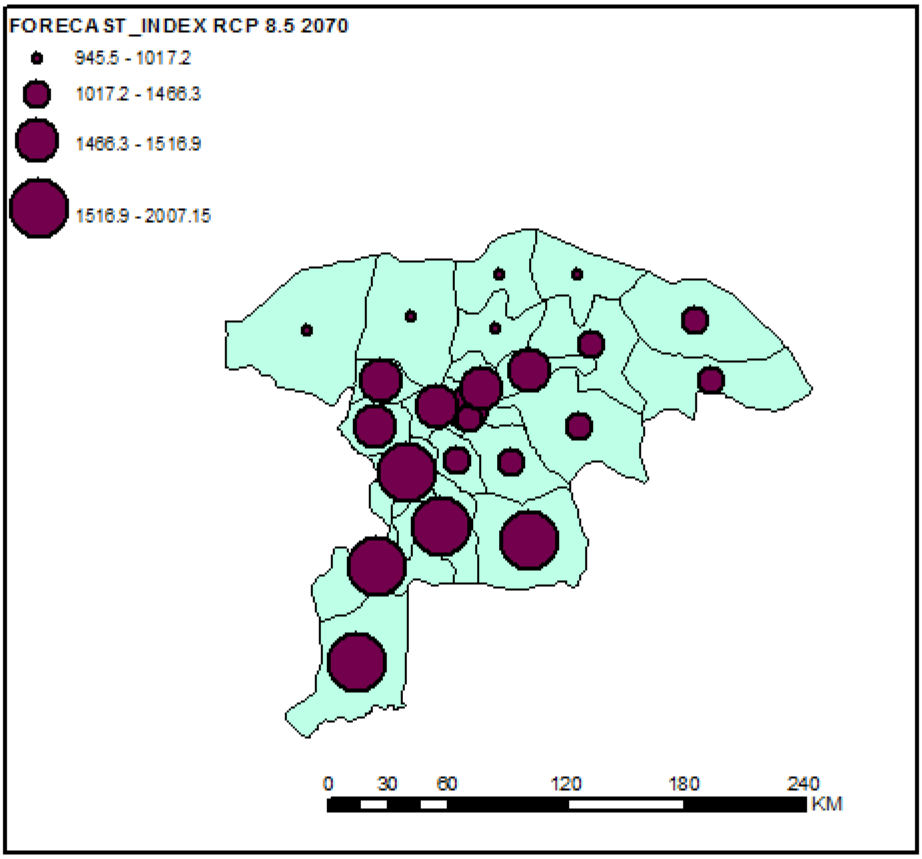


Figure 5-31: Density map of Sokoto State showing forecast risk indices for F.gigantica. The model was developed using monthly climate from HADGEM2-ES model based on RCP8.5 of 2070. The lowest limit of temperature used for the development of F.gigantica was 16^{O}C. The high-risk areas spread from southern part of the state towards the centre leaving only a few areas with low risk.

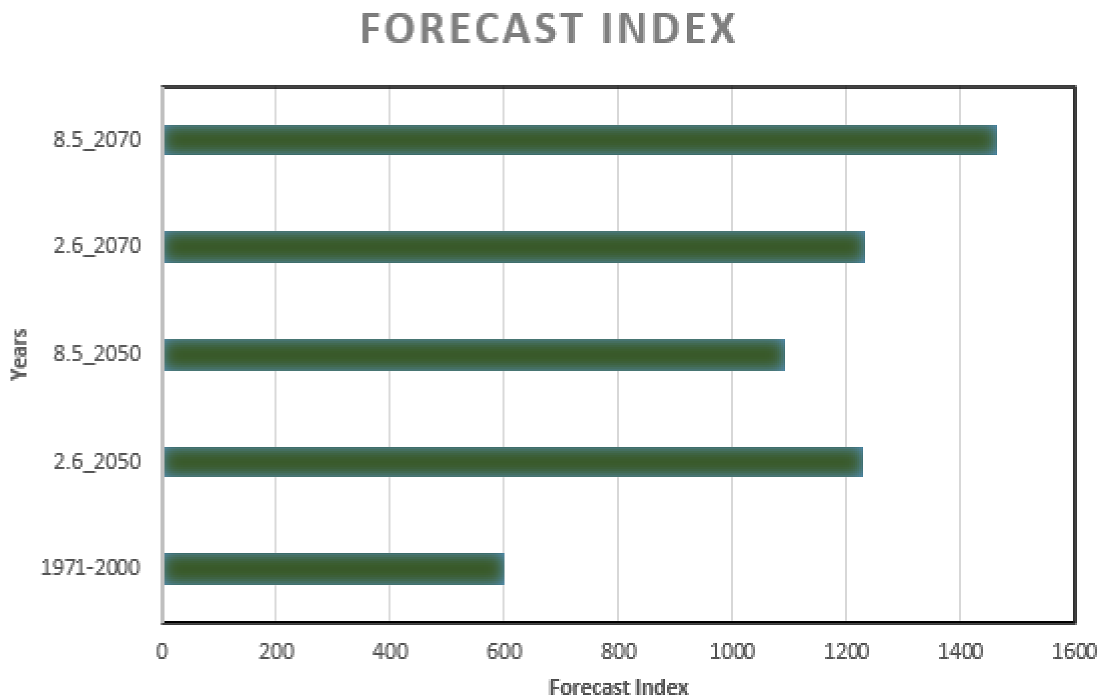


Figure 5-32: Comparison of past and future risk. This indicates that fascioliasis risk increases from immediate past climate (1970-2000) towards the future years reaching peak in RCP 8.5 of 2070. This situation therefore demands appropriate control measures should be taken against the prevalence of F.gigantica in Sokoto state.

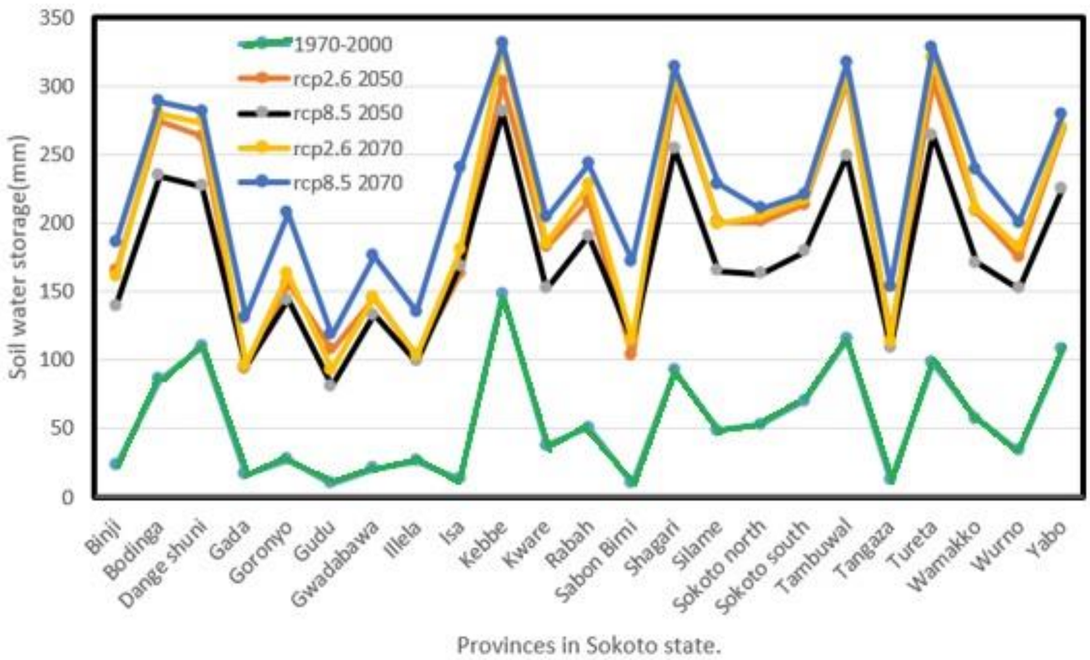


Figure 5-33: This shows the spatial variability in soil water storage based on water budget across the 23 provinces in Sokoto State. The differences in each province reflect the pattern of rainfall distribution over the entire state.

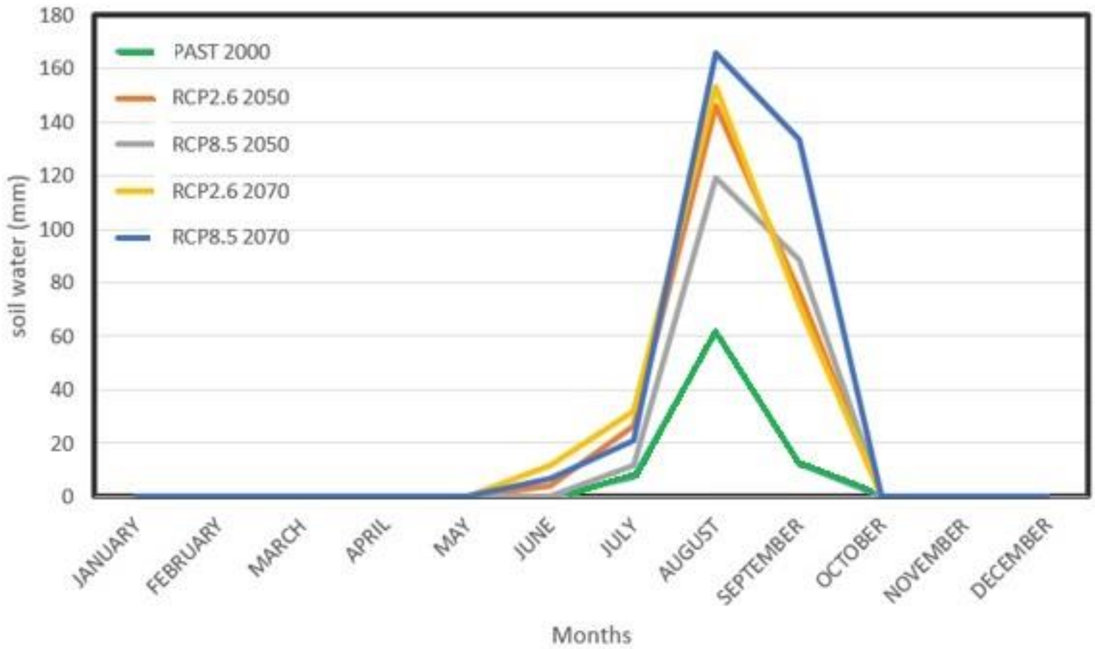


Figure 5-34: The temporal changes in the amount of soil water with July and August having the highest amount indicating a high risk of F.gigantica infection.

5.8.3 Monthly forecast indices across all the provinces

The seasonal pattern of transmission of *F. gigantica* in the study area is shown using the short-term average based on rainfall (Table 5-8) and soil moisture (Table 5.9), long-term [immediate past climate data] (Table 5-10), future RCP 2.6 2050 (Table 5.11), RCP 8.5 2050 (Table 5-12), RCP 2.6 2070 (Table 5-13) and RCP 8.5 2070 (Table 5-14). 3-4 months of shedding period of cercariae per year from June to September is evident in most of the provinces in Sokoto State with a clear distinction between dry and wet seasons (Figure 5-19). Based on short term average (Table 5-8) cercariae-shedding commenced in June for only one province each for Gwadabawa and Isa zones, but two provinces in Sokoto zone indicated a restriction of shedding time to only three months.

Similarly, with long-term average (past climate data) for which the shedding period was only for two to three months (July to September). About the future projection of cercariae shedding, the year 2050 witnessed a different prediction between RCP 2.6 (Table 5-11) and RCP8.5 (Table15-2) which were three to four months (June to September) and two to three months (July to September) respectively. The trend in the cercariae shedding is almost similar between RCP 2.6 (Table 5-13) and RCP8.5 (Table 5-14) in the year 2070 where the shedding commenced in June to September for only

Sokoto and Tambuwal zones while Gwadabawa and Isa zones the simulation was in July to September only.

However, using soil moisture (Table 5-9) revealed longer cercariae shedding period from June-January (Figure 5-20) which indicated the extension into dry season months of October, November, December, and January. The shedding period extended to February for Silame in Gwadabawa zone, Rabah and Boding in Isa zone, Dange shuni in Sokoto zone and all the four provinces in Tambuwal zone.

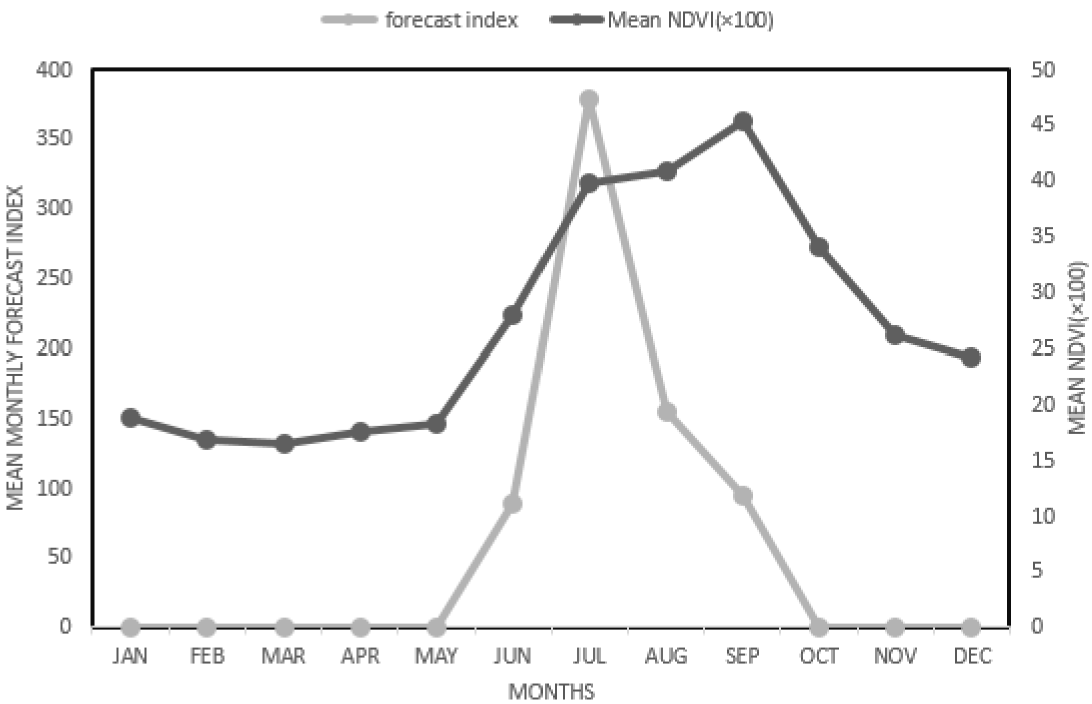


Figure 5-35: Monthly F. gigantica forecast (equation 2) for all the provinces in Sokoto State indicating a seasonal pattern of cercariae-shedding and the most appropriate times for preventing and curative measures for the whole state and other parts of North- western Nigeria. That is based on the consideration of rainfall variable only where two periods from January to May and from October to December are recommended both for prevention and curative measures against F. gigantica infections respectively.

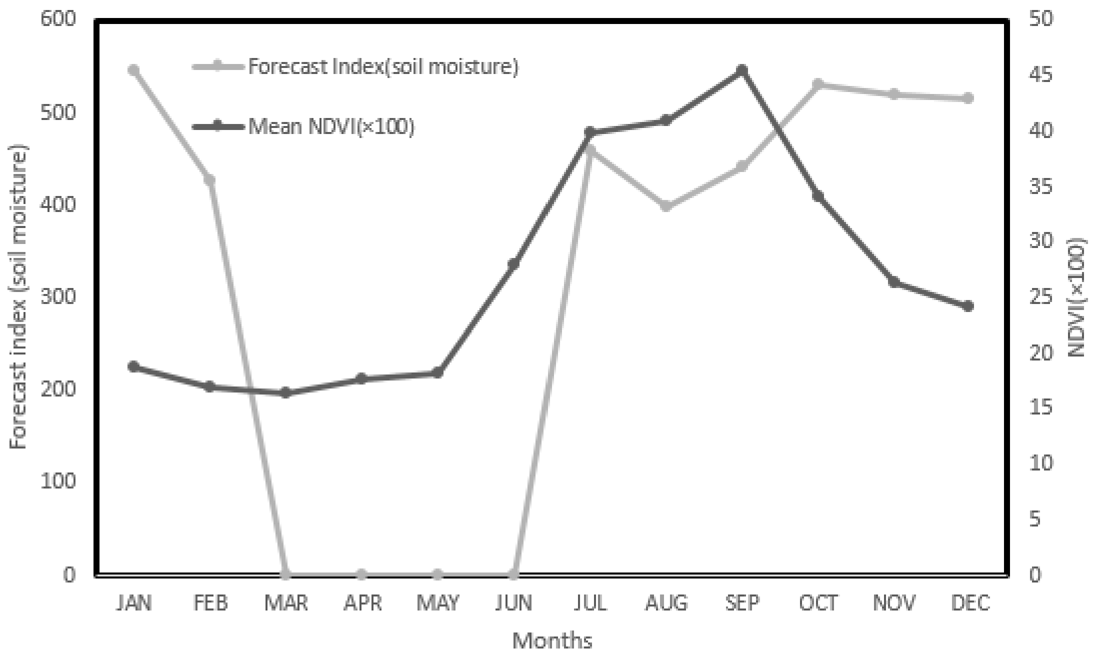


Figure 5-36: Monthly F. gigantica forecast(equation 6) for all the provinces in Sokoto State indicating a seasonal pattern of cercariae-shedding and the most appropriate times for preventing and curative measures for the whole state and other parts of North- western Nigeria. That is based on consideration of soil moisture variable where one period from March to June is recommended both for prevention and curative against F. gigantica infections.

Table 5-8: Monthly forecast and the patterns of cercariae-shedding for F. gigantica in the four agricultural zones of Sokoto State based on 10 year monthly average. The shedding commenced in June in some provinces such as Gada, Goronyo, Sokoto north and and south and ended in August. In Gwadabawa, there was no risk based on ten-year avearge as the total monthly rainfall recorded was lower than the monthly averaged evapotranspiration. The cumulative index for the state indicates medium risk based on a 10-year monthly average.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	458	398	0	0	0	0	856
	Gada	0	0	0	0	0	514	458	0	0	0	0	0	972
	Gudu	0	0	0	0	0	0	458	0	0	0	0	0	458
	Gwadabawa	0	0	0	0	0	0	0	0	0	0	0	0	0
	Illela	0	0	0	0	0	0	458	0	0	0	0	0	458
	Silame	0	0	0	0	0	0	458	398	0	0	0	0	856
	Tangaza	0	0	0	0	0	0	506	0	0	0	0	0	506
ISA	Goronyo	0	0	0	0	0	558	503	0	0	0	0	0	1061
	Isa	0	0	0	0	0	0	458	0	0	0	0	0	458
	Rabah	0	0	0	0	0	0	0	398	0	0	0	0	839
	Sabon B	0	0	0	0	0	0	458	0	0	0	0	0	458
	Wurno	0	0	0	0	0	0	458	0	0	0	0	0	458
SOK	Bodinga	0	0	0	0	0	0	493	382	0	0	0	0	875
	Dange S	0	0	0	0	0	0	0	398	441	0	0	0	840
	Kware	0	0	0	0	0	0	458	0	0	0	0	0	458
	Sokoto N	0	0	0	0	0	559	503	0	0	0	0	0	1061
	Sokoto S	0	0	0	0	0	514	458	0	0	0	0	0	972
	Tureta	0	0	0	0	0	0	0	398	441	0	0	0	840
	Wamakko	0	0	0	0	0	0	458	398	0	0	0	0	972
TAMB	Kebbe	0	0	0	0	0	0	458	398	441	0	0	0	1298
	Shagari	0	0	0	0	0	0	458	398	0	0	0	0	856
	Tambuwal	0	0	0	0	0	0	458	398	441	0	0	0	1370
	Yabo	0	0	0	0	0	0	458	398	0	0	0	0	856

Table 5-9: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on 10-year average (soil moisture). The length of the shedding period extended when on soil moisture variable replaced rainfall in the computation of the risk index. In most of the provinces, shedding starts in July and ends in January of the following year. However, in Silame, Rabah, Bodinga, Dange shuni, Kebbe, Shagari, Tambuwal and Yabo the end of shedding was in February. The areas noted with a shorter period of cercarael shedding include Gudu, Gwadabawa, Tangaza, Goronyo and Bodinga.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	545	0	0	0	0	0	458	398	442	530	519	516	3407
	Gada	545	0	0	0	0	514	458	398	442	530	519	516	3921
	Gudu	0	0	0	0	533	0	458	398	442	0	0	0	1832
	Gwadabaw	0	0	0	0	0	514	458	398	441	530	519	0	2862
	Illela	545	0	0	0	0	0	458	398	441	530	519	515	2862
	Silame	545	426	0	0	0	0	458	398	441	530	519	515	2800
	Tangaza	0	0	0	0	0	0	507	399	474	583	531	460	2955
ISA	Goronyo	0	0	0	0	0	0	503	427	468	561	521	467	2948
	Isa	545	0	0	0	0	0	0	398	442	530	519	516	2949
	Rabah	545	426	0	0	0	0	458	398	442	530	519	516	3833
	Sabon B	545	0	0	0	0	0	548	398	442	530	519	516	3407
	Wurno	545	0	0	0	0	0	548	398	442	530	519	516	3407
SOK	Bodinga	0	400	0	0	0	0	493	382	414	497	508	495	3189
	Dange S	545	426	0	0	0	0	458	398	441	530	519	516	3834
	Kware	545	0	0	0	0	0	458	398	441	530	519	516	2862
	Sokoto N	505	0	0	0	0	559	502	427	468	561	521	467	4011
	Sokoto S	545	0	0	0	0	514	458	398	441	530	519	516	3921
	Tureta	545	0	0	0	0	0	458	398	442	530	519	515	2373
	Wamakko	545	0	0	0	0	0	458	398	442	0	519	516	2877
TAM	Kebbe	545	426	0	0	0	0	458	398	442	530	519	516	3407
	Shagari	545	426	0	0	0	0	458	398	442	530	519	516	3834
	Tambuwal	545	426	0	0	0	0	0	399	442	530	519	516	3375
	Yabo	544	426	0	0	0	0	458	398	442	530	519	516	3833

Table 5-10: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on the monthly average of past climate (1970-2000). The risk index values were more concentrated in August across all across all the provinces in the state. In September only Dange Shuni and Tureta had higher rainfall average than potential evapotranspiration. Also, the period of cercariael shedding was 2 to 3 months. The cumulative risk was also at the medium stage

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	0	276	0	0	0	0	276
	Gada	0	0	0	0	0	0	333	290	0	0	0	0	623
	Gudu	0	0	0	0	0	0	335	284	0	0	0	0	619
	Gwadabawa	0	0	0	0	0	0	0	288	0	0	0	0	288
	Illela	0	0	0	0	0	0	344	298	0	0	0	0	642
	Silame	0	0	0	0	0	0	319	276	0	0	0	0	595
	Tangaza	0	0	0	0	0	0	0	299	0	0	0	0	299
ISA	Goronyo	0	0	0	0	0	0	319	281	0	0	0	0	600
	Isa	0	0	0	0	0	0	0	257	0	0	0	0	257
	Rabah	0	0	0	0	0	0	328	273	0	0	0	0	602
	Sabon B	0	0	0	0	0	0	312	270	0	0	0	0	582
	Wurno	0	0	0	0	0	0	319	278	0	0	0	0	597
SOK	Bodinga	0	0	0	0	0	0	303	260	0	0	0	0	563
	Dange S	0	0	0	0	0	0	299	257	287	0	0	0	843
	Kware	0	0	0	0	0	0	325	278	0	0	0	0	603
	Sokoto N	0	0	0	0	0	0	321	284	0	0	0	0	605
	Sokoto S	0	0	0	0	0	0	331	276	0	0	0	0	607
	Tureta	0	0	0	0	0	0	282	242	273	0	0	0	697
	Wamakko	0	0	0	0	0	0	329	274	0	0	0	0	604
TAMB	Kebbe	0	0	0	0	0	0	264	231	252	0	0	0	746
	Shagari	0	0	0	0	0	0	289	246	277	0	0	0	814
	Tambuwal	0	0	0	0	0	0	287	243	275	0	0	0	805
	Yabo	0	0	0	0	0	0	308	265	295	0	0	0	869

Table 5-11: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on RCP 2.6 2050. In comparison with the past climate average, the shedding period increased by one month. Binji, Gwadabawa, Tangaza and Isa recorded higher total monthly average ranfall than potential evapotranspiration and hence posed high fascioliasis risk based on this future projection under RCP 2.6. The provinces with four months cercariae shedding period were Tureta, Kebbe, Shagari and Tambuwal.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	450	383	440	0	0	0	1271
	Gada	0	0	0	0	0	0	0	386	441	0	0	0	826
	Gudu	0	0	0	0	0	0	0	361	417	0	0	0	778
	Gwadabawa	0	0	0	0	0	0	449	381	438	0	0	0	1269
	Illela	0	0	0	0	0	0	0	395	455	0	0	0	850
	Silame	0	0	0	0	0	0	437	375	432	0	0	0	1244
	Tangaza	0	0	0	0	0	0	0	392	451	0	0	0	845
ISA	Goronyo	0	0	0	0	0	0	430	366	420	0	0	0	1217
	Isa	0	0	0	0	0	0	423	361	417	0	0	0	1201
	Rabah	0	0	0	0	0	0	428	361	425	0	0	0	1214
	Sabon B	0	0	0	0	0	0	432	369	422	0	0	0	1223
	Wurno	0	0	0	0	0	0	437	369	429	0	0	0	1235
SOK	Bodinga	0	0	0	0	0	0	426	363	416	0	0	0	1205
	Dange S	0	0	0	0	0	0	420	355	410	0	0	0	1185
	Kware	0	0	0	0	0	0	442	372	437	0	0	0	1250
	Sokoto N	0	0	0	0	0	0	439	369	429	0	0	0	1237
	Sokoto S	0	0	0	0	0	0	434	364	423	0	0	0	1221
	Tureta	0	0	0	0	0	467	403	346	396	0	0	0	1611
	Wamakko	0	0	0	0	0	0	440	367	429	0	0	0	1237
TAMB	Kebbe	0	0	0	0	0	514	440	367	429	0	0	0	1751
	Shagari	0	0	0	0	0	481	409	347	399	0	0	0	1636
	Tambuwal	0	0	0	0	0	469	403	344	392	0	0	0	1608
	Yabo	0	0	0	0	0	0	420	360	413	0	0	0	1192

Table 5-12: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on RCP 8.5 2050. The fascioliasis risk index under this future projection was highest in August and September. Also, the shedding period was slightly shorter across all the provinces except for Rabah, Bodinga, Dange Shuni, Sokoto north, Tureta and all the provinces in Tambuwal zone.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	0	440	497	0	0	0	936
	Gada	0	0	0	0	0	0	0	442	498	0	0	0	938
	Gudu	0	0	0	0	0	0	0	446	506	0	0	0	951
	Gwadabawa	0	0	0	0	0	0	0	437	495	0	0	0	932
	Illela	0	0	0	0	0	0	0	0	451	0	0	0	961
	Silame	0	0	0	0	0	0	0	434	489	0	0	0	923
	Tangaza	0	0	0	0	0	0	0	420	471	0	0	0	891
ISA	Goronyo	0	0	0	0	0	0	0	423	478	0	0	0	901
	Isa	0	0	0	0	0	0	0	415	473	0	0	0	887
	Rabah	0	0	0	0	0	0	485	417	480	0	0	0	1382
	Sabon B	0	0	0	0	0	0	0	442	498	0	0	0	939
	Wurno	0	0	0	0	0	0	0	425	486	0	0	0	910
SOK	Bodinga	0	0	0	0	0	0	483	420	471	0	0	0	1374
	Dange S	0	0	0	0	0	0	476	414	467	0	0	0	1356
	Kware	0	0	0	0	0	0	0	430	492	0	0	0	922
	Sokoto N	0	0	0	0	0	0	0	426	488	0	0	0	913
	Sokoto S	0	0	0	0	0	0	493	422	482	0	0	0	1396
	Tureta	0	0	0	0	0	0	459	405	453	0	0	0	1316
	Wamakko	0	0	0	0	0	0	0	427	488	0	0	0	914
TAMB	Kebbe	0	0	0	0	0	0	434	389	413	0	0	0	1294
	Shagari	0	0	0	0	0	0	467	406	455	0	0	0	1327
	Tambuwal	0	0	0	0	0	0	498	426	488	0	0	0	1411
	Yabo	0	0	0	0	0	0	479	418	468	0	0	0	1365

Table 5-13: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on RCP 2.6 2070. The future projections based on this long-term average revealed fascioliasis infection risk occurring in three to four months. That shows an increase in total monthly average rainfall than potential evapotranspiration in June, July, August and September. The cumulative index was at the medium stage.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	449	381	434	0	0	0	1264
	Gada	0	0	0	0	0	0	0	383	435	0	0	0	818
	Gudu	0	0	0	0	0	0	0	487	443	0	0	0	830
	Gwadabawa	0	0	0	0	0	0	450	380	434	0	0	0	1263
	Illela	0	0	0	0	0	0	0	394	447	0	0	0	841
	Silame	0	0	0	0	0	0	437	374	428	0	0	0	1238
	Tangaza	0	0	0	0	0	0	0	391	446	0	0	0	836
ISA	Goronyo	0	0	0	0	0	0	427	364	416	0	0	0	1208
	Isa	0	0	0	0	0	0	423	359	411	0	0	0	1194
	Rabah	0	0	0	0	0	0	426	360	419	0	0	0	1204
	Sabon B	0	0	0	0	0	0	429	367	416	0	0	0	1264
	Wurno	0	0	0	0	0	0	0	436	367	0	0	0	1227
SOK	Bodinga	0	0	0	0	0	0	427	361	411	0	0	0	1197
	Dange S	0	0	0	0	0	0	418	355	405	0	0	0	1178
	Kware	0	0	0	0	0	0	440	372	431	0	0	0	1243
	Sokoto N	0	0	0	0	0	0	437	367	425	0	0	0	1228
	Sokoto S	0	0	0	0	0	0	433	363	419	0	0	0	1214
	Tureta	0	0	0	0	0	471	402	344	392	0	0	0	1608
	Wamakko	0	0	0	0	0	0	440	367	425	0	0	0	1232
TAMB	Kebbe	0	0	0	0	0	435	377	332	356	0	0	0	1498
	Shagari	0	0	0	0	0	485	407	346	395	0	0	0	1632
	Tambuwal	0	0	0	0	0	471	403	344	389	0	0	0	1606
	Yabo	0	0	0	0	0	0	422	358	408	0	0	0	1188

Table 5-14: Monthly forecast and the patterns of cercariae shedding for F. gigantica in the four agricultural zones of Sokoto State based on RCP 8.5 2070. The shedding period under this RCP of climate change was mainly three months across all the provinces except for Tambuwal zone and Tureta. That indicates the spread of fascioliasis risk across all the localities in the future.

AG ZONE	Province	J	F	M	A	M	J	J	A	S	O	N	D	Annual forecast
GWD	Binji	0	0	0	0	0	0	530	459	528	0	0	0	1516
	Gada	0	0	0	0	0	0	0	460	432	0	0	0	993
	Gudu	0	0	0	0	0	0	0	465	540	0	0	0	1005
	Gwadabawa	0	0	0	0	0	0	0	435	510	0	0	0	946
	Illela	0	0	0	0	0	0	0	471	546	0	0	0	1017
	Silame	0	0	0	0	0	0	518	451	521	0	0	0	1481
	Tangaza	0	0	0	0	0	0	0	468	543	0	0	0	1011
ISA	Goronyo	0	0	0	0	0	0	510	440	512	0	0	0	1462
	Isa	0	0	0	0	0	0	502	434	504	0	0	0	1440
	Rabah	0	0	0	0	0	0	505	436	510	0	0	0	1450
	Sabon B	0	0	0	0	0	0	512	443	511	0	0	0	1466
	Wurno	0	0	0	0	0	0	516	443	518	0	0	0	1476
SOK	Bodinga	0	0	0	0	0	0	504	437	501	0	0	0	1442
	Dange S	0	0	0	0	0	0	496	431	497	0	0	0	1423
	Kware	0	0	0	0	0	0	522	448	525	0	0	0	1495
	Sokoto N	0	0	0	0	0	0	518	443	517	0	0	0	1478
	Sokoto S	0	0	0	0	0	0	513	439	512	0	0	0	1463
	Tureta	0	0	0	0	0	538	479	422	480	0	0	0	1919
	Wamakko	0	0	0	0	0	0	519	443	518	0	0	0	1480
TAMB	Kebbe	0	0	0	0	0	500	452	406	435	0	0	0	1793
	Shagari	0	0	0	0	0	553	485	423	481	0	0	0	1943
	Tambuwal	0	0	0	0	0	538	481	422	474	0	0	0	1914
	Yabo	0	0	0	0	0	576	499	436	497	0	0	0	2007

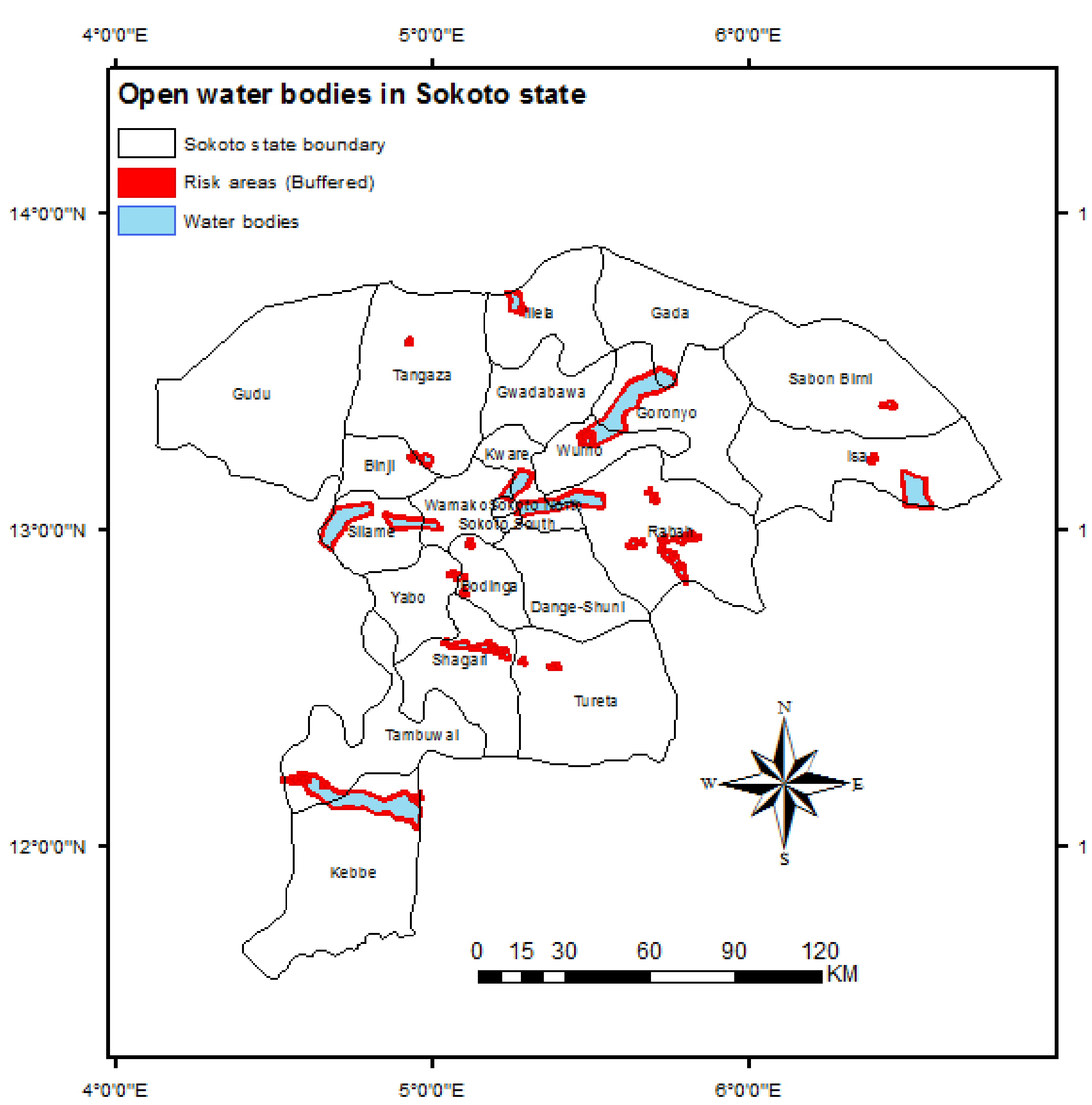


Figure 5-37: Open water bodies in Sokoto state, Nigeria (source: World Wildlife Fund WWF)

5.9 Discussion

The WorldClim data of the immediate past climate (often referred to as current climate) on maximum, minimum temperature and precipitation have indicated good agreement with the ground-based station's data in the north-west ecological zone of Nigeria, especially in Sokoto State. The accuracy between WorldClim data estimate and ground stations observations on temperature had the lowest RMSE than rainfall over the same period. That was because the temperature is determined by latitudes and elevation which makes it more consistent than rainfall estimates that have high spatio-temporal variabilities even across adjacent locations (Fick & Hijmans, 2017). Similarly, temperature achieves higher accuracy than precipitation between estimated and observed values in other World climate surfaces (New et al., 2002). These findings suggests that the result of this study can be extrapolated to all the states in the north western part of Nigeria regarding designing control strategies for preventing infection from *F. gigantica*.

In the present study, the validation was carried out using the available database based on liver condemnations from abattoirs and slaughter slabs. *Fasciola gigantica* infection prevalence record was in agreement with the NDVI, soil moisture, mean temperature and potential evapotranspiration. The record was the best database available as the veterinary health workers documented it after inspection of the slaughtered animals. However, this may not represent the complete number of livers infected with fascioliasis due to the tendency of butchers to resist full inspection based on their 'attachment of too much monetary value to the liver'(Danbirni et al., 2015). Similarly, the first study in East Africa by Yilma and Malone (1998) showed that fascioliasis prevalence record in Ethiopia was significantly correlated to rainfall, available soil moisture, mean temperature and potential evapotranspiration. This fascioliasis forecast index was a modification of the model developed in the UK by Ollerenshaw and Rowlands (1959) in formulating control strategies against *F. hepatica* prevalence. Their study has indicated the suitability of climate-based forecast index in the study of both species of fascioliasis. In the same vein, a study was carried out in the province of Punjab in Pakistan by Afshan et al. (2014) that focused on investigating the impact of climate change on transmission risk of both human and animal fascioliasis. In their study, they also made use of climate-based fascioliasis forecast index which they used in formulating appropriate preventive measures against fascioliasis prevalence in that country. The study was validated by comparing the available fascioliasis prevalence record to forecast indices and NDVI through correlation coefficient. The main limitation of their study is that it was based on immediate past climate without looking at the effects of long-terms climate projections in predicting the risks of fascioliasis.

The first report of fascioliasis dated back to 1939 in northern Nigeria according to Danbirni et al. (2015) and since then only a few studies had been carried out to investigate its spatio-temporal variability across the country as a function of climatic variables. Even in northern Nigeria where the fascioliasis originated and spread to other parts of the country due to an abundant population of animals (Okiki, 2017) no species-specific distribution modelling study has been established to assess the dynamics of *F. gigantica* transmission. However, in the UK, the fascioliasis forecast index created by Ollerenshaw and Rowlands (1959) is still in use today as a basis for predicting the outbreak of fascioliasis to farmers with a reasonable level of reliability (Fox et al., 2011). This study presents the first attempt in the modification of Ollerenshaw and Rowlands (1959) index applicable to the semi-arid ecological zone of West Africa, in creating *F.gigantica* monthly forecast index.

The short-term risk map indicated the many localities in Gwadabawa and Isa agricultural zones were free of *F.gigantica* according to the forecast index. On the other hand, long-term map (immediate past climate) shows that the high risk of *F.gigantica* infection occurred in Sokoto and Tambuwal zones with a reduction of free risk areas as occurred in the short-term period. For example, localities such as Gudu, Tangaza, Gwadabawa, Isa, Illela, Goronyo, Sabon Birni and Kware were without any risk of *F.gigantica* during short-term but the risk increased in Isa, Gwadabawa and Tangaza based on long-term records. The two areas of highest risk corresponds to areas that are lying in the southern part of Sokoto State where the total rainfall is invariably higher than the northern part of the state. That is because in Nigeria and all parts of West Africa especially the Sahel, rainfall decreases from the southern coasts to the continental interior (Nicholson, 2013, Yosef et al., 2018) which equally reflects the pattern of rainfall in Sokoto State. According to Sultan and Janicot (2000), the rainfall over the Sahel or semi-arid part of West Africa is influenced by the movement of moist air originating from the Gulf of Guinea that shifts the Inter-Tropical Convergence Zone and related rainfall maxima to the northernmost position in August.

It is pertinent to note that the only model drivers used are temperature, rainfall and how they interacted with each other. Rainfall in sufficient quantity always aids the transmission of fascioliasis in all the localities in Sokoto State since the temperature is always above the $16^{O}C$ threshold and hence not restrictive. It is explicitly clear that high risk occurred in areas with higher rainfall and soil moisture, which reflects the pattern in any area around the globe where fascioliasis thrives (Yilma & Malone, 1998, Pfukenyi et al., 2006, Fox et al., 2011, Afshan et al., 2014). Conversely, all areas that have higher temperature couple with low rainfall especially around the northern tip of Sokoto State that borders the Niger republic will face moisture deficit that threatened the survival of *F.gigantica*. The only caution to be exercised when referring to these areas as free of risk is when we consider the presence of lakes and water bodies (Figure 5-22) since temperature is always not a limiting factor.

The present study suggests that in Sokoto State, temperature and soil moisture are crucial in influencing the seasonal patterns of *F.gigantica* infection due to its effects on every stage in the life cycle of the parasite and activity of the intermediate snail. Nevertheless, the spread of the infection in various parts of the state requires the knowledge of the effects of other risk determinants that are related to herd, farmer status and pasture management. Kantzoura et al. (2011a) reported that risk factors for fasciola infection in sheep and goats when combined with the use of environmental variables in modelling using GIS could provide 'possibilities for regionally adapted control measures'(Beck et al., 2000, Bennema et al., 2009). However, this study was carried out in Thessaly, Greece and the risk factors considered were about the prevalence and transmission of *F. hepatica* and animals were restricted to sheep and goats. Similarly, drinking water sources such as ponds, streams and lakes were noted in Ethiopia as risk factors especially during the period of the dry season when animals congregate thereby aiding transmission of the infection (Njau et al., 1988). It is therefore essential to incorporate the knowledge of risks factors in complementing the use of climate-based models in order to design appropriate methods of controlling the transmission of fascioliasis infection in the study area and other parts of northern Nigeria. Also, this study did not utilise the existence of water bodies in building the model which according to Yilma and Malone (1998) are very significant factors in determining the transmission of fascioliasis infection, especially in the Sahel.

In this study, the annual forecast index values for the year 2070 under RCP 2.6 and 8.5 were higher than the year 2050 based on the preceding RCPs and the immediate past climate. That, therefore, suggests that the risk of fascioliasis in the study area is increasing reflecting the situation in most EU countries and is evident in the UK (de Waal T et al., 2007, Fox et al., 2011). These findings are in agreement with the annual differentiation in the intensity of transmission across areas of fascioliasis prevalence in response to climate in the UK by Ollerenshaw and Rowlands (1959). The present study, therefore, suggests regional scale annual forecast can be initiated for north-west or entire northern Nigeria by using contemporary or current data from satellite or ground-based stations to run monthly climate-based fascioliasis forecasts system.

This chapter further suggests that the appropriate timing for prevention of fascioliasis is November to January that is the period immediately after the raining season and the preventive period is February to May before the beginning of the raining season. During the latter period, it is recommended to take drugs that are effective against the young and old flukes.

Conclusion

i. Fascioliasis forecast index based on GDD and water-based budget (GDD-WB) using monthly climate data can be applied in Nigeria. Due to the relevance of these models they were adapted and applied in various parts of the world, and the results of such studies were published (UK, Colombia, USA, East Africa in Ethiopia and southern Brazil)
ii. The results suggest that there is spatial variation in *F. gigantica* risk in Sokoto State and northern Nigeria with risk extending to more localities due to changes in climate under the two RCP scenarios in 2050 and 2070.

iii. The results further suggest that temporal variation occurs in terms of transmission intensity in Sokoto State and northern Nigeria that calls for the establishment of yearly *F. gigantica* forecast to inform the livestock farmers of climate years that would result into high risk due to possibility of wet grazing areas that would require year round treatment during the rainy season.
iv. Findings unique to this study suggest that soil moisture can be used instead of rainfall to calculate the risk of *F. gigantica* in the semi-arid ecological zone of Nigeria and West Africa.
v. The appropriate time for the treatment of herd by adulticidal fluke drugs as this study suggests is February to May in northern Nigeria when the transmission is not high due to soil moisture deficit and is the period during which drugs are more effective in stopping the development of flukes to bile duct stages.
vi. The spatio-temporal variability in transmission as the results of this study suggest indicating where both human and capital resources should be targeted for effective monitoring. The data obtained from such monitoring can enhance our understanding of the likely impacts of changes in climate on *F. gigantica* prevalence and information can be derived that can assist in designing appropriate adaptive measures.

CHAPTER 6

Investigation of risk determinants of *Fasciola gigantica* infection in slaughtered cattle based on a cross-sectional survey in Sokoto State, Nigeria.

6.1Preface

In the previous chapters (4 and 5) species distribution models were used in determining the geographic distribution range and transmission pattern of *F.gigantica* in Sokoto State. These models were developed using abiotic or physical factors only. However, biotic factors or biological characteristics of animals affect the incidence of fascoliasis (Soberon & Peterson 2005, Yatswako & Alhaji, 2017).

This chapter incorporated both biotic factors and abiotic factors in investigating their influence in *F.gigantica* infections prevalence among the slaughtered cattle at abattoirs. Binary logistic regression is a technique that applies to species distribution models in finding the associations between a binary response variable and explanatory or independent variables (Franklin, 2009b).

6.2 Introduction

Fasciola gigantica is a significant constraint on the health and wellbeing of 16 million cattle in Nigeria due to the increasing number of condemned livers in various abattoirs in all the geopolitical zones of the country (De Bont J et al., 1994, Elelu et al., 2016a). Conraths et al. (2011) reported that there is a change in the economic status of low-income class into middle class across the world. Hence, they added that the demand for animal products might rise by 30% up to 2030 which would stimulate animal production globally. In the Nigerian economy alone, the contribution of livestock specifically cattle according to the Central Bank of Nigeria, CBN (1999) was about 12.7% of total agriculture gross domestic product (GDP). However, disease such as fascioliasis with a cosmopolitan distribution is affecting animal's productivity, and therefore the World Health Organisation has recommended the need to formulate appropriate strategies to control the disease (WHO, 2006). Also, the economic losses due to fascioliasis have been estimated to be over US$800 million per annum in Africa's 200 million cattle population (Spithill et al., 1999b). According to Orlandi et al. (2002), *F. gigantica* being one of the species of trematodes has recently been enlisted as a significant disease by Food Technologist' Expert Panel on Food Safety and Nutrition.

It was highlighted by Bunza et al. (2008b) that two major categories of factors have been affecting the geographical distribution of *F. gigantica* which include climatic and environmental factors on one hand and livestock characteristics as well as associated practices of grazing management factors on the other hand. That has been corroborated by Tum et al. (2004) who reported that the risk of infection of fascioliasis could be 'influenced' by the population of animals and also a system of animal grazing that determines their accessibility to both contaminated water and pasture. This approach of study that focuses on practices of herd management as potential risk factors when complemented with climatic factors can assist significantly in recognising infection sources and most effective way of designing control programs (Roberts & Suhadono, 1996)

There is a plethora of research on the influence of climate in the spatial dispersal and transmission pattern of fascioliasis across the various regions of the world (Yilma & Malone, 1998, Fox et al., 2011, Kantzoura et al., 2011b). In contrast, according to Adedokun et al. (2008), only a few known studies have investigated the effects of non-climatic factors such as sex, breed of the animal and age in the prevalence of fascioliasis in different ecological zones of the globe. These non-climatic determinants influence indirectly on the parasite through the definitive hosts via livestock and incidentally even humans.

In Nigeria, no known study focused on risk determinants based on herd management practices of slaughtered animals at abattoirs for *F. gigantica* infection. In northern Nigeria, a major producer of livestock to other parts of the country, the knowledge of risk factors for fascioliasis infection is scanty with only a few studies documenting risk factors at herd level and slaughtered cattle at abattoirs. (Schillhorn Van Veen et al., 1980, Ardo et al., 2014, Elelu et al., 2016a). This study presents the first effort at identifying the effects of both biotic and abiotic factors on fascioliasis infection in slaughtered cattle at an abattoir in Sokoto State. The research would serve as a guide in designing effective control measures against fascioliasis infection prevalence.

6.3 Materials and methods

6.3.1 Climate and environmental variables

This chapter used yearly averages of relevant climatic variables that affect the life cycle of fascioliasis and its intermediate host snails in binary regression techniques as independent variables while the binary response was presence and absence of *F.gigantica* infections. These variables include rainfall, temperature, NDVI, soil moisture and elevation.

6.3.1.1Rainfall

Refer to section 4.2.3.6 in chapter 4 for the description of the rainfall dataset used in the present chapter.

6.3.1.2 Land Surface Temperature

The land surface temperature used in this chapter was described in section 4.2.3.4 of chapter 4.

6.3.1.3 NDVI

The description of NDVI dataset used in this chapter refer to section 4.2.3.5 in chapter 4

6.3.1.4 Soil moisture

The soil moisture variable used in this chapter was described in chapter 4 section 4.2.3.7

6.3.1.5 Elevation

This chapter used elevation as described in section 4.2.3.3 in chapter 4

6.3.2 Study design and sampling

A cross-sectional survey was carried out in July to August to investigate the prevalence of *F. gigantica* infections and herd management practices risk factors in cattle in 10 provinces of Sokoto State, northwestern Nigeria. These provinces were drawn to represent the four agricultural zones of Sokoto State, which encompass the entire 23 local government areas. The agricultural zones include Sokoto, Isa, Gwadabawa and Tambuwal (Abubakar et al., 2013). In Sokoto zone Rabah was selected, in Isa zone, Goronyo was selected, in Gwadabawa zone, Silame was selected, in Tambuwal zone both Dange shuni and Shagari were selected.

A total of 300 slaughtered cattle were randomly sampled for *F. gigantica* infections. For each sampled cattle the owner of the herd from which it belongs was selected. *Sarkin fawa* (King of the abattoir) was very handy in tracing the owners of each of the sampled slaughtered cattle.

6.3.3 Data collection

This study administered two questionnaires to elicit relevant information regarding the biological characteristics of each slughtered cattle and socio-demographic status of the the owners of slaughtered cattle. The biological characteristics of each slaughtered cattle include breed, its source, age, sex and age. In addition, cattle owners socio-demographic characteristics centred on herd management system and the knowledge of the disease among others. The disease fasciolosis is known in the study area by different names as butchers and herdsmen refer to it as “ciwon hanta” as well as “Fadama”. The latter name implies the association of the parasite with moisture due to its association with the marshy areas that are common along the river sides in the study area (Muhammad, 2007).

6.3.4 Faecal test

Faecal samples were collected from the rectum of each sampled slaughtered cattle with the aid of plastic gloves in line with Hansen and Perry (1994) report. The plastic glove was carefully twisted inside out and taken under suitable conditions to Parasitology laboratory of Usmanu Danfodio Veterinary Teaching for analysis. Also, the bile from the gall bladder of each selected cattle was obtained along with the faeces.

Sedimentation technique was applied by this study as adopted by MAFF (1986), Hansen and Perry (1994), Bunza (2007), Magaji et al. (2014), (Sah et al., 2018). The following equipment was required: Beakers, tea strainer, measuring cylinder, means of shaking the mixtures, test tubes, cover slips, teaspoons as well as a microscope. A beaker is a cylinder container made up of glass commonly used in the laboratory. The tea strainer is a device used in the filtering of small solid particles from the liquid. A test tube is a tube like a device made of glass with only one opening that can contain a small number of substances for laboratory testing. The microscope is an optical device that can magnify an image of either animal or plant or animal cells for viewing.

In the laboratory, a quantity (3g) of faeces contained in a test tube was mixed with 40-50ml of tap water. That would result in a solution with suspended particles of faeces. The tea strainer was used in filtering the suspension after blending with the aid of a fork and then poured into a test tube. In order to allow the suspension to settle properly the sediment was left for five minutes after adding 10% formalin. Then the suspended particles in the form of liquid substances referred to as supernatant were ejected with utmost caution. The resulting sediment containing eggs of fascioliasis in the test tube was centrifuged at 2000rpm. These sediments were later mixed with the 5 ml of water and 1ml of diethyl-ether and then gradually allowed to settle for another five minutes. That was also again followed by ejecting supernatant cautiously as done previously. Microscopic examination was carried out on the sediment that was strained with a drop of methylene blue that was poured on to micro slide enclosed with a cover slip at a magnification of 10*10.

6.3.5 Statistical techniques for data analysis

In this study, the percentage of *F. gigantica* prevalence at each of the sampled locality was computed as the total number of cattle that were positive (with infection) divided by the population of all the sampled slaughtered cattle. Chi-square is a statistical measure that can be applied in a situation where there is a categorical or discrete variable with the sole aim of testing the fitness of 'each category' to a 'theoretical expectation'(McDonald, 2008). Hence this technique was used in this study to evaluate the associations between the *F. gigantica* prevalence and practices of herd management and also cattle data. The equation for calculating chi-square is

$$\chi^2 = \sum \frac{(O - E)^2}{E} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots equation\ 1$$

where O is the observed values about the total number of the infected and not- infected cattle, E is the expected value(McDonald, 2008).

In the calculation of Chi-square the response variable was fascioliases cattle infection status which was represented as a binary variable (B=absence; A = presence) and the independent or predictor variables were the characteristics of the slaughtered cattle, practices of cattle management, individual cattle data and satellite based climate and environmental data. The coding of each factor as a response from the respondents was entered into excel spread sheet along with its corresponding status in terms of infection either positive (A) or negative (B) (see Tables A-4, A-5 and A-6 in appendix). For example gender (F=female, M=male), animal source (1= local, 2=exotic), herd acquisition (1=purchased, 2=gift, 3=inherited), water source (1=Dams/fadama/lakes, 2=Tap/well water), grazing areas (1=fringes of lakes/rivers/ponds, 2=Market, 3=government reserved areas), tribe (A= Hausa/Zabarma, B=Fulani). Similarly, the values of each climatic variable was entered in respect of the sampled slaughtered cattle across the selected localities (see Table A-6 in the appendix). This Chi-square technique was used in analysing the associations between fascioliasis infections and both biotic and abiotic factors by various studies (Kantzoura et al., 2011a, Magaji et al., 2014, Elelu et al., 2016a, Yatswako & Alhaji, 2017).

In addition to Chi-square, this study applied binary regression in order to estimate the likelihoods of (example) infection prevalence as a function of independent or predictor variables; $\pi = \Pr(Y = 1|X = x)$ (Boonrak, 2017). This method was used to determine the proportion of fascioliases infections in the population of the sampled slaughtered cattle. Risk factors such as gender, age, the source of each cattle, the tribe of the herdsmen and climatic variables were used in assessing their influence in causing the infections among the slaughtered cattle. For example, consider any of these independent variable as X in causing the infection of fascioliases. So the likelihood of infection with the disease will depend on the influence of each risk factor.

$$\pi_{i=\mathrm{P}_r}\left(Y_{i=1}\middle|X_{i=x_i}\right) = \frac{exp\left(\beta_0 + \beta_{1x_i}\right)}{1 + exp(\beta_0 + \beta_1 x_i)} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . equation\ 2$$

where Y represents categorical or binary variable indicating presence or absence of infection

Y_i= 1 if the infection is present in the sampled slaughtered cattle

Y_i= 0 if the infection is absent in the sampled slaughtered cattle within observation i

Exp = is the odds of being in one of the categories

X= (X_1, X_2.,…, X_k) being a collection of independent variables that can be nominal, categorical and the risk factors are age, gender, origin/source of cattle and the tribe of the herdsmen.

The use of binomial regression in this study is appropriate since it involved examining the influence of a set of predictor variables on categorical or binary response variables (Stevens, 1980). This technique was very flexible in assessing the odds of becoming a member in one of the classes in the binary variable (infected and not infected) as a response to the influence of the set of independent variables. Minitab 17 Statistical Software was used in this study due to its flexibility in running the binary logistic regression model especially through the inclusion of various indices of goodness-of-fit as reported by Peng et al. (2002). The test of statistical significance for the binary model of logistic regression was analysed using the χ^2 test table of model coefficients. The value of OR showed the odd ratio that is predicting the likelihood of the disease occurrence in the sampled slaughtered cattle at a 95% confidence interval.

In this study, the goodness-of-fit which imply the fitness of the regression model to the data on *F.gigantica* infection often regarded as model's predictive performance (Guffey, 2012) was carried out using Hosmer-Lemeshow. This technique was described as an appropriate measure of calibration in the evaluation of the predictive performance of the logistic regression model (Steyerberg et al., 2010). The Hosmer-Lemeshow calibration indices evaluate the overall agreement between the model's predicted likelihood of the disease occurrence and the empirical observation. The formula after (Hosmer & Lemeshow, 1980) is:

$$\widehat{HL} = \sum_{i}^{K} \frac{(o_i - n_i\bar{p}_i\ )^2}{n_i\bar{p}_i(1-\bar{p}_i)}\ \sim X^2_{k-2} \dots \dots \dots \dots \dots \text{equation 3}$$

where o_i the number of infected disease cases as observed outcome cases in group i, n_i is the number of all the sampled cases as the totality of observations in group i, $\bar{p}_i$ is the mean predicted likelihood of disease occurrence in group i, and K is the number of risk factors or group in the model.

Contrary to other measures of statistical test, in Hosmer-Lemeshow the *P* values of above 0.05 indicate a good fit to the model (Steyerberga et al., 2001, Boonrak, 2017). That implies the absence of statistically significant differences for even a single group in the predictions of the number of events in comparison to the total number of observations (Guffey, 2012). According to Schuppert (2009) binary logistic regression has an advantage over linear regression of avoiding any assumptions of linearity, normality and about the sameness of variances.

6.4 Results

6.4.1Cattle management and slaughtered cattle data

The characteristics of the owners of the slaughtered cattle in the selected localities during the field survey are shown in table 6:1. Males constitute 88.3% of the respondents while females were only 11.7 %. Likewise, the age group between 16-45 years were the majority (61.6%) while the group with the lowest number of respondents were those in the age category of 60 and above (mean age was 36.45, SD± 14.59, range 17-63 years). A more significant number of the respondents were married (71.7%) and without any formal education (73%). Most of the respondent acquired their cattle through inheritance

(56.7%) while those whose cattle were given as a gift to them constitute only 14.3%. The slaughtered cattle were reared mostly by Fulani (54%) then the Hausa/Zabarma ethnic group (46%).

A total of 300 hundred cattle were slaughtered with a mean age (in months) of 44.1 (SD ±17.302, range 23-74 months). Female cattle were slaughtered more (51.3%) than male cattle (48.7%). Regarding the breed composition, Sokoto Gudale was the most dominant (52.7%) followed by Red Bororo with 28.7% while the white Fulani breed constitutes only 18.7% of the slaughtered cattle.

Table 6 -15 : Demographic characteristics of the owners of the slaughtered cattle in studied provinces in Sokoto State, Nigeria

Demographic characteristics	Frequency	Percentage
Sex		
Male	265	88.3
Female	35	11.7
Total	300	100
Age(years)		
16-45	185	61.6
46-60	90	30
Above 61	25	8.4
Total	300	100
Marital status		
Single	85	28.3
Married	215	71.7
Total	300	100
Education level (formal)		
Primary	80	43.3
Secondary/ Higher institution	10	3
None	220	53.7
Total	300	100
Source of cattle		
Purchase	87	29
Inherited	170	56.7
Gift	43	14.3
Total	300	100
Tribe		
Hausa/Zabarma	138	46
Fulani	162	54
Total	300	100

6.4.2 Faecal test data

A faecal test analysis of 300 samples from the slaughtered cattle in 10 provinces revealed that 92 (30.7%) were positive for the presence of *F.gigantica* parasite while 208 (69.3%) were unaffected. The spread of infections was found across all the surveyed localities ranging from 26% to 43% (Table 6:2). The highest *F.gigantica* infection was documented in Kebbe (43%), Sokoto North (40%) and Shagari (40) (Figure 6:1).

Table 6 -16: Slaughtered cattle F.gigantica infections from the provinces studied in Sokoto State, Nigeria

Provinces	Slaughtered cattle	Sample size	Infected	Percent positive
Goronyo	223	30	09	30
Kebbe	119	30	13	43
Wurno	196	30	09	30
Gada	203	30	06	20
Sokoto N	535	30	12	40
Gudu	205	30	06	20
Silame	251	30	08	26
Shagari	121	30	12	40
Dange shuni	108	30	08	26
Rabah	124	30	09	30
Total	2085	300	92	30.7%

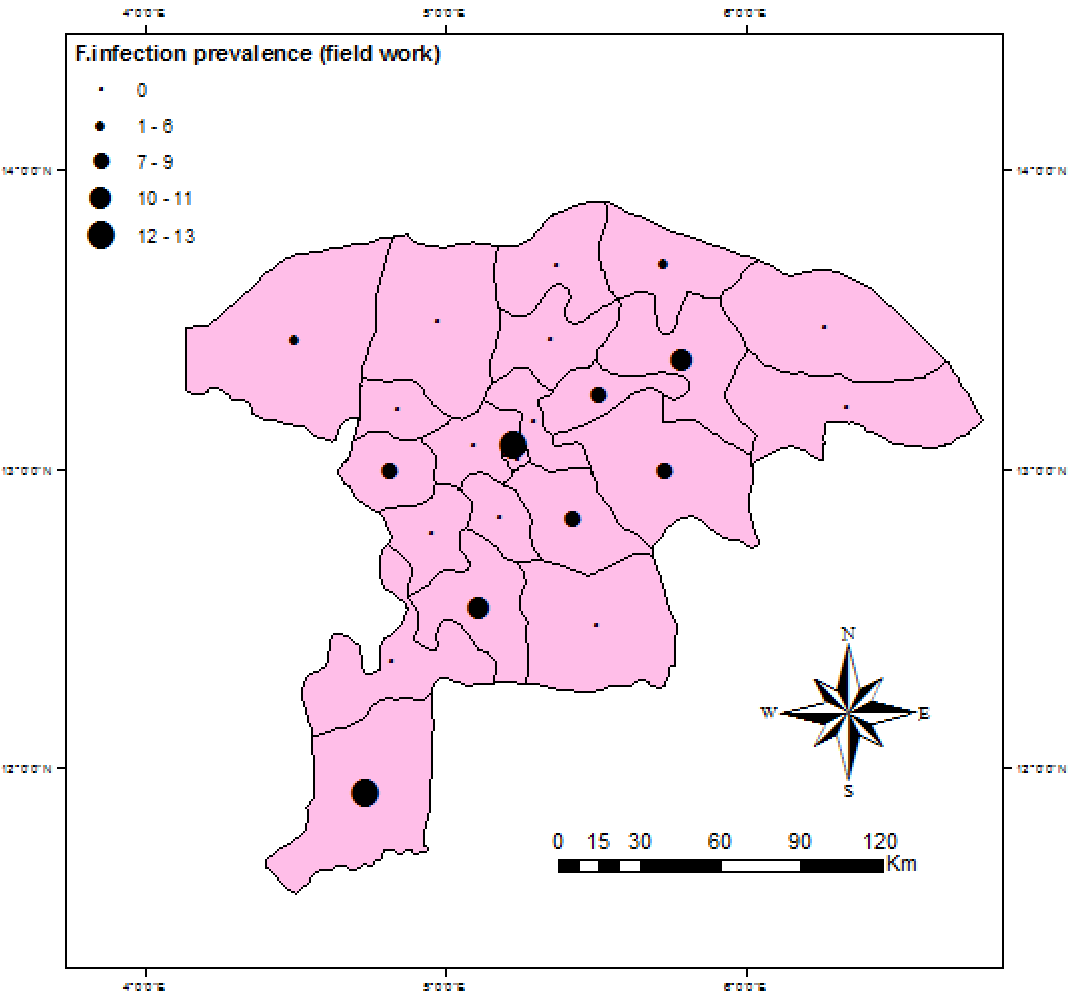


Figure 6-38: Prevalence of fascioliasis infection across the 10 provinces studied in Sokoto State. The different dots indicate varying prevalence rates as recorded during the analyses of the faecal samples of the slaughtered cattle while dot that represents *zero value shows areas that were not surveyed.*

6.4.3 Associations between risk factors and *F.gigantica* infections

The relationships between the slaughtered cattle characteristics and *F.gigantica* infections were explored using Chi Square statistical test. The analysis revealed that there is a significant association between the characteristics of the slaughtered cattle that bordered on the source of cattle (from either local or exotic), age and breed and *F.gigantica* infection. However, the relationship between gender of the slaughtered cattle and fascioliasis infection was not significant (P>0.05) as shown in Table 6:3.

The association between the practices of cattle management with *F.gigantica* infection was investigated in Table 6:4. The respondent's responses regarding how they acquired the slaughtered cattle, the source of drinking water for their cattle as well as the tribes of the cattle holders were significantly associated with the *F.gigantica* infection. This study further confirmed that the type of pastures where the slaughtered cattle of the respondents grazed was not significantly associated with fascioliasis infection.

The climatic variables such as temperature, NDVI, rainfall, soil moisture and elevation were found to be associated with *F.gigantica* but not significantly as shown in table 5.

Table 6-17: Association between the slaughtered cattle characteristics and F.gigantica infection in selected abattoirs and slaughter slabs in Sokoto State.

Risk factors	Chi-Square	df	*P*-Value
Animal source	10.05	1	< 0.001***
Age	28.96	1	< 0.001***
Breed	5.40	1	<0.05***
Gender	2.16	1	>0.05

***= significant test

Table 6-18: Association between practices of herd management and F.gigantica infection in selected abattoirs and slaughter slabs in Sokoto State.

Risk factors	Chi-Square	df	*P*-Value
Cattle/herd acquisition	14.40	1	< 0.001***
Grazing areas	0.25	1	>0.05
Water source	8.69	1	<0.05***
Tribe	17.41	1	<0.05***

Table 6-19: Association between Climatic factors and F.gigantica infection in selected abattoirs and slaughter slabs in Sokoto State

Risk factors	Chi-Square	df	*P*-Value
Temperature	1.50	1	> 0.05
NDVI	0.52	1	> 0.05
Rainfall	0.05	1	> 0.05
Soil moisture	0.03	1	> 0.05
Elevation	0.00	1	> 0.05

6.4.4 Effects of risk factors on fascioliasis infection

The result of the binomial logistic regression is shown (in Table 6:6) explains the effects of the source or origin of cattle, age, breed and gender on *F.gigantica* infection. All these factors were statistically significant (*P*<0.05) except gender (*P*>0.05). The Hosmer-Lemeshow test indicated that the model fitted the data well (*P*=0.716). Moreover, the analysis showed that the source of animals that is weather exotic or local was not related to an increased likelihood of *F.gigantica* infections (OR: 0.2734; 95% confidence interval CI: 0.1137-0.6570). Age of cattle more significant than 24 months was found to be more likely to fascioliasis infection (OR: 1.0498; 95% CI: 1.0305-1.0695) than the younger ones. The breed of cattle of being either white Fulani, Red Bororo and Sokoto Gudale was associated with an increased likelihood of infection with *F.gigantica* (OR: 1.5934;

95% CI: 1.0641-2.3860). Male cattle were 0.6 times less likely to be infected with *F.gigantica* (OR: 0.6213; 95% CI: 0.3302-1.1688) than female cattle.

The likelihoods for *F.gigantica* infection due to the practices of cattle management were shown in table 6:7. The ways the cattle were acquired either through inheritance, been purchased from the market or received as a gift was found to be related to increased probability of fascioliasis infection (OR: 1.9700; 95% CI: 1.3612-2.8510). Similarly, cattle belonging to Fulani were more likely to be infected with *F.gigantica* (OR: 3.1229; 95% CI: 1.7959-5.4303) than those cattle that belonged to Hausa/Zabarma ethnic groups. However, grazing areas and source of drinking water for cattle were found to be associated with decreased likelihood of infection with *F.gigantica*(OR: 0.8980; 95% CI: 0.5895-1.3679) and (OR: 0.3539; 95% CI: 0.1696-0.7381) respectively. The model that used practices of cattle management associations with the likelihood of infections with *F. gigantica* was well fitted according to the Hosmer-Lemeshow test (*P*=0.644).

Climatic factors and their associations with the probability of infections with *F. gigantica* is shown in table 7. Although the associations of all the variables in the model were not statistically significant (*P*>0.05), the data fitted the model as revealed by the Hosmer-Lemeshow test (*P*=0.984). Elevation has an association with increased likelihood of infection with *F.gigantica* infections (OR: 1.0004; 95% CI: 0.9796-1.0216). NDVI (at 95% confidence interval) indicated an increased likelihood of infection with fascioliasis ((OR: 0.1753; 95% CI: 0.0016-19.7182).

Table 6-20: Slaughtered cattle characteristics and the likelihood of F.gigantica infection using binary logistic regression

Risk factors	Odds Ratio	95% Confidence Interval
Animal source	0.2734	(0.1137-0.6570)
Age	1.0498	(1.0305-1.0695)
Breed	1.5934	(1.0641-2.3860)
Gender	0.6213	(0.3302-1.1688) NS

Table 6-21: Practices of herd management and the likelihood of F.gigantica infection using binary logistic regression

Risk factors	Odds Ratio	95% Confidence Interval
Cattle/herd acquisition	1.9700	(1.3612-2.8510)
Grazing areas	0.8980	(0.5895-1.3679)
Water source	0.3539	(0.1696-0.7381)
Tribe	3.1229	(1.7959-5.4303)

Table 6-22: Climatic factors and the likelihood of F.gigantica infection using binary logistic regression

Risk factors	Odds Ratio	95% Confidence Interval
Temperature	0.7904	(0.5422-1.1520) NS
NDVI	0.1753	(0.0016-19.7182) NS
Rainfall	0.9993	(0.9929-1.0057) NS
Soil moisture	0.9963	(0.9531-1.0414) NS
Elevation	1.0004	(0.9796-1.0216) NS

6.5 Discussion

This study presents the first efforts towards determining the prevalence and possible risk factors associated with the slaughtered cattle in Sokoto State, Nigeria. Not long ago, it has been reported by Moll et al. (2000) and Coles (2005) that the conventional method of using drugs for the treatment of *F.gigantica* infection is no longer beneficial. This situation, therefore, demands to investigate risk determinants associated with the slaughtered cattle in order to design a more accurate way of decreasing the infection and for the improvement of meat quality.

The sedimentation technique employed by this study to test for the presence of *F.gigantica* parasite revealed 30.7% infection. This percentage is higher than 27.6% reported by Magaji et al. (2014) which was based on only one abattoir in Sokoto metropolis. The prevalence rates recorded by Ardo et al. (2014) in Adamawa was 21.8% and also in south eastern Nigeria Ikeme and Obioha (1973) reported 26% which were all lower than the prevalence rate reported in this study. In Bauchi, north central Nigeria Sugun et al. (2010) reported 76.9 % and also Elelu et al. (2016a) recorded 74.9% in Kwara state north-central Nigeria. These variations in prevalence may be due to environmental factors and animal density between the areas of study. Also, separate cattle management systems employed by different localities may have accounted for such differences (Abunna et al., 2010). The *F.gigantica* prevalence rate recorded in this research is higher than 26% obtained in the Sahelian area of Kenya by Mungube et al. (2006) but lower than 36.5% obtained in Uganda based on the study by Magona et al. (1999) but almost similar to 31.7% reported by Pfukenyi and Mukaratirwa (2004) in Zimbabwe.

Regarding age, the prevalence of *F.gigantica* infection was significantly more associated with older cattle then younger ones. This finding may be due to a decrease in immunity to fascioliasis infection in respect of the older cattle and comparatively higher in younger ones. This view was supported by Esch (1977) and Anon (1992). Also, studies by Schillhorn Van Veen et al. (1980) and Pfukenyi et al. (2006) reported that older cattle were more susceptible to *F.gigantica* infection due to prolonged exposure at regular grazing sites. Similar to this study, older cattle were found by Ardo et al. (2014) had higher *F.gigantica* infection rate than the younger slaughtered cattle in Adamawa state, north-eastern Nigeria. This type of findings was also reflected in Tanzania by Nzalawahe et al. (2014) and Botswana by Mochankana and Robertson (2018). The study area composed of agrarian society and hence have been using cattle for various purposes including transportation and in ploughing. In that regard older cattle over time may have lost the ability to carry out such operations. So most of the respondents offer them for sale in exchange for younger ones that can work on farms and in the provision of milk. That, therefore, may be responsible for having a higher number of older cattle that were slaughtered in most of the abattoirs in Sokoto State, and perhaps some parts of Nigeria. Also, older cattle are significant preferences when the need to raise money for 'religious' and 'domestic purposes' arises as reported by Elelu et al. (2016b).

This study reveals that there is a statistically significant relationship between breeds of cattle and infection of *F.gigantica* in Sokoto State. Sokoto Gudale and Red Bororo were the most predominant breeds with higher prevalence rate. The variations in infection rate across different breeds may be attributed to physiology, immunology and genetics of each breed which according to Molina (2005) and Yatswako and Alhaji (2017) can influence 'resistance and resilience to *F.gigantica* infections'. Similar to the findings in this study Sokoto Gudale breed was having higher prevalence rates as reported by Magaji et al. (2014) in the abattoir of Sokoto metropolis. Contrary to our findings, Red Bororo had more infections then the other breeds in Adamawa by Ardo et al. (2014). In Botswana, also various breeds of cattle indicated differences in fascioliasis infection tolerance as reported by Mochankana and Robertson (2018).

Regarding the gender of the animals, in this female study cattle had a higher burden of *F.gigantica* infection (51.3%) than males (the bulls) (48.7%). Some reports in Nigeria by Yatswako and Alhaji (2017) and Ulayi et al. (2007) were in agreement with our studies. Fatima and Chislti (2008) also recorded a higher prevalence of *F.gigantica* in cows than bulls in Egypt. This imbalance in infection rate among the female cattle was due to reproductive processes that tend to undermine their immunity to *F.gigantica* infection. This observation got support from Soulsby (1982) and Schillhorn Van Veen (1997). In contrast to our findings in some abattoirs in Gwagwalada and Jalingo in northern Nigeria Idris and Madara (2005) and Obadiah (2010) respectively reported bulls were more susceptible to fascioliasis infection than the female cows.

Analysis of modes of acquiring the ownership of cattle as a risk factor has indicated inheritance as a most crucial predictor of *F.gigantica* in the study area. That is because the act of keeping cattle in Sokoto State is a traditional farming practice that has been passed on from successive generations using the same methods of management. Hence, exposure of cattle to the risk of infection would increase owing to the high illiteracy rate among the cattle owners as confirmed by this study (Table1). A study in support of this observation was carried out by Elelu et al. (2016b) who reported that the significant custodians of cattle in Nigeria have inadequate knowledge of risk determinants associated with animal diseases including *F.gigantica*. Similarly, tribe or ethnic background of the respondents proved to be a significant factor that has a high likelihood of increasing the risk of *F.gigantica* infections in Sokoto State. That is because Fulani ethnic group had the largest population of cattle not only in Sokoto state but the whole of Nigeria(FMAWR, 2008). They are described as pastoralist (Elelu et al., 2016b) that are constantly on the move in search of water and grass for their animals. Even sedentary Fulani's (those that area settled permanently at one place) in the study area inhabit settlements where the primary sources of water for their livestock are ponds, streams, lakes and irrigation sites. These sites present appropriate conditions for gathering of animals in search of pasture and for drinking which eventually aids the transmission of fascioliasis. This situation has already been captured in a study by Njau et al. (1988) and Durr et al. (2005).

The fitness of the regression model used in this study has not only been limited to determinants of risk such as cattle characteristics, herd management and cattle holders' status in increasing the likelihood of cattle infection with *F.gigantica* but also climatic factors. The binomial regression model identified these climatic variables as important determinants of *F.gigantica* risks in the study area. Although these factors were statistically non-significant, the result reflects the advantage of biological characteristics as a more critical determinant of *F.gigantica* risk at individual cattle slaughtered at the abattoir. That is because in the present study (chapter 4 and 5) and other studies have demonstrated the significant roles of climatic and environmental conditions in influencing fascioliasis infection risks at different spatial units-local, regional and continental levels (McCann et al., 2010a, Fox et al., 2011, Caminade et al., 2015, Malone et al., 1998a). Thus, the main conclusion of this study is that botic factors were more significantly affecting fascioliasis infections at individual slaughtered cattle at the abatoirs than abiotic factors. Similar to this study, Kantzoura et al. (2011a) reported that there was a non significant relationship between climatic risk factors and fascioliasis infection among sheep and goats using the binary regression model in Thessaly, Greece.

6.5.1 Conclusions

This study has indicated the prevalence of *F.gigantica* infections in slaughtered cattle in Sokoto State using coprological analysis. However, other techniques of testing for the presence of fascioliasis include a haematological and seropositive analysis which were very useful indicators but outside the scope of our study. Other studies have applied these approaches (Kantzoura et al., 2011a, Elelu et al., 2016a). Regression techniques are an essential tool in species distribution modelling(Franklin, 2009b). In that light, Cringoli et al. (2004) and Fuentes et al. (2006) added that new development in the study of diseases is to apply regression model to a specific area of study and then extrapolate the modelling predictions to a different area (s).

Given that, extrapolation of the result of this study should be done cautiously as even within the north-west ecological zone of Nigeria variations may exist regarding risk factors examined in the present study. Nigeria is a large country with diverse ecological conditions. Hence, there is a need for another study from the southern part in order to investigate potential risk factors affecting *F.gigantica* infections. Moreover, research on the influence of seasons on fascioliasis are limited (Adedokun et al., 2008, Sah et al., 2018) future studies should incorporate such significant directions. Nevertheless, the effects of the risk factors that were investigated using regression model in this study can be precious in designing effective control methods for *F.gigantica* prevention in slaughtered cattle in Nigeria.

Chapter 7

General discussion, Conclusions, and future research recommendations

7.0 Introduction

This study indicated the relevance of species distribution models in the predictions of the spatial distribution of *F.gigantica* in semi-arid Sokoto State. Despite non-inclusion of biotic factors (such as competition between species, migrations or geographic obstacles to dispersal), the species distribution models using abiotic factors proved to be useful indicators of fascioliasis risk across different parts of the world (Fox et al., 2011, Caminade et al., 2015, Malone et al., 1998a, Islam et al., 2014, Khanjari et al., 2014). In addition, this research shows the relevance of both BioClim and satellite-based aggregated climate data in model construction. Besides, the study used the most recent field survey data on biological characteristics of slaughtered cattle and examined their associations with fascioliasis infections in the study area.

Including the future climate data projections in both generic and species-specific models in this thesis was in appreciation of the dynamic nature of climate due to both natural and anthropogenic activities. Intergovernmental Panel on Climate Change (IPCC, 2007) projected that the world experienced a rise in temperature of $0.7^{O}C$ since 1970 and towards the end of the 21^{st} century the increase in temperature would be $1\text{-}6^{O}C$. In Nigeria, the climate of the current conditions indicated $0.014^{O}C$ and 6mm day increases for temperature and rainfall between 1970 and 2000 respectively in all the ecological zones (Babatunde et al., 2011). Regarding future projections, Dike et al. (2015) reported potential changes in temperature and precipitation for northwest Nigeria under RCP 8.5 of climate change scenario based on HADGEM2-ES model for the year 2080. Also, the occurrence of extreme hydrological events recently caused severe floods across all parts of Nigeria including Sokoto State due to reduced frequency but heavy rains and higher evapotranspiration (Etuonovbe, 2011, Yusuf & Jones, 2014). These changes are disproportionately affecting developing countries like Nigeria and more pronounced in the northwest that encompass the study area. Regarding that, Diffenbaugh and Giorgi (2012) described entire northwestern Nigeria as a hot spot of climate change. Thus it is essential to understand how this changes in climate at both temporal and spatial scales affect the distribution range and intensity of fascioliasis incidence using species distribution models in the study area.

Chapter 4 compared presence-only generic species distribution models in determining the geographic range of fascioliasis and also applied the use of BioClim and satellite-based variables in model constructions in different scenarios. However, general species model scenarios developed with only BioClim variables provided the most accurate predictions of the geographic distribution of *F.gigantica* infections in Sokoto State. That was because BioClim variables were more suitable than aggregated yearly averaged climate variables in influencing the biological machanism of plants and animal species (Kriticos et al., 2014, Reddy et al., 2015). In addition, the chapter examined the long-term effects of climate projections on a future geographic range of *F.gigantica*.

In chapter 5, the focused was on both short term and long term future projections of *F.gigantica* risk. The application of the index presents the first adaptation of fasciolaisis risk index using GIS analysis in semi-arid West Africa. Chapter 6 explored the associations between intrinsic and extrinsic factors on fascioliasis infections among slaughtered cattle in Sokoto State. Given that, the chapter examined for the first time the socio-economic characteristics of the owners of the slaughterd cattle and their relationships with *F.gigantica* infections in Sokoto state. This chapter presents the general discussions, conclusions, and future research recommendations.

7.1 Conclusions

In this study, the overall aim was to develop spatial species distribution models to predict liver fluke *(F.gigantica*) in cattle, a case study of Sokoto State using relevant drivers (summarised at the end of chapter 1). To achieve this main aim the following specific objectives were accomplished:

1. **To compare the performance of MaxEnt, Domain, and BioClim in modelling the geographic range of fascioliasis.**

MaxEnt modelling technique has higher AUC than BioClim and Domain models and hence produced a more statistically significant spatial distribution range of fascioliasis in Sokoto State. Also, the use of threshold-dependent measures of accuracy such as sensitivity, specificity, TNR, FPR, and kappa all indicated MaxEnt as having the more significant performance. MaxEnt also got higher scores than BioClim and Domain models based on TSS and biserial correlation measures of the accuracy. Given this, MaxEnt proved to be an appropriate modelling technique that suits the species and the study area. In addition, MaxEnt performed well due to some additional reasons. Firstly, MaxEnt is a presence-only technique whose performance is not affected negatively by a few numbers of occurrence records (Phillips et al., 2006). This advantage makes it more applicable to third world countries where absence data for species distribution is scarce. Hence, the use of presence/absence techniques (such as GLM, GAM, Artificial Neural Network) in species distribution modelling presents some challenges in the study area. Secondly, the algorithm of MaxEnt is complex and deterministic in producing efficient modelling result (Elith et al., 2011). Given that, MaxEnt has upper hand in modelling the geographic range of both plants and animal species than regression techniques as previously reviewed (Pearce & Boyce, 2006, Phillips et al., 2006, Olden et al., 2008). In this study, the main benefits of using MaxEnt arise from their versatility regarding accountability for the relationships between fascioliasis prevalence, which is non-linear with each predictor variables. And secondly, the combined effects of associations of variables collectively on fascioliasis prevalence.

In this study, the performances of MaxEnt were statistically significant ($P<0.05$) in all the accuracy measures employed in this research. In addition, the AUC scores were higher than random predictions (>0.5) in all the six scenarios that used a different combination of variables.

2. To evaluate MaxEnt in modelling the spatial distribution of fascioliasis based on WorldClim derived climate data (BioClim) and satellite data using independent validation data.

Given the preceding discussion, it is evident and reasonable for MaxEnt to identify soil moisture and rainfall as the dominant predictor variables across the Bioclim and non-Bioclim scenarios in the study area. That, therefore, reflects the reality on the ground as the study area lies in the semi-arid ecological zone where the main source of moisture was rainfall that lasts for only 3 to 4 months of a year (Abdulrahim et al., 2013). In addition, other secondary sources of moisture for the survival of the parasite were the existing extensive floodplains or fadamas, irrigation sites, areas adjoining perennial lakes and streams. Similar to the findings of this study Yilma and Malone (1998) developed the geographic information system (GIS) forecast model to predict fascioliasis using rainfall and temperature variables in Ethiopia, East Africa. The results revealed that areas of high soil moisture content resulting from rainfall were more risky areas for fascioliasis prevalence. Other areas of high risk as revealed by their study include terrains that were proximate to permanent water bodies as well as at the fringes of dams where dry season farming of crops was taking place. Khanjari et al. (2014) and Pfukenyi et al. (2006) also reported that availability of soil moisture was among the top predictors that aid the growth of the *F. gigantica* parasite into various stages.

Precipitation is identified by this study as very important variable that influenced the distribution of fascioliasis in Sokoto State, through seasonal supply of moisture needed for the dispersal, reproduction and free-living stages of fascioliasis (Andrews, 1999, Altizer et al., 2006, Mas-Coma et al., 2009). According to Bunza et al. (2008b), rainfall also influences the activities of infected snails in the distribution and transmission of fascioliasis. That illustrates the significance of rainfall in affecting every stage of the lifecycle of fascioliasis. However desiccation or moisture deficit conditions and dryness for some period will lead to mortality of the parasite (Spithill et al., 1999b). Fox et al. (2011) also reported that rainfall is one of the most influential factors in the prevalence of *F. gigantica* especially in the semi-arid ecological zones of the World.

The MaxEnt modelling also predicted mean diurnal temperature as the most important determinants of *F. gigantica* distribution in the study area. Due to the location of the Sokoto State in the tropics, the prevailing temperature condition hardly falls below the minimum value required for the completion of the life cycle of *F. gigantica* throughout the year (at optimum range of) 16^0 to 45^0 C (Saleha, 1991, Andrews, 1999, Graczyk & Fried, 1999, Fairweather et al., 1999, Spithill et al., 1999b, Mas-Coma et al., 2009, Fox et al., 2011). According to Andrews (1999), the processes of embryonation and evolution in the life cycle of fascioliasis are being significantly influenced by temperature within tolerable limits that is between 23^0C to 30^0C. Valencia-López et al. (2012) further confirmed that temperature variables are very significant predictors of fascioliasis.

Normalised Difference Vegetation Index (NDVI) is an index that assesses the density and greenness of vegetation and was found by this study to be a very significant predictor of *F. gigantica* distribution. The locations of most suitable areas lie in the fadama of Sokoto State that supports vegetation around lakes, ponds and streams. NDVI 'proved' to be an essential determinant of risk due to fascioliasis (Afshan et al., 2014). In a similar development, Fuentes et al. (2001) and (Kantzoura et al., 2011b) described NDVI as an instrumental variable in the risk assessment due to fascioliasis.

Elevation made a significant contribution to the modelling of fascioliasis distribution in this study. That is because of the relationships between elevation and hydrological, geomorphological as well as biological processes (Moore et al., 1991). Elevation also affects the temperature regime, precipitation formation and in the flow and accumulation of rainfall water at lowland areas of the landscape which subsequently determines soil moisture availability (Franklin, 2009b). Moreover, soil moisture affects the growth of grass that animals feed on and if (the grass is) contaminated with cercariae aids the transmission of *F. gigantica*. In a related development, Zumaquero-Rı´os et al. (2013) and Rahman et al. (2017) report that low-elevation was found to be very suitable 'hotspots' and 'clusters' for the prevalence of *F. gigantica* specifically in Asia and Africa. The example is given in Figure 4-25.

The Sokoto north and south being the core areas of suitability as predicted by MaxEnt probability map supports extensive fadama areas where agriculture including animal rearing, and food production are providing a livelihood for over 50,000 people (Adams, 1993, Dan-Azumi, 2010). Moreover, Abubakar et al. (2013) reported that Sokoto north and south had higher soil moisture content in the lowland areas at the valley of river Rima where animal graze during most times of the year. Similarly, such area supports a high density of animals (Table 4-7) which is consistent with the findings of a study by Tum et al. (2004) that applied geographic information system to create a model for mapping risk of fascioliasis in cattle in Cambodia where cattle density was confirmed to be a risk factor for fascioliasis transmission. Fabiyi and Adeleye (1982) corroborated that fact that in Nigeria the morphology of fascioliasis prevalence is consistent with zones of high animal density among others.

.3. To predict the spatial distribution of fascioliasis in the future under scenarios of climate change based on two Representative Concentration Pathways (RCP2.6 and 8.5) for two time periods of 2050 and 2070.

Fascioliasis is a disease with the highest widespread globally, and according to Mas-Coma et al. (2009), climate change has a significant impact on its present and future distributions. That is evident in this study where spatially the predicted areas were expanding between the current and future climatic condition due to climate change under RCP 2.6 and 8.5 for the years 2050 and 2070. It has also been reported that fascioliasis incidence is on the increase in EU member countries by de Waal et al. (2007) and also even in the U.K (VIDA). Therefore, the finding from this study illustrates the use of species distribution modelling specifically in developing countries in forecasting the potential distribution of *F. gigantica* under future climate projections in the semi-arid ecological zone of West Africa.

This study also revealed that precipitation and soil moisture were the most important factors that determined the geographic range of *F.gigantica* in the study area. Hence, the risk is expected to increase in the future in view of the simulated increase in these variables over the entire northwest ecological zones of Nigeria by some global circulation models including RCM, GFDL CM3 and CCSM4 (Vizy et al., 2013). That also supports the findings in this study, which indicated an expansion in the areal extent of suitable areas for *F.gigantica* prevalence based on RCP 2.6 and RCP 8.5 of the years 2050 and 2070.

4. To predict spatiotemporal changes in fascioliasis transmission risk through the use of the species-specific model under two Representative Concentration Pathways (RCP2.6 and 8.5) for two time periods of 2050 and 2070 in the study area.

Chapter 5 revealed the use of rainfall and temperature variables in providing a sound indication of both short-term and long-term future risk of fascioliasis infections in the study area through the applications of species-specific models. The fascioliasis forecast index has its origin in the correlative model developed by Ollerenshaw and Rowlands (1959) using the climatic conditions of temperature and moisture. Also, the reliability of the index expanded its applications in various parts of the world including East Africa where it was modified to suit both species of fascioliasis by Malone et al. (1998a). To date, as noted by Fox (2012) no method of modelling fascioliasis risk 'supersedes' that of Ollerenshaw index due to the paucity of accurate and reliable prevalence record. Ollerenshaw (1966) admitted that insufficient data on fascioliasis prevalence was the most significant impediments in the formulation of climate-sensitive and 'not a notifiable' disease forecasting including fascioliasis. Besides, documented incidences were only a few without precise inclusions of mortality rates among sheep and also lack of reporting data on annual variations in outbreaks (Ollerenshaw, 1966). In Africa, meat inspection from abattoirs is an essential information source for research due to limited ability to utilise laboratories for disease diagnosis (Phiri, 2006, Cadmus & Adesokan, 2009). Hence, meat inspection during abattoir surveillance provides disease information for documentation to relevant agencies in all the states in Nigeria including Sokoto State.

However, according to World Health Organisation (WHO, 2006) fascioliasis climate forecast in the United Kingdom served as a basis for establishment of early warning system (EWS) that for long arose the interest of various areas including academic, politics and practitioners. Given that, the National Animal Disease Information Service (NADIS, 2016) disseminates fascioliasis forecast information monthly to 1) Registered veterinary organisations in the UK, 2) farmers' cooperative societies with interest in ruminant livestock (English Beef and Sheep Meat Industry, Hybu Cig Cymru Meat Promotion Wales and Quality Meat Scotland, 3) to the Animal Medicine Training central coordinating agency via their ongoing Professional Training Development and 4) to animal farm related businesses. This study, will therefore be the first to stimulate the creation of fascioliasis forecast in northwestern Nigeria, where there is largest population of livestock.

The prediction of risk by the modelling technique in this study based on short-term (2005-2014) was in agreement with the fascioliasis distribution prevalence map within the same temporal range. Most of the areas with the highest disease incidences correspond to areas with the highest risk index. Regarding long-term projections, the validation is needed from time to time to keep pace with changing the climate. As reported by Fox (2012) correlative models based on long-term projections need continuous 'validation' and 'refinement' to confirm the status of relationships under new, different conditions of climate.

The future risk maps have shown that Sokoto State and other parts of the north-west ecological zone of Nigeria may experience a more severe fascioliasis epidemic within the next 50 to 70 years than the previous past years. The pockets of high-risk areas are expected to be southernmost part of the study area that constitutes Sokoto and Tambuwal zones. The prediction of the rainfall applied in this study was in line with emission scenarios used for future climate change by HadGEM2-es model based on RCP 2.6 and RCP 8.5 for the years 2050 and 2070. Hadgem2-es model has an outstanding predictive ability especially in Nigeria regarding estimates of rainfall and temperature. A study by Dike et al. (2015) confirmed that there was a high correlation between HadGEM2-es estimates of rainfall and temperature with ground based observations in the north, east and west of Nigeria. The relationship was statistically significant particularly in the northern station, which indicated an increase in the cycle of precipitation and temperature. This future prediction of fascioliasis risk based on the HadGEM2-es model should be treated with caution as there are uncertainties regarding future emission of radiative forcing gases upon which the model was based. However, this study can serve as providing a warning of a potential increase in the future risk of fascioliasis in Sokoto State as is presently the case in the UK (Fox et al., 2011) and other parts of the world.

Diffenbaugh and Giorgi (2012) described north-western Nigeria as ‘hot spots’ of climate change and hence expected to be impacted negatively due to the vulnerable populace (Suk & Semenza, 2011). Consequently, climate change has many impacts, which includes promoting disease prevalence and spread (Conraths et al., 2011), affecting Nigeria’s agriculture and public health sector (Abiodun et al., 2011). Also, global change in climate enhanced resistance to anthelmintic drugs (Wolstenholme et al., 2004) and also on the physiology of the hosts of infection (Harle et al., 2007). Given these, Fox et al. (2011) reported that a gap exists regarding scales at which the actual changes in the disease transmission and spatio-temporal variability in climate modelling which when combined with the above mentioned factors can make a climate-based forecast as being ‘indicative’. However, risk maps developed in this study reflects variability in respect of changing climate in the spread of fascioliasis infection thereby indicating the role of climate in influencing these variabilities.

5. To find out the associations between extrinsic and intrinsic factors on recent fascioliasis infections data among slaughtered animals.

Chapter 6 assessed the associations between intrinsic factors (biological characteristics) and extrinsic factors (climatic/environmental) on fascioliasis infections among slaughtered cattle in the study area. This study presents the first attempt at evaluating the associations between socio-economic characteristics of the cattle holders and *F.gigantica* infections among slaughtered cattle in Nigeria. The majority of the cattle belongs to Fulani’s that are pastoralist always in search of pasture for their animals and hence without access to any form of education as confirmed by this study. Given this, any new control strategies against the spread of animal diseases may be challenging to implement by the majority of livestock holders. In this regard, animal diseases in the study area may continue to pose a threat to the health and productivity of livestock due to high literacy rate (>70%) among livestock holders. In addition, the health of humans in the study is at risk due to the zoonotic nature of some animal diseases especially *F gigantica*. Besides, other factors such as the breed, age of the animal proved to be essential determinants of risk due to *F.gigantica*. White Fulani breed showed some level of resistance to *F.gigantica* infections than other breeds of cattle and hence raising them in the study area is at this moment encouraged. In the provision of the milk and other cattle products, younger calves are preferred based on their immunity to *F.gigantica* than the older ones that are more frequently exposed.

Although climatic factors fitted the model well, their contributions in the infections among the slaughtered cattle at abattoirs were not statistically significant. This result might be due to more influence of biotic factors on *F.gigantica* prevalence at the level of individual cattle slaughtered at abattoirs. This result does not contradict the relevance of climate in overall effects on fascioliasis infections at localities level where variations might exist between localities regarding prevailing climatic conditions. Hence, fascioliasis infections among aggregated numbers of slaughtered cattle between separate localities may associate significantly with climatic conditions across the localities. However, at an abattoir of a particular locality, the slaughtered cattle experienced the same climatic conditions of that locality, and binary logistic regression technique could not detect any associations with fascioliasis infections at individual cattle level. The biological characteristics on the other hand always differ between one slaughtered cattle to another regarding sex, age, breed and management systems even of common origin or locality. Similar to this result, in modelling spatial distribution to predict fascioliasis in cattle at an abattoir in Victoria, Australia, rainfall was having 'inconsistent' association with fascioliasis infections data obtained from slaughterhouses. This study by Durr et al. (2005) confirmed the relevance of irrigation as the essential predictor of fascioliasis risk. Also, Tum et al. (2004) in Cambodia did not include temperature and rainfall variables as a determinant of *F.gigantica* risk in the developed GIS model due to their uniform conditions throughout the year. However, other factors considered as important include altitude, the distance from the river as well as flooding (inundation).

7.2 Research limitations

This research applied species distribution models in the prediction of *F.gigantica* in Sokoto State using various models, techniques, and data in achieving the main objectives of the research. Given that, there are uncertainties (Negga, 2007) in indicating the reality by the developed models due to the integration of information from different sources. The worldClim database as the source of climate data in this study applied interpolation method (Hijmans et al., 2005) in creating climate surfaces which presents uncertainty.

Also, the measurement of these variables might pose some challenges especially rainfall data that has high spatio-temporal variablity and hence not very precise (Negga, 2007).

The basis of the general spatial species distribution modelling in this research (MaxEnt, BioClim and DOMAIN) was on the concept of niche as consisting of species occurrence information together with the climatic parameters about the study area within both short term and long-term periods. Given that, the modelling result reflected only 'the snapshot' of the anticipated association between climate and the species (Guisan & Thuiller, 2005, Negga, 2007). This technique of species distribution models referred to as correlative modelling only captures the use of physical factors (abiotic) in determining the distribution range of species. Thus the method does not consider biological factors (Soberon & Peterson 2005) in influencing the occurrence of species despite their importance. As a consequence, the model indicated only the potential habitat where the species occupied (fundamental niche) instead of that portion (realised niche) where biological factors (competition with the same species or different species and predation) might cause the exclusion of the species (Peterson, 2006, Pulliam, 2000). The potential effects of these biological factors on species dispersal has distorted the actual spatial species range. As a result of this observation, species dispersal across space is limited by biological relationships which conform to the concept of realised niche described by Hutchinson (Guisan & Thuiller, 2005). Overall, the model result is quite acceptable as indicating fundamental niche occupied by *F.gigantica* species and its intermediate hosts in the study area.

This study also made use of geostatistically processed remotely sensed data from MODIS, AIRS, SRTM, and GLDAS to the same common projection, extent, and spatial resolution. This reason presents another limitation of this research that could affect the predictive abilities of species distribution modelling techniques.

7.3 Future Research Recommendations

In modelling spatial distribution of *F.gigantica*, future study should incorporate irrigation factor as another essential variable that affects the prevalence of infections. In Sokoto State, there are dams and other open water bodies, which all affect fascioliasis transmission, through the provision of habitat to the parasite and its hosts, especially in the dry season. Given that, the species model will give a more realistic indication of high-risk areas rather than relying on rainfall and temperature variables as the only determinants.

Biotic interactions, dispersal, and evolutionary factors should also be incorporated in future studies using species distribution models to understand the occupied niche that suits the survival of fascioliasis and its intermediate snails in the study area.

In the computation of evapotranspiration, it is also recommended to use another technique such as the Penman-Monteith equation which is the most excellent method by Food and Agricultural Organization (FAO).

Future studies should also focus on increasing the extent of the study area to obtain a broader coverage of fascioliasis endemic localities in Nigeria. Given that, will enable effective monitoring of the parasite prevalence at the national scale for the formulation of control strategies. Future work will also ensure adding the existing fascioliasis occurrence locations to GBIF as currently only a few records (3) exist in Nigeria.

Fascioliasis is a zoonotic disease, and hence the future approach should investigate the prevalence of fascioliasis infections among humans especially the inhabitants of settlements proximate to riverine areas in the state. In Nigeria with more than 60% fascioliasis prevalence in animals, there is a possibility for human infections, which should be the focus of the future studies.

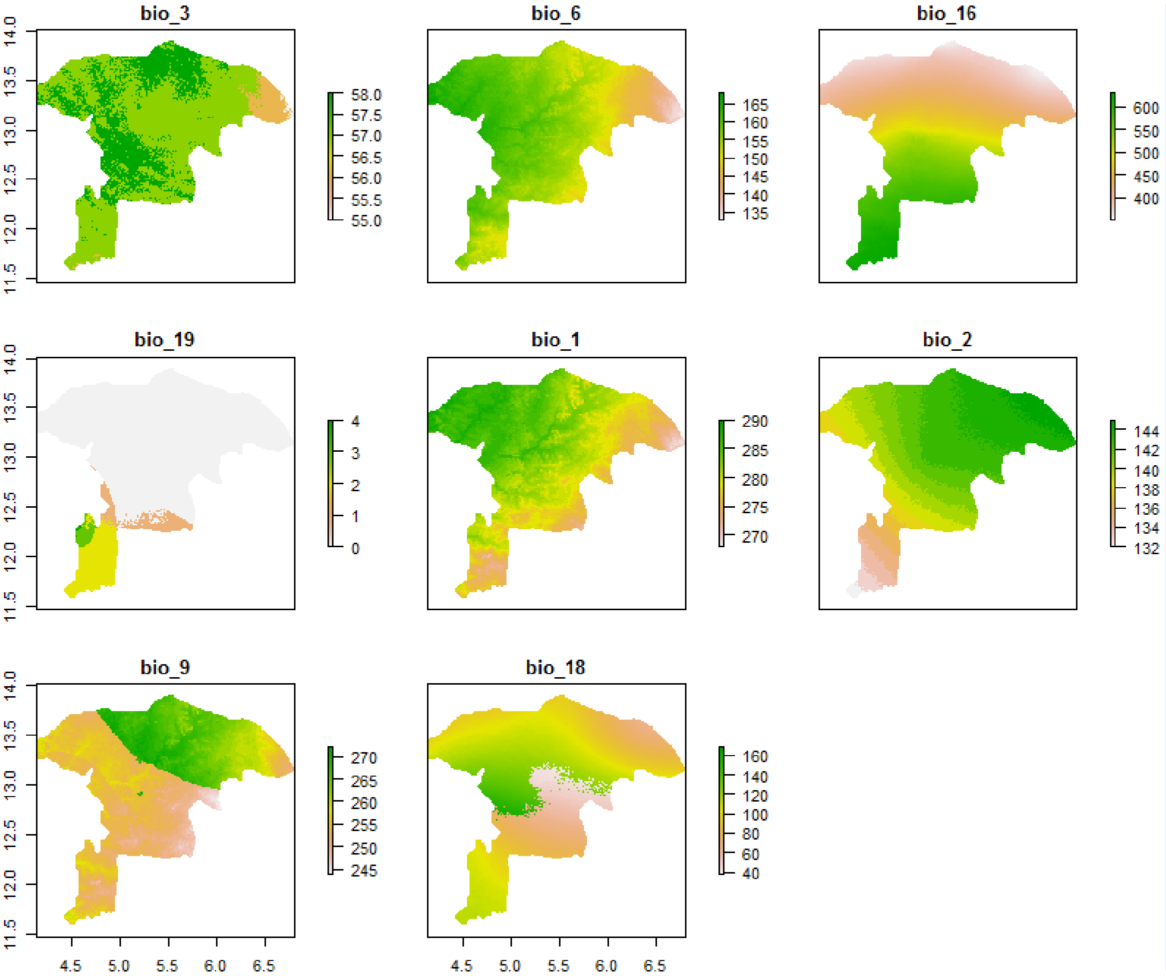


Figure A-39: BioClim variables

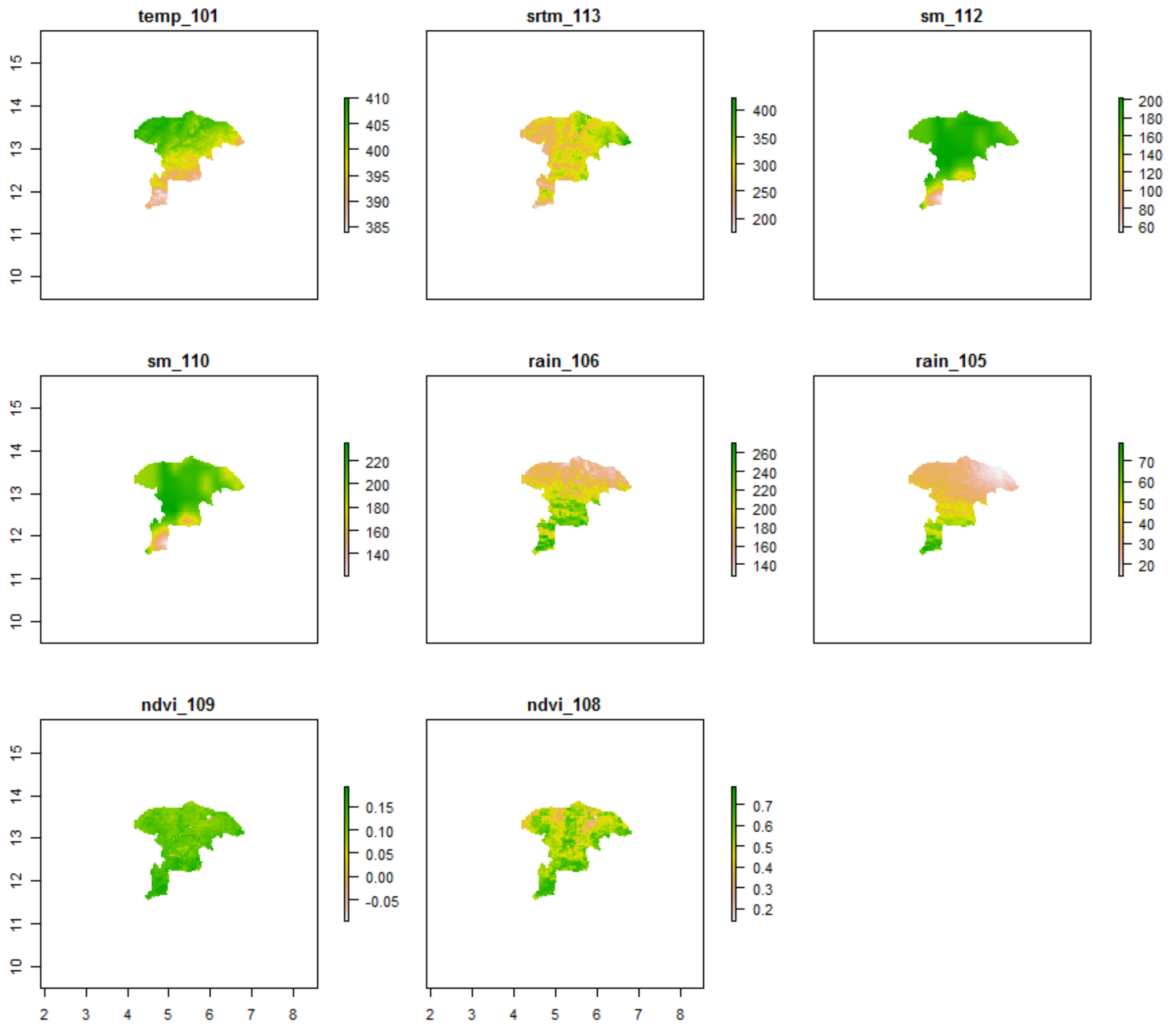


Figure A-40 Satellite-based variables

Table A-23 Fasciola gigantica occurrence locations, Sokoto state.

species	x	y
fascioliasis_gigantica	5.7021	13.41427
fascioliasis_gigantica	5.62682	13.36062
fascioliasis_gigantica	5.59485	13.30568
fascioliasis_gigantica	5.63799	13.32342
fascioliasis_gigantica	5.55472	13.35502
fascioliasis_gigantica	5.83678	13.55986
fascioliasis_gigantica	5.89882	13.56986
fascioliasis_gigantica	5.86366	13.52776
fascioliasis_gigantica	5.15263	12.8441
fascioliasis_gigantica	5.14597	12.82673
fascioliasis_gigantica	5.11733	12.84294
fascioliasis_gigantica	5.12636	1.83608
fascioliasis_gigantica	5.13429	12.83297
fascioliasis_gigantica	5.13077	12.84528

fascioliasis_gigantica	5.11672	12.87515
fascioliasis_gigantica	5.11729	12.87192
fascioliasis_gigantica	4.97791	13.29739
fascioliasis_gigantica	4.96926	13.34122
fascioliasis_gigantica	4.94878	13.3659
fascioliasis_gigantica	4.95999	13.26212
fascioliasis_gigantica	4.97648	13.2723
fascioliasis_gigantica	4.99686	13.30821
fascioliasis_gigantica	4.99369	13.30511
fascioliasis_gigantica	4.99544	13.32938
fascioliasis_gigantica	5.01398	13.33554
fascioliasis_gigantica	5.01369	13.33118
fascioliasis_gigantica	5.00978	13.323265
fascioliasis_gigantica	5.00529	13.3247
fascioliasis_gigantica	5.01475	13.32473
fascioliasis_gigantica	5.21606	13.05312
fascioliasis_gigantica	5.20567	13.07371
fascioliasis_gigantica	5.20049	13.07403
fascioliasis_gigantica	5.19707	13.07346
fascioliasis_gigantica	5.22658	13.07206
fascioliasis_gigantica	5.22248	13.07326
fascioliasis_gigantica	4.80093	12.46834
fascioliasis_gigantica	4.9587	12.50529
fascioliasis_gigantica	4.98967	12.48384
fascioliasis_gigantica	4.99407	12.47088
fascioliasis_gigantica	5.01812	12.40856
fascioliasis_gigantica	5.10437	12.29934
fascioliasis_gigantica	4.9962	12.41878
fascioliasis_gigantica	5.0197	12.44788
fascioliasis_gigantica	4.99162	12.46395
fascioliasis_gigantica	4.64181	12.40596
fascioliasis_gigantica	5.64605	13.75556
fascioliasis_gigantica	5.69901	13.80663
fascioliasis_gigantica	5.69748	13.79848
fascioliasis_gigantica	5.68757	13.80254
fascioliasis_gigantica	5.62264	13.7498
fascioliasis_gigantica	5.62416	13.74388
fascioliasis_gigantica	5.74221	13.56142
fascioliasis_gigantica	5.73348	13.54228
fascioliasis_gigantica	5.72165	13.51617
fascioliasis_gigantica	5.98154	13.66356
fascioliasis_gigantica	5.96911	13.65142
fascioliasis_gigantica	5.99801	13.69259
fascioliasis_gigantica	5.00108	13.69531

fascioliasis_gigantica	5.00959	13.69413
fascioliasis_gigantica	5.01872	13.69441
fascioliasis_gigantica	6.01678	13.68246
fascioliasis_gigantica	6.02385	13.68493
fascioliasis_gigantica	6.03899	13.67125
fascioliasis_gigantica	4.91645	13.22609
fascioliasis_gigantica	4.93619	13.24994
fascioliasis_gigantica	4.94444	13.24745
fascioliasis_gigantica	4.95542	13.28089
fascioliasis_gigantica	4.88759	13.2658
fascioliasis_gigantica	4.8573	13.29216
fascioliasis_gigantica	4.84947	13.29715
fascioliasis_gigantica	4.90392	13.25502
fascioliasis_gigantica	4.86831	13.2423
fascioliasis_gigantica	4.85962	13.24257
fascioliasis_gigantica	4.82878	13.24365
fascioliasis_gigantica	5.23719	13.36145
fascioliasis_gigantica	5.24543	13.35571
fascioliasis_gigantica	5.30826	13.59517
fascioliasis_gigantica	5.34608	13.58817
fascioliasis_gigantica	5.35396	13.56411
fascioliasis_gigantica	5.29998	13.22064
fascioliasis_gigantica	5.30174	13.21704
fascioliasis_gigantica	5.3115	13.22142
fascioliasis_gigantica	5.32221	13.22262
fascioliasis_gigantica	5.32834	13.22508
fascioliasis_gigantica	5.37379	13.08628
fascioliasis_gigantica	5.3722	13.08647
fascioliasis_gigantica	5.37282	13.09008
fascioliasis_gigantica	5.38872	13.11091
fascioliasis_gigantica	5.3917	13.09638
fascioliasis_gigantica	5.43426	13.14061
fascioliasis_gigantica	5.4692	13.15582
fascioliasis_gigantica	5.63623	13.02759
fascioliasis_gigantica	5.62262	13.0642
fascioliasis_gigantica	5.62948	13.04762
fascioliasis_gigantica	5.29521	12.57681
fascioliasis_gigantica	5.28336	12.59876
fascioliasis_gigantica	5.2758	12.58416
fascioliasis_gigantica	5.3854	12.58219
fascioliasis_gigantica	5.32284	12.35084
fascioliasis_gigantica	5.42932	12.40073
fascioliasis_gigantica	5.42288	12.41775
fascioliasis_gigantica	5.46183	12.53963

fascioliasis_gigantica	5.41563	12.57323
fascioliasis_gigantica	5.57395	12.67444
fascioliasis_gigantica	6.45098	13.20129
fascioliasis_gigantica	6.37634	13.13888
fascioliasis_gigantica	6.36152	13.13889
fascioliasis_gigantica	6.35862	13.16567
fascioliasis_gigantica	6.35743	13.19916
fascioliasis_gigantica	6.34528	13.22029
fascioliasis_gigantica	6.35918	13.23265
fascioliasis_gigantica	6.3599	13.23844
fascioliasis_gigantica	6.12059	13.36034
fascioliasis_gigantica	6.65407	13.29256
fascioliasis_gigantica	4.6854	13.50346
fascioliasis_gigantica	4.68521	13.50744
fascioliasis_gigantica	4.71082	13.47143
fascioliasis_gigantica	4.53331	13.30127
fascioliasis_gigantica	4.46255	13.24397
fascioliasis_gigantica	4.15907	13.3586
fascioliasis_gigantica	4.5101	13.649
fascioliasis_gigantica	4.60059	13.7088
fascioliasis_gigantica	5.26211	13.06519
fascioliasis_gigantica	5.28162	13.02854
fascioliasis_gigantica	5.28922	13.0342
fascioliasis_gigantica	5.27444	13.04018
fascioliasis_gigantica	5.28916	13.05239
fascioliasis_gigantica	4.84808	13.03231
fascioliasis_gigantica	4.7638	13.01301
fascioliasis_gigantica	4.75795	13.01544
fascioliasis_gigantica	4.91591	13.01482
fascioliasis_gigantica	4.81824	12.9211
fascioliasis_gigantica	4.84689	12.97317
fascioliasis_gigantica	4.84386	12.95826
fascioliasis_gigantica	4.84509	12.93958
fascioliasis_gigantica	4.84562	12.94173
fascioliasis_gigantica	4.87048	12.00522
fascioliasis_gigantica	4.99309	12.62707
fascioliasis_gigantica	4.96963	12.62563
fascioliasis_gigantica	4.98113	12.59338
fascioliasis_gigantica	4.97993	12.58602
fascioliasis_gigantica	4.96198	12.53556
fascioliasis_gigantica	4.95786	12.53395
fascioliasis_gigantica	4.95459	12.53355
fascioliasis_gigantica	5.10257	12.6327
fascioliasis_gigantica	5.10092	12.60885

fascioliasis_gigantica	5.08459	12.70341
fascioliasis_gigantica	5.08367	12.70396
fascioliasis_gigantica	5.094	12.76689
fascioliasis_gigantica	5.01415	12.7204
fascioliasis_gigantica	5.0111	12.70517
fascioliasis_gigantica	4.98988	12.68123
fascioliasis_gigantica	4.98355	12.67515
fascioliasis_gigantica	4.98405	12.67175
fascioliasis_gigantica	4.97626	12.68467
fascioliasis_gigantica	4.97682	12.67786
fascioliasis_gigantica	4.96703	12.67873
fascioliasis_gigantica	4.95586	12.69071
fascioliasis_gigantica	4.95179	12.69972
fascioliasis_gigantica	4.93358	12.67499
fascioliasis_gigantica	4.87387	12.82152
fascioliasis_gigantica	4.87381	12.82623
fascioliasis_gigantica	4.89323	12.82509
fascioliasis_gigantica	5.22225	13.297
fascioliasis_gigantica	5.18338	13.26805
fascioliasis_gigantica	5.18114	13.26787
fascioliasis_gigantica	5.17532	13.2672
fascioliasis_gigantica	5.17596	13.27097
fascioliasis_gigantica	5.17131	13.27745
fascioliasis_gigantica	5.23289	13.29974
fascioliasis_gigantica	5.25935	13.31321
fascioliasis_gigantica	5.18978	13.26691
fascioliasis_gigantica	5.264426	13.21154
fascioliasis_gigantica	5.33309	13.16922
fascioliasis_gigantica	5.33213	13.162
fascioliasis_gigantica	5.27975	13.1034
fascioliasis_gigantica	5.35687	13.7219
fascioliasis_gigantica	5.4102	13.77076
fascioliasis_gigantica	5.41613	13.77464
fascioliasis_gigantica	5.3609	13.68605
fascioliasis_gigantica	5.32083	13.62351
fascioliasis_gigantica	5.31416	13.63782
fascioliasis_gigantica	5.42203	13.51892
fascioliasis_gigantica	5.42318	13.51132
fascioliasis_gigantica	5.44522	13.49252
fascioliasis_gigantica	5.44621	13.49597
fascioliasis_gigantica	5.26918	13.53883
fascioliasis_gigantica	5.39064	13.26159
fascioliasis_gigantica	5.41109	13.28643
fascioliasis_gigantica	5.4362	13.28307

fascioliasis_gigantica	5.42537	13.27382
fascioliasis_gigantica	5.43253	13.27122
fascioliasis_gigantica	5.45667	13.2278
fascioliasis_gigantica	5.47059	13.16966
fascioliasis_gigantica	5.48118	13.21636
fascioliasis_gigantica	5.35888	13.24507
fascioliasis_gigantica	5.36702	13.1768
fascioliasis_gigantica	5.36605	13.19062
fascioliasis_gigantica	5.39831	13.1496
fascioliasis_gigantica	5.10811	13.03003
fascioliasis_gigantica	5.16727	13.05468
fascioliasis_gigantica	5.19461	13.11404
fascioliasis_gigantica	5.19423	13.11476
fascioliasis_gigantica	5.19727	13.11747
fascioliasis_gigantica	5.19881	13.11541
fascioliasis_gigantica	5.20348	13.10909
fascioliasis_gigantica	5.20725	13.11547
fascioliasis_gigantica	5.18833	13.05281
fascioliasis_gigantica	5.19585	13.02797
fascioliasis_gigantica	5.1996	12.96534
fascioliasis_gigantica	5.19175	12.99063
fascioliasis_gigantica	5.18044	12.99036
fascioliasis_gigantica	5.18983	12.9714
fascioliasis_gigantica	5.19183	12.97272
fascioliasis_gigantica	5.22594	13.00587
fascioliasis_gigantica	5.22933	13.00591
fascioliasis_gigantica	4.5927	11.81603
fascioliasis_gigantica	4.59159	11.8228
fascioliasis_gigantica	4.5023	11.5349
fascioliasis_gigantica	4.49636	11.64495
fascioliasis_gigantica	4.49475	11.64909
fascioliasis_gigantica	4.50042	11.53925
fascioliasis_gigantica	4.64456	11.67927
fascioliasis_gigantica	4.6881	11.69767
fascioliasis_gigantica	4.80217	12.17174

Table A-24 Fascioliasis occurrence locations from field survey

species	Longitude	Latitude
fascioliasis_gigantica	5.67202	13.44602
fascioliasis_gigantica	4.48776	11.70457
fascioliasis_gigantica	4.81976	12.13627
fascioliasis_gigantica	5.42416	13.285
fascioliasis_gigantica	5.39854	13.12939
fascioliasis_gigantica	5.65835	13.75537
fascioliasis_gigantica	5.96986	13.67035
fascioliasis_gigantica	5.24735	13.06706
fascioliasis_gigantica	5.25524	13.0825
fascioliasis_gigantica	4.55923	13.57824
fascioliasis_gigantica	4.16723	13.27847
fascioliasis_gigantica	4.84808	13.03231
fascioliasis_gigantica	4.99309	12.62707
fascioliasis_gigantica	5.55944	12.70357
fascioliasis_gigantica	5.50948	13.11946

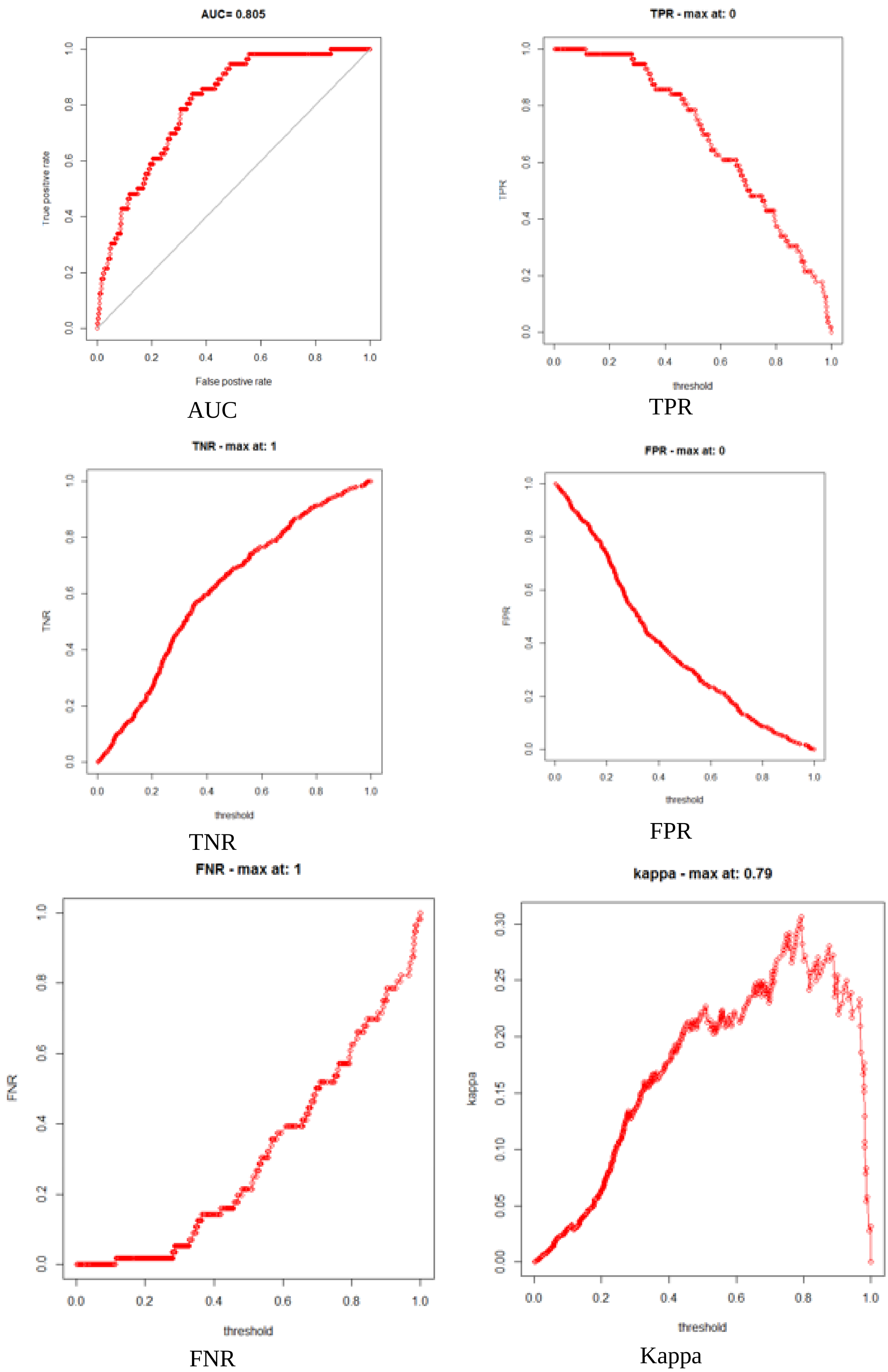


Figure A-41 MaxEnt evaluation measures

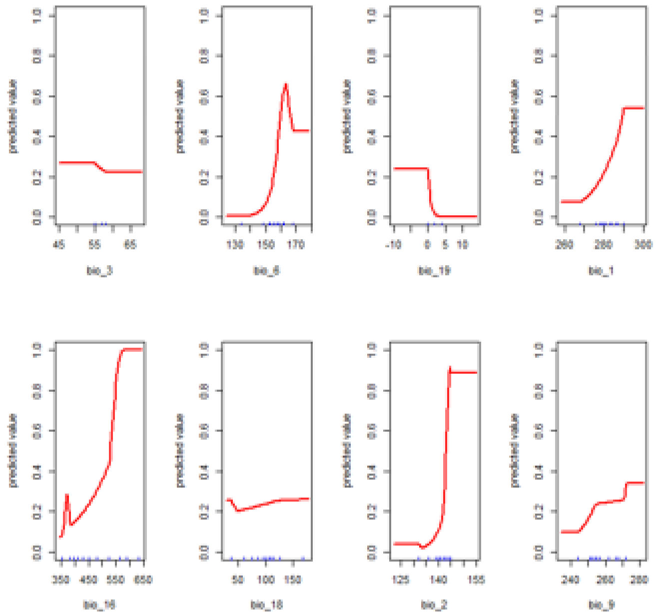
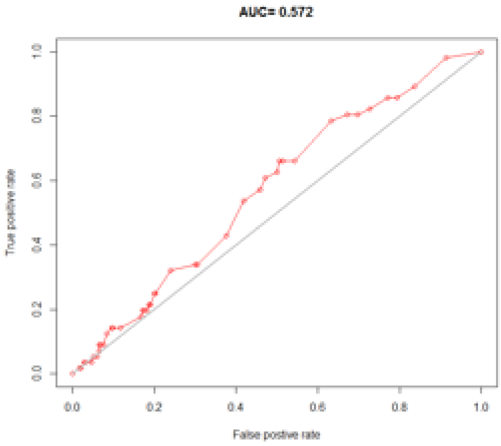
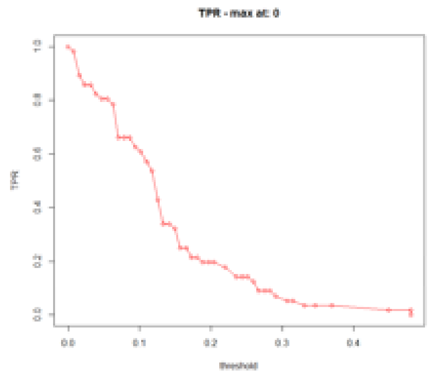


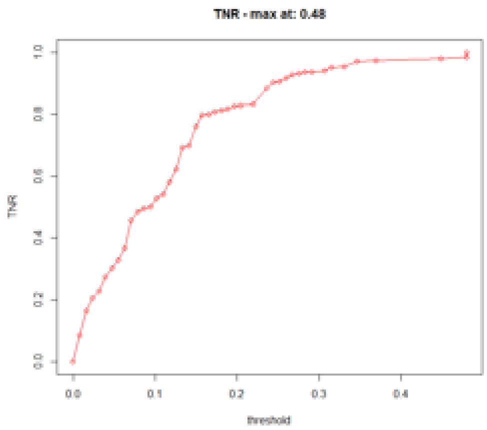
Figure A-42: MaxEnt modelling response curves



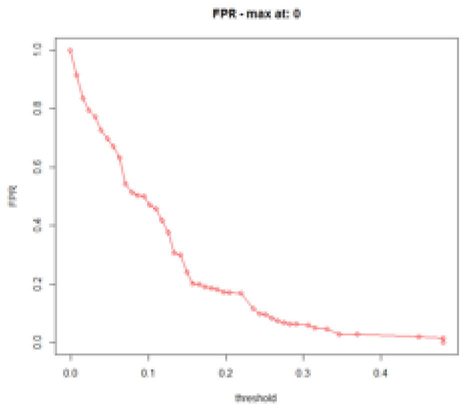
AUC



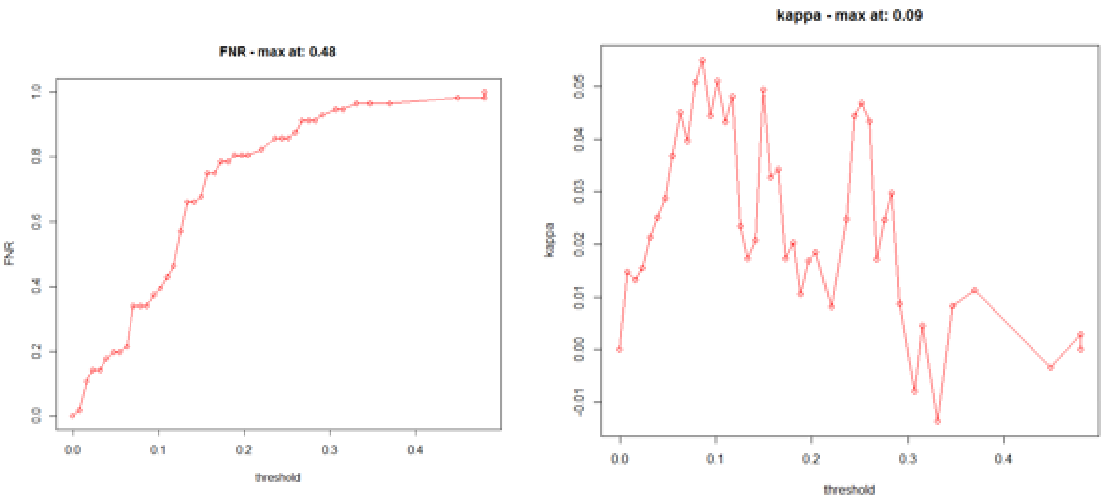
TPR



TNR



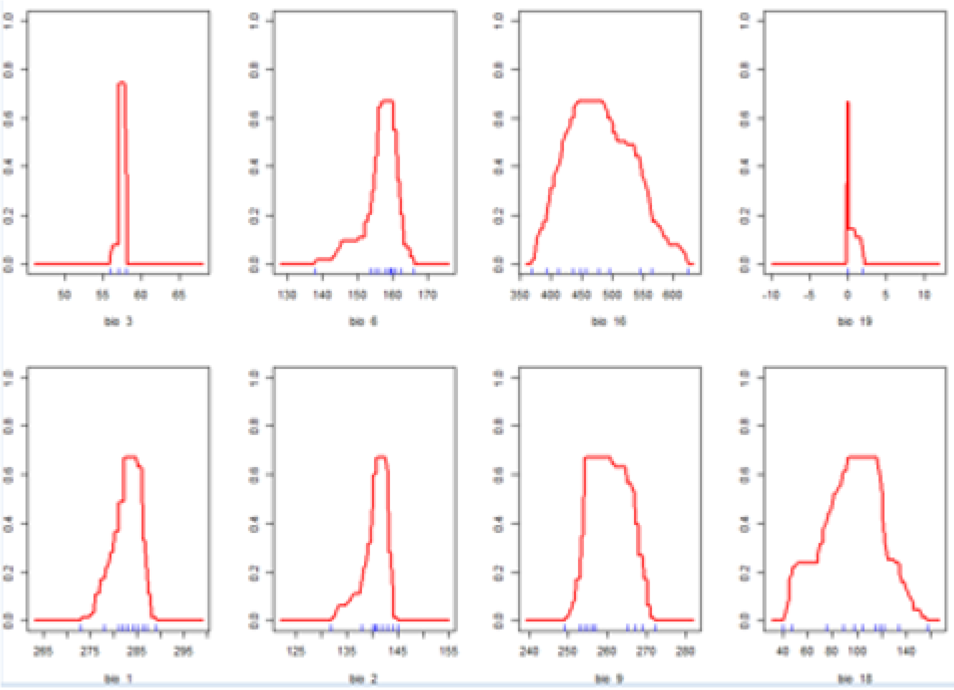
PPR



FNR

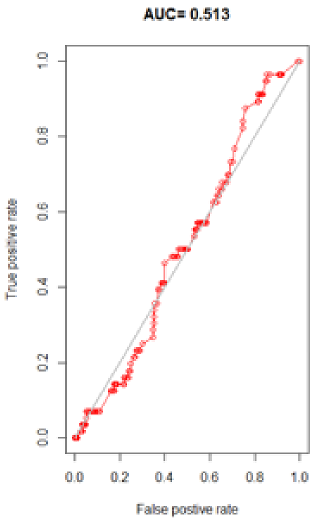
Kappa

Figure A-43 BioClim evaluation measures

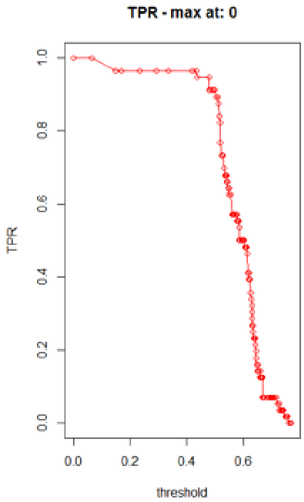


Response curves

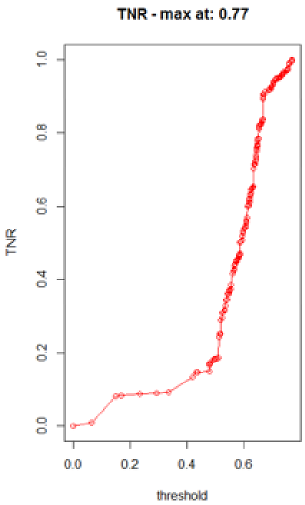
Figure A-44 Response curves BioClim modelling



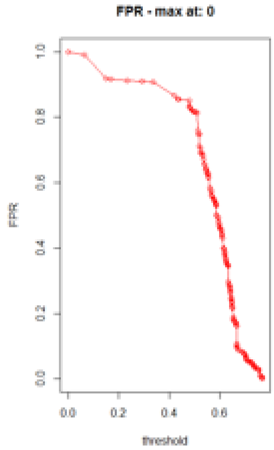
AUC



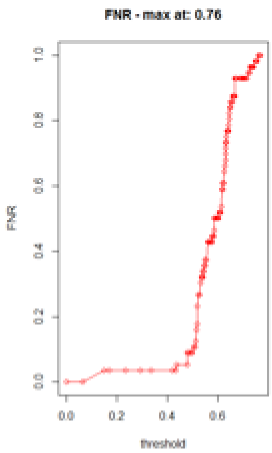
TPR



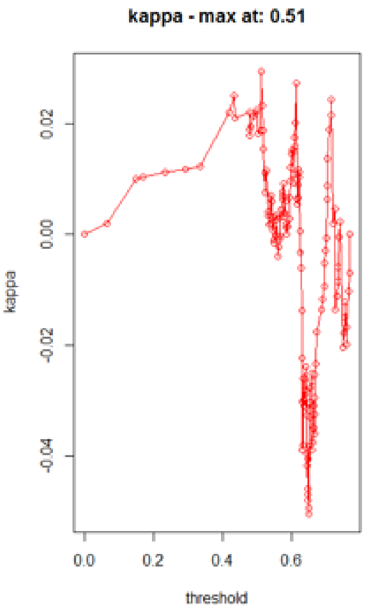
TNR



FPR



FNR



Kappa

Figure A-45 Domain model evaluation measures

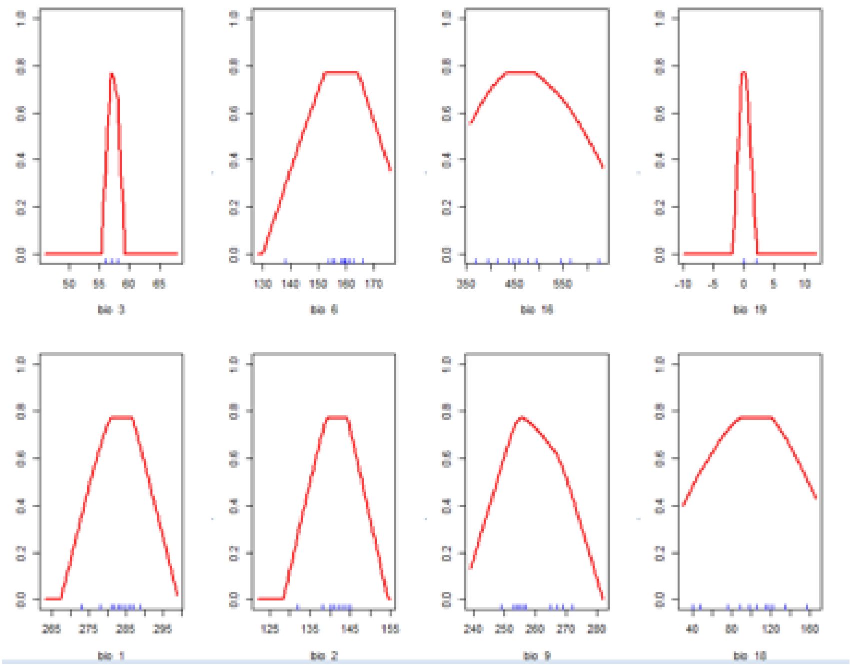


Figure A-46 Response curves Domain model

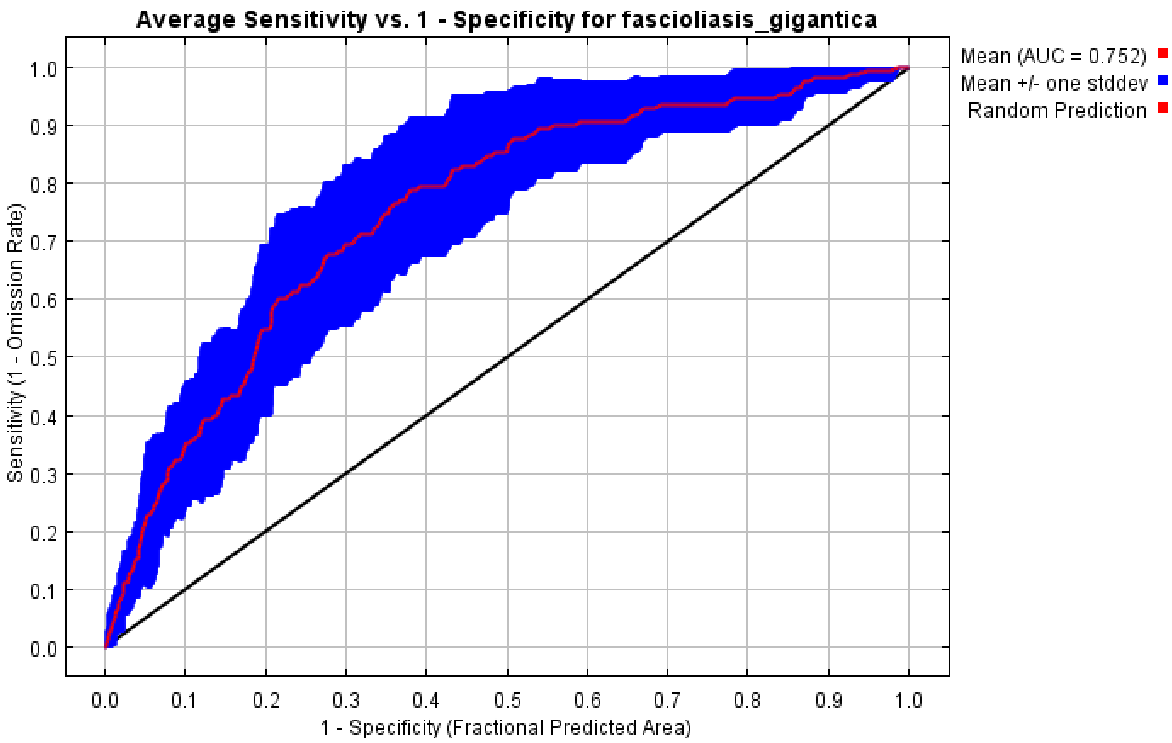


Figure A-47 Scenario 1

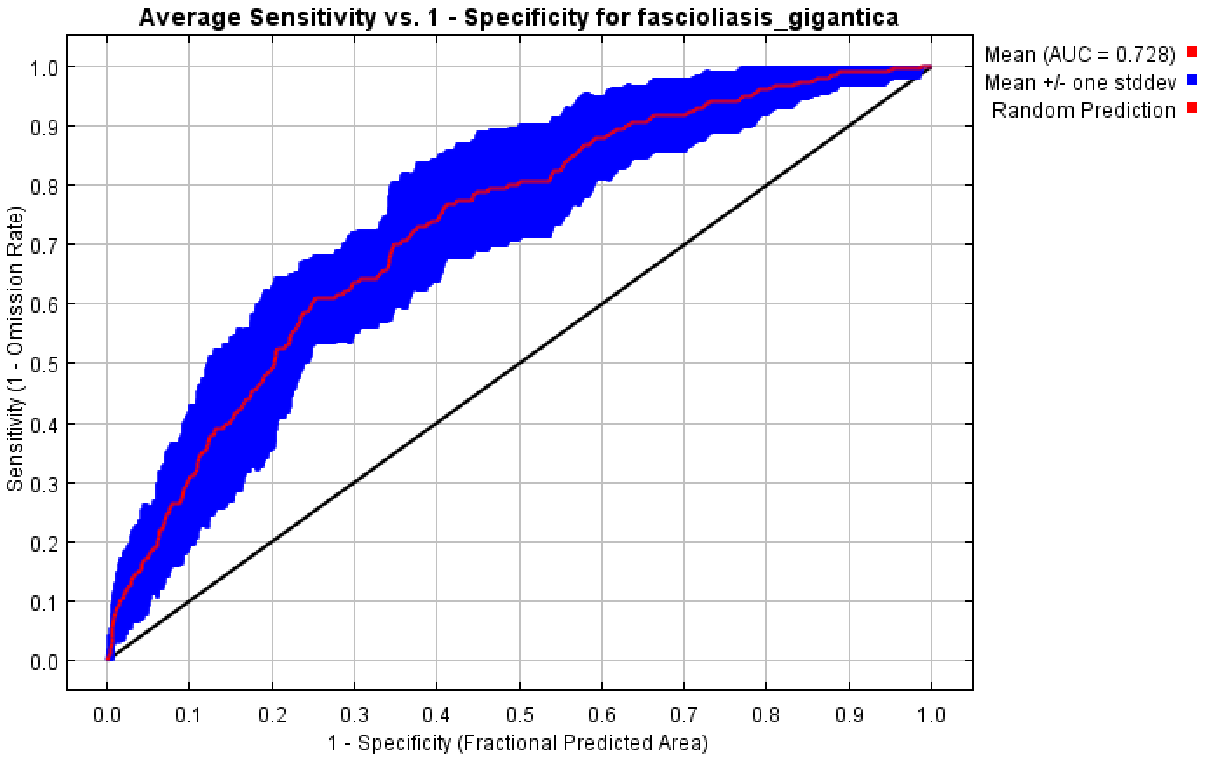


Figure A-48 Scenario 2

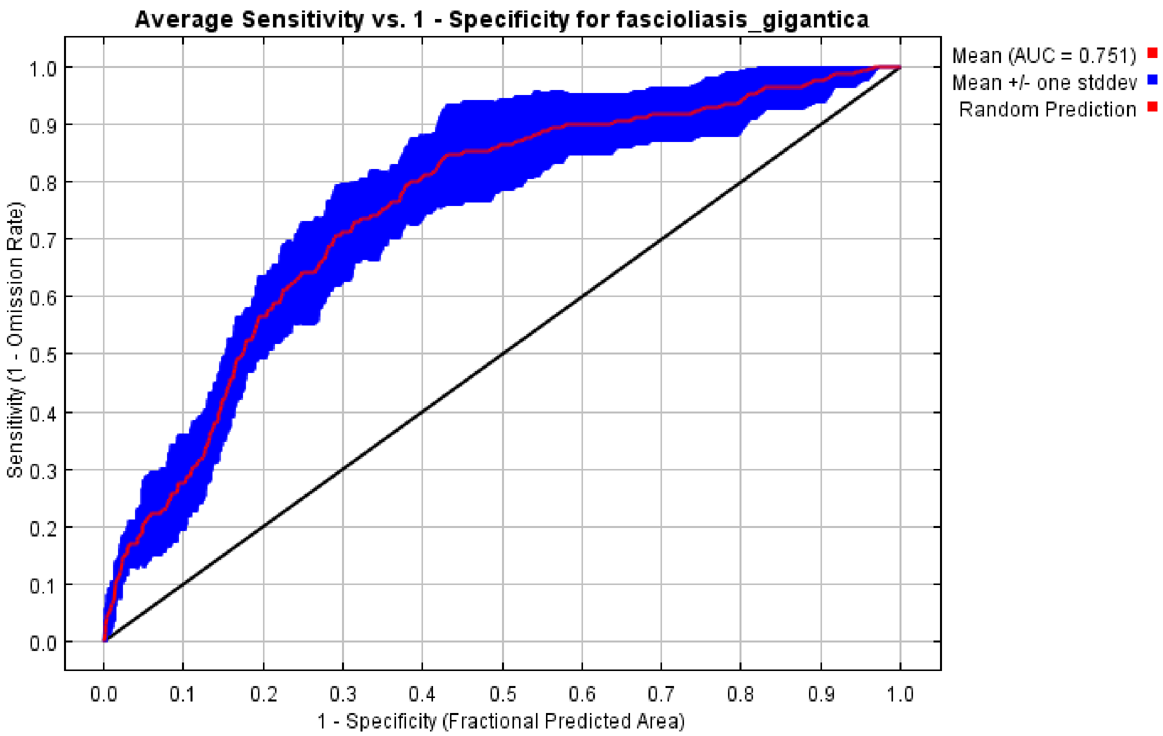


Figure A-49 Scenario 3

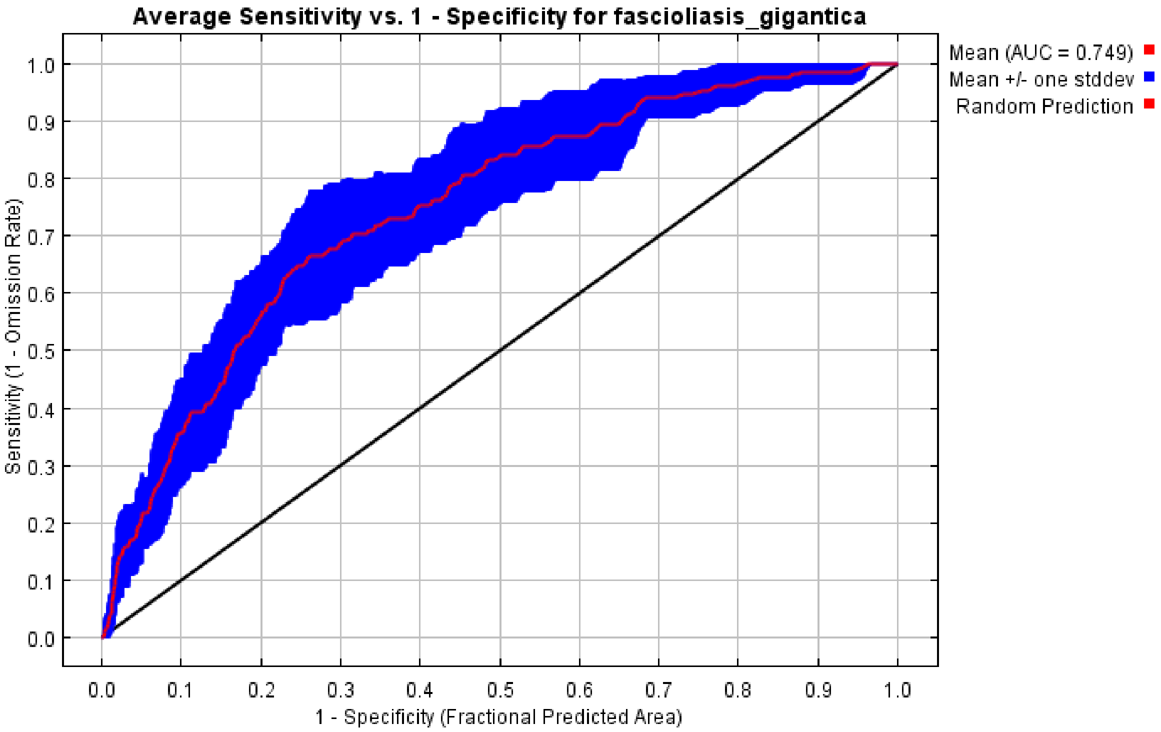


Figure A-50 Scenario 4

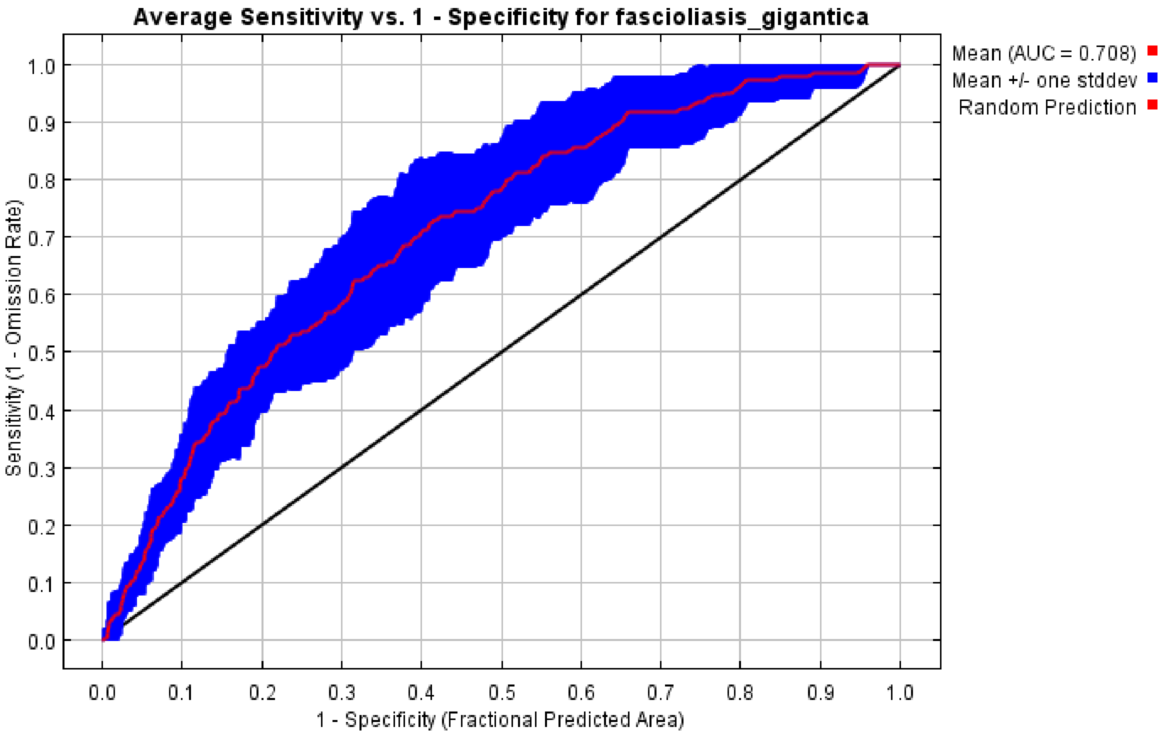


Figure A-51 Scenario 5

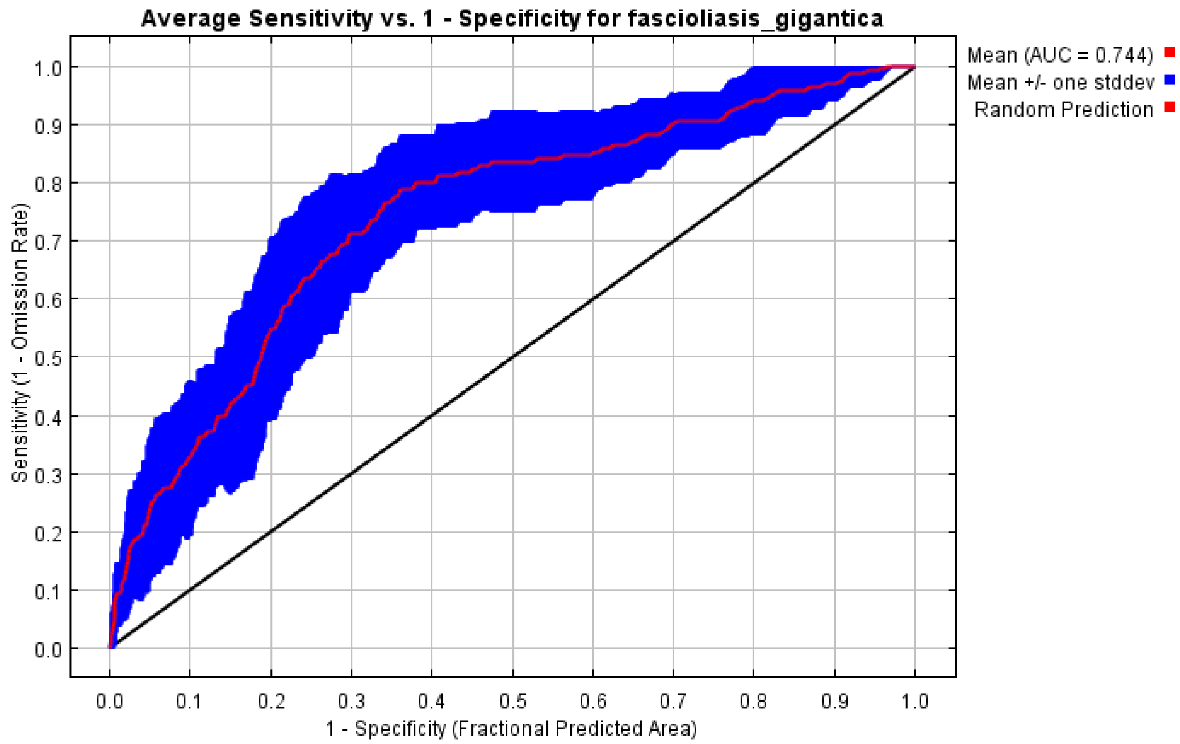


Figure A-52 Scenario 6

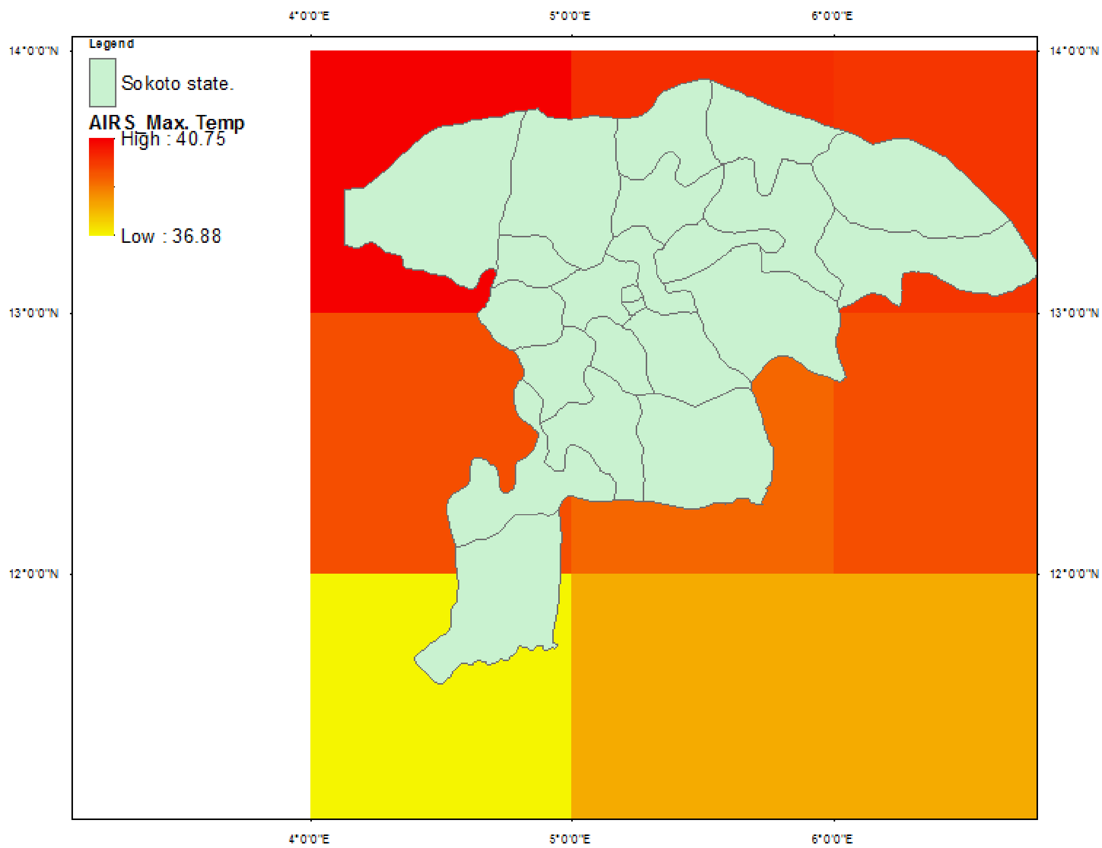


Figure A-53 AIRS data

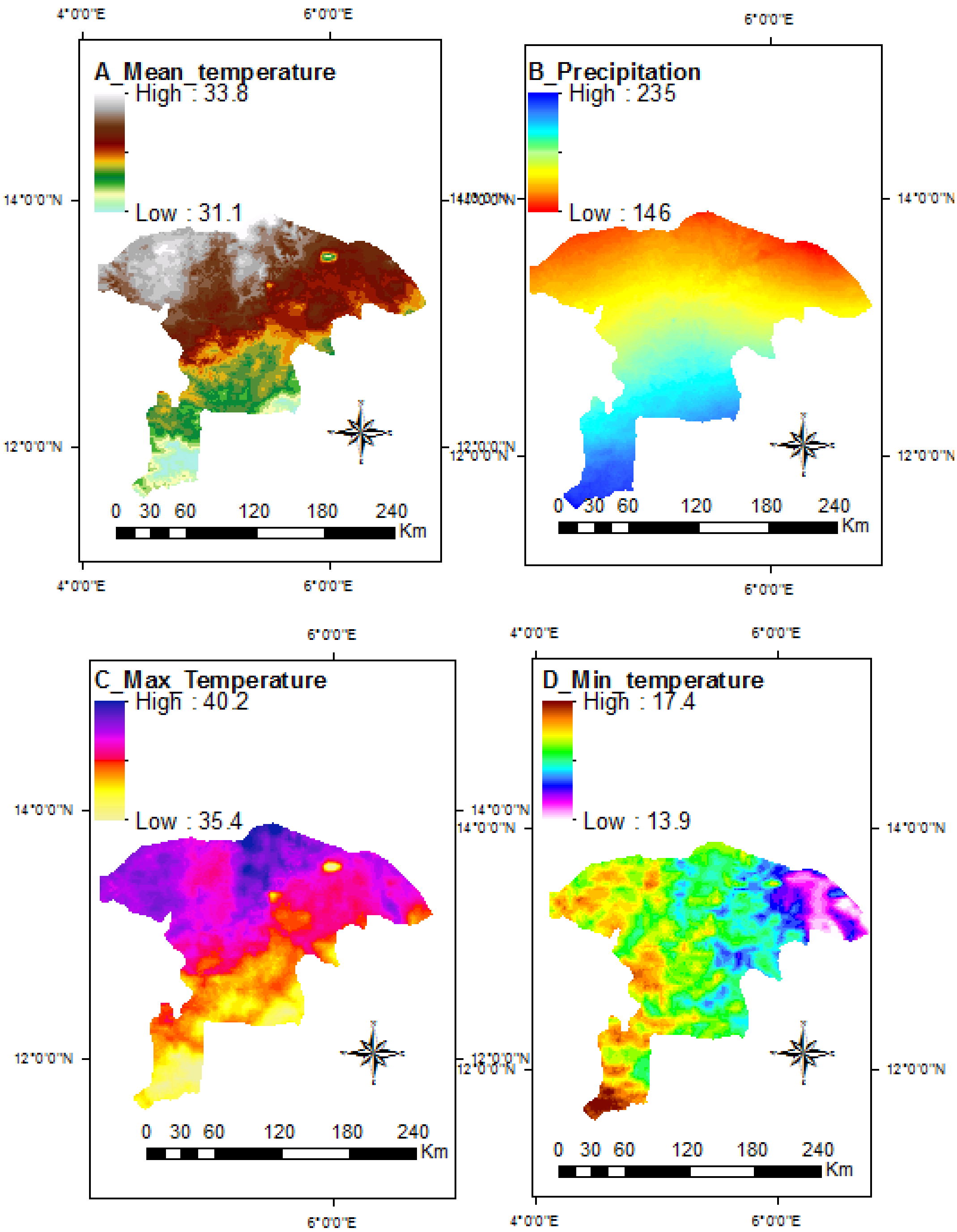


Figure A-54 Mean, Max, Min and precipitation1970-2000 (WorldClim)

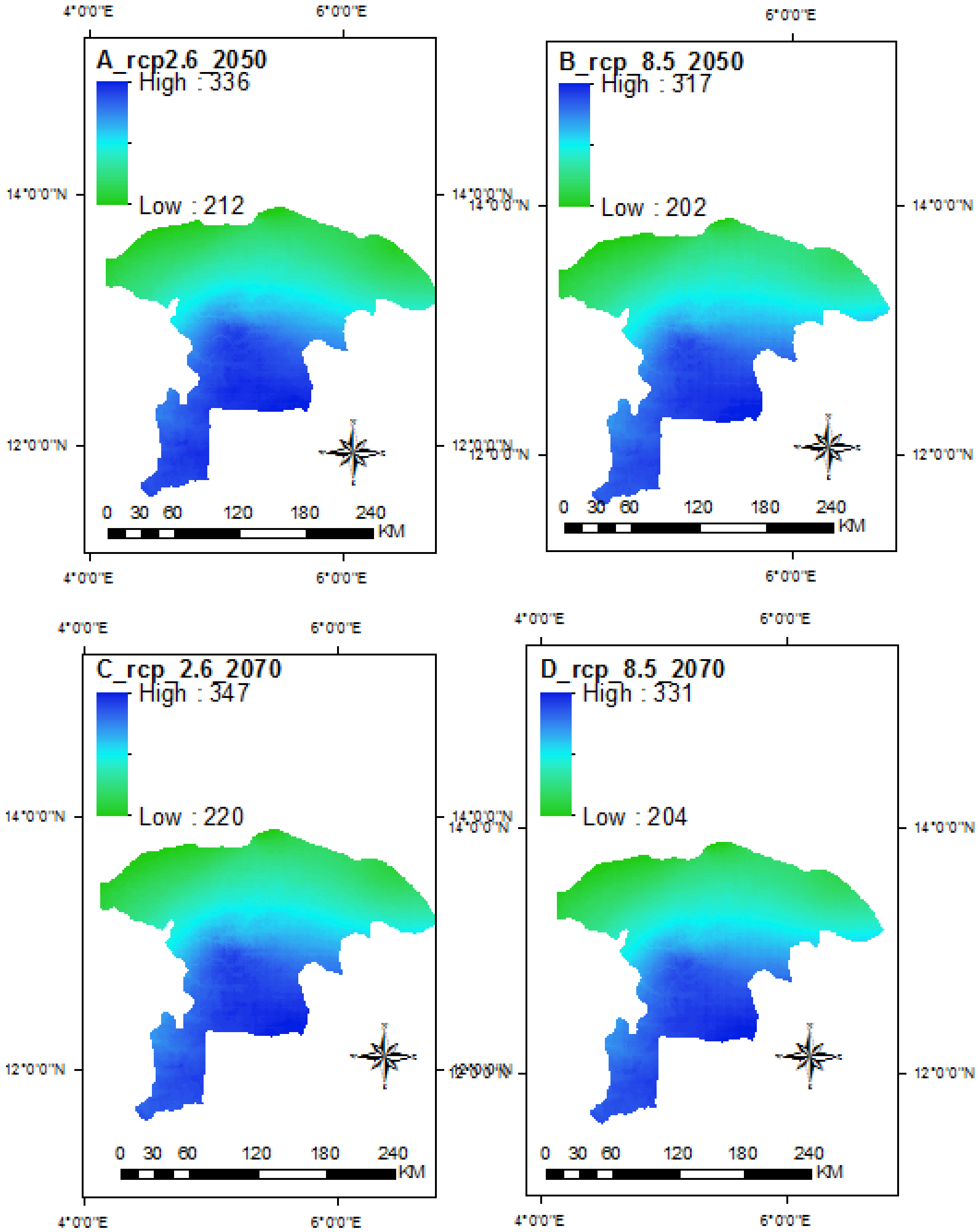


Figure A-55 Precipitation for August (WorldClim, HadGEM2-es, RCP 2.6 2050, RCP 8.5 2050, RCP 2.6 2070, RCP 8.5 2070 respectively)

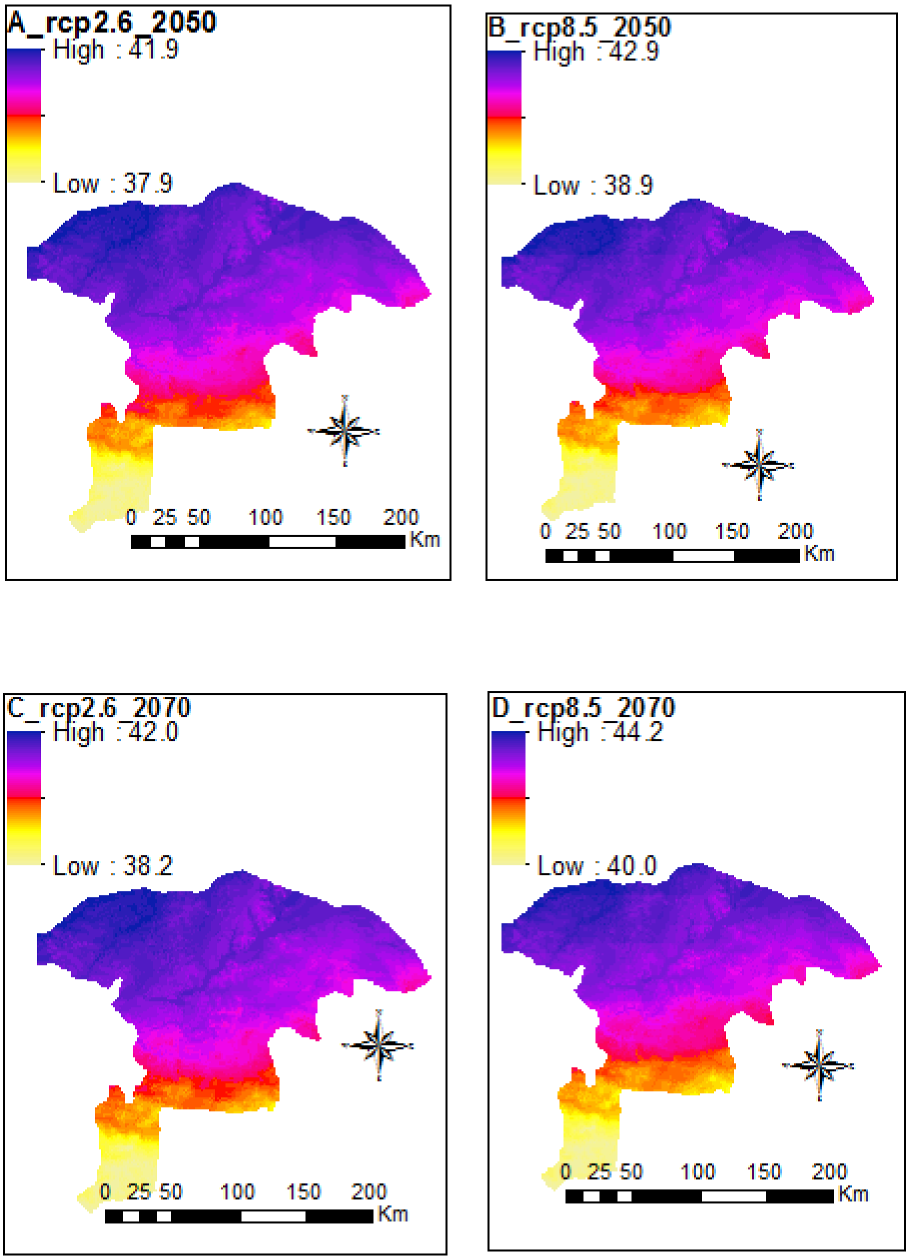


Figure A-56 Maximum temperature for May (WorldClim, HadGEM2-es, RCP 2.6 2050, RCP 8.5 2050, RCP 2.6 2070, RCP 8.5 2070 respectively)

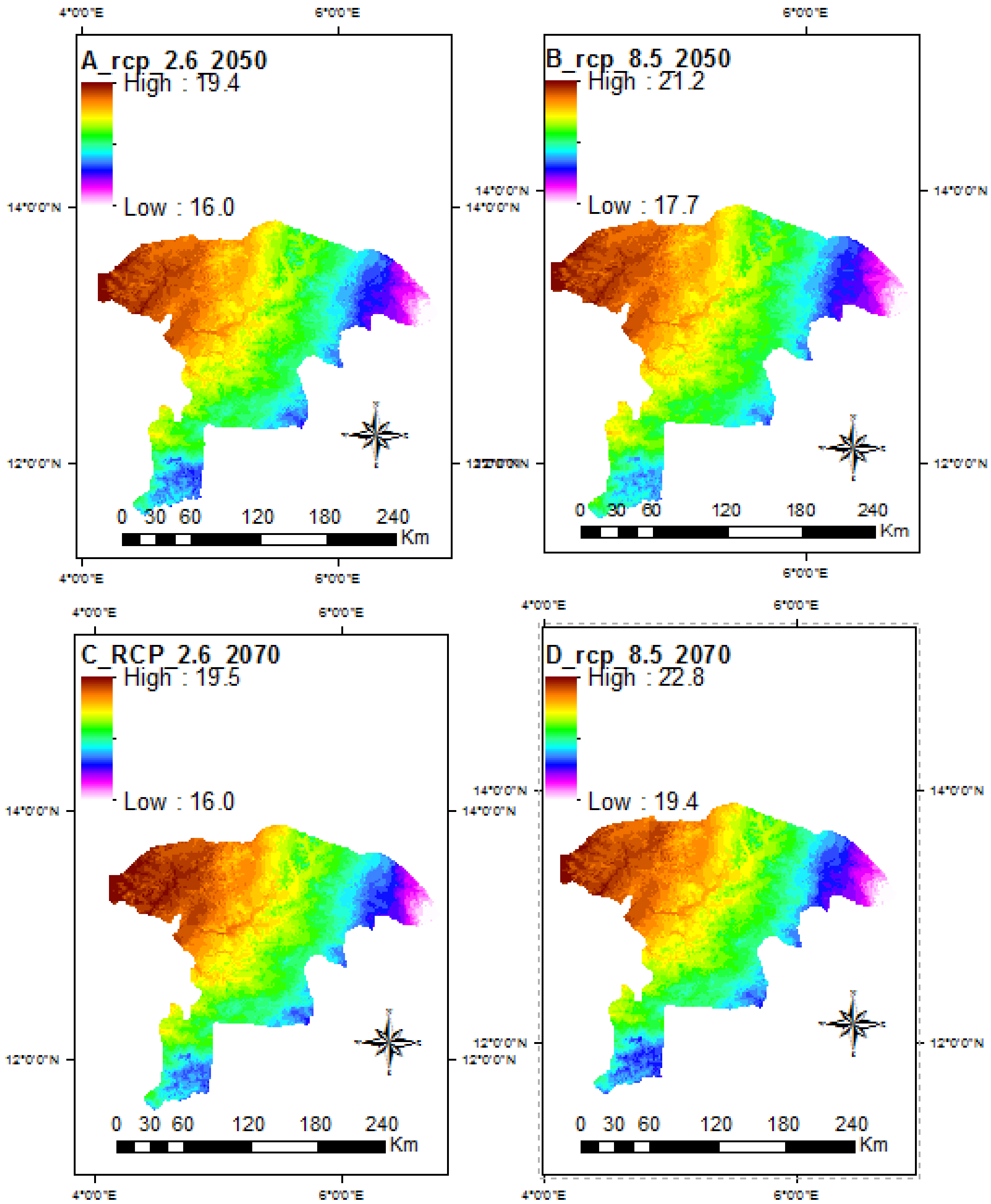


Figure A-57 Minimum temperature for December Figs17-19: Maximum temperature for May (WorldClim, HadGEM2-es, RCP 2.6 2050, RCP 8.5 2050, RCP 2.6 2070, RCP 8.5 2070 respectively).

Table A-25 Fasciola gigantica prevalence and climatic/environmental variables 2005-2014 aggregated yearly average

Provinces	Faciola prev.	rain	sm_1	index_1	ndvi	mean temp_1	PET_1
GORONYO	61	660	198.3859304	503	0.264960631	30.5	205.8137702
BODINGA	82	805	230.8611526	875	0.390944881	30	203.360897
TANGAZA	52	750	228.469724	506	0.36312336	30.5	210.2734431
SOKOTO NORTH	76	769	213.8361982	1061	0.318024935	30.5	207.5637702
TAMBUWAL	96	850	230.3324992	856	0.407808395	30.5	213.6185885
GADA	90	770	221.3130836	972	0.337926508	30.5	206.43955
SABON BIRNI	40	663	196.5179672	458	0.231594489	30.5	208.9968472
BINJI	66	756	225.006635	856	0.357316272	30.5	208.9817764
GWADABAWA	38	746	209.8301805	456	0.260301838	30.5	210.2567137
RABAH	89	873	231.441831	839	0.473425196	30	203.360897
TURETA	57	711	210.3857511	811	0.378772967	30	203.360897
ISA	49	719	215.0818329	302	0.272572178	30.5	208.9968472
GUDU	58	715	200.9968472	458	0.304954067	30.5	209.7151097
SOKOTO SOUTH	68	780	220.2754339	972	0.288024935	30.5	208.8637702
SILAME	52	736	235.9005	856	0.372506562	30.5	204.6935885
SHAGARI	98	866	235.5986328	856	0.354363517	30	204.5875259
YABO	114	796	235.9005	856	0.387795276	30.5	204.7221544
DANGE SHUNI	95	866	233.1367671	840	0.341469817	30	204.110897
KWARE	50	730	230.0884972	458	0.283333333	30.5	207.6137702
ILLELA	77	724	219.7914314	458	0.2460958	30.5	209.6137702
WURNO	45	717	229.3095652	458	0.228576116	30.5	207.6137702
WAMAKKO	50	719	220.5254339	972	0.343536746	30.5	208.8637702
KEBBE	117	848	200.0303318	1298	0.401377952	30	202.7071721

Faculty of Science and Engineering

University of Leicester

Questionnaire number:

Date:

The purpose of this questionnaire is to investigate the relationships between environmental variables and biological characteristics of slaughtered cattle with *F. gigantica* infections in Sokoto state, Nigeria. This is a PhD research that is being conducted through the University of Leicester, United Kingdom. It is intended to elicit information about your experiences, knowledge as well as involvement in livestock management with particular reference to the slaughtered cattle at this abattoir. There is no need to write your name on the questionnaire, and you are at this moment assured that all information would be treated with confidence. You should feel free to give your responses and as such should be as convenient as possible which should take an estimated 10 minutes to supply.

Questionnaire for owners of the slaughtered cattle at the abattoir

1. Sex…………

2. Marital status………………

A single

B Married

3. Age…………….

A-16-45

B. 46-60

C. Above 61

4. Educational level

A Primary

B. Secondary/Higher institution

C. None

5. Tribe

A. Hausa/Zabarma

B. Fulani

6. Regarding the source of ownership of cattle, which of the following applies to you

A. Inheritance

B. Given as a gift

C. Purchased

7. If purchased, please select any option that matches you from below

A. From the local environment

B. From the country Nigeria

C. Outside the country.

8. Which of the following is the source of pasture for your cattle?

A.At the fringes of rivers, ponds and lakes

B. Market

C. Government reserved areas

9). Where is the source of drinking water for your cattle during both dry and wet seasons?

A. Fadama

B. Dams

C. Tap water

10. How do your cattle intermingle with other cattle?

A. They congregate during drinking water around the water source

B. They mix during grazing

C. They do not mix at all

11. Are you familiar with the symptoms of liver fluke disease?

A Yes

B. No

If 'Yes' continue to question 12

12. Which part of the year do you notice those symptoms to be more severe?

……………………………………………..

13. How intensive do you assess the livestock farming in Sokoto state

A Very intensive

B. Intensive

C. Less intensive

Faculty of Science and Engineering

University of Leicester

Questionnaire number:

Date:

The purpose of this questionnaire is to investigate the relationships between environmental variables and biological characteristics of slaughtered cattle with *F. gigantica* infections in Sokoto state, Nigeria. This is a PhD research that is being conducted through the University of Leicester, United Kingdom. It is intended to elicit information about your experiences, knowledge as well as involvement in livestock management with particular reference to the slaughtered cattle at this abattoir. There is no need to write your name on the questionnaire, and you are at this moment assured that all information would be treated with confidence. You should feel free to give your responses and as such should be as convenient as possible which should take an estimated 10 minutes to supply.

Biological characteristics of the slaughtered cattle at the abattoir

1. Where is the source of your cattle?

A. Local

B. Exotic

2. Please state the age of your cattle….

3. What is the breed of your cattle?

A. White Fulani

B. Red Bororo

C. Sokoto Gudale

4. The sex of the cattle

A. Female (cow)

B. Male (bull)

Table A-26: Biological characteristics of slaughtered Cattle and fascioliasis infection (Data for logistic regression)

ID	Provinces	F.Infection	Animal source	AGE	Gender	Breed
1	Goronyo	A	1	73	F	1
2		B	2	24	F	1
3		B	1	73	F	1
4		B	2	24	M	1
5		B	2	36	M	2
6		B	1	24	F	2
7		A	1	73	F	2
8		B	1	36	M	1
9		B	2	24	F	2
10		B	1	36	M	1
11		A	1	73	F	2
12		B	1	36	F	2
13		B	1	36	M	1
14		B	2	24	M	3
15		A	1	72	F	3
16		B	1	36	M	2
17		B	1	24	M	1
18		B	2	24	F	3
19		A	1	48	F	3
20		B	1	36	M	2
21		B	1	72	F	3
22		A	1	48	M	3
23		B	1	36	M	3
24		B	1	72	M	2
25		B	1	48	M	3
26		B	1	72	F	3
27		B	1	24	M	3
28		B	2	36	F	2
29		B	1	72	F	3
30		B	1	73	F	3
31	Kebbe	A	1	24	M	2
32		A	1	73	F	2
33		B	2	24	M	1
34		B	2	36	M	2
35		B	1	24	F	3
36		A	1	73	F	2
37		B	1	36	M	2
38		B	2	24	F	1
39		B	1	36	M	3
40		A	1	73	F	3
41		B	1	36	F	2
42		B	1	36	M	3

43		B	2	24	M	2
44		A	1	72	F	2
45		B	1	36	M	1
46		B	1	24	M	2
47		A	1	48	F	2
48		A	1	48	F	2
49		B	1	36	M	3
50		B	1	72	F	3
51		A	1	48	M	3
52		B	1	36	M	3
53		B	1	48	M	2
54		A	1	48	M	3
55		B	1	72	F	2
56		B	1	24	M	3
57		B	2	36	F	2
58		A	1	48	F	3
59		B	2	48	F	1
60		B	1	36	M	2
61	Wurno	A	1	73	F	1
62		B	2	24	F	2
63		A	1	73	F	2
64		B	2	24	M	2
65		B	2	36	M	1
66		B	1	24	F	3
67		B	1	73	F	1
68		B	1	36	M	2
69		B	2	24	F	3
70		B	1	36	M	3
71		A	1	73	F	2
72		B	1	36	F	1
73		B	1	36	M	2
74		B	2	24	M	2
75		A	1	48	F	3
76		B	1	36	M	1
77		B	1	24	M	3
78		A	1	48	F	2
79		B	1	48	F	3
80		B	1	36	M	1
81		B	1	72	F	3
82		B	2	48	M	3
83		B	1	36	M	1
84		A	1	72	M	3
85		B	1	48	M	3
86		B	1	72	F	2
87		B	1	24	M	3
88		B	2	36	F	3

89		A	1	72	F	3
90		B	2	48	F	3
91	Gada	B	1	36	M	1
92		A	1	48	F	2
93		B	2	24	F	1
94		B	1	73	F	2
95		B	2	24	M	1
96		B	2	36	M	2
97		B	1	24	F	2
98		B	1	73	F	1
99		B	1	36	M	2
100		B	2	24	F	1
101		B	1	36	M	2
102		A	1	73	F	2
103		B	1	36	F	2
104		B	1	36	M	3
105		B	2	24	M	3
106		A	1	72	F	3
107		B	1	36	M	1
108		B	1	24	M	3
109		A	1	48	F	3
110		A	1	48	F	3
111		B	1	36	M	3
112		B	1	72	F	3
113		A	2	48	M	3
114		B	1	36	M	3
115		A	1	72	M	3
116		B	1	48	M	3
117		B	1	36	F	3
118		B	1	24	M	1
119		B	2	36	F	3
120		A	1	48	F	3
121	Sokoto north	A	2	48	F	1
122		B	1	36	M	2
123		A	1	48	F	1
124		B	2	24	F	2
125		B	1	73	F	2
126		A	1	24	M	2
127		B	2	36	M	2
128		B	1	24	F	1
129		A	1	73	F	2
130		B	1	36	M	3
131		B	2	24	F	3
132		B	1	36	M	1
133		A	1	73	F	3

134		B	1	36	F	3
135		A	1	36	M	3
136		B	2	24	M	2
137		A	1	72	F	3
138		B	1	36	M	3
139		B	1	24	M	3
140		A	1	48	F	3
141		A	1	48	F	3
142		B	1	36	M	3
143		B	1	72	F	3
144		A	2	48	M	3
145		B	1	36	M	3
146		A	1	72	M	3
147		A	1	48	M	3
148		B	1	36	F	3
149		B	1	72	M	3
150		B	2	36	F	3
151	Gudu	B	1	48	F	1
152		B	2	48	F	3
153		B	1	36	M	2
154		A	1	73	F	1
155		B	2	24	F	3
156		A	1	73	F	2
157		A	2	24	M	3
158		B	2	36	M	2
159		B	1	24	F	1
160		A	1	73	F	3
161		B	1	36	M	2
162		B	2	24	F	3
163		B	1	36	M	3
164		A	1	73	F	3
165		B	1	36	F	3
166		A	1	36	M	3
167		B	2	24	M	3
168		A	1	72	F	3
169		B	1	36	M	3
170		A	1	24	M	3
171		A	2	48	F	3
172		B	2	48	F	3
173		B	1	36	M	3
174		A	1	48	F	3
175		B	2	48	M	3
176		B	1	36	M	3
177		A	1	72	M	3
178		B	1	48	M	3
179		B	1	36	F	3

180		A	1	72	M	3
181	Silame	B	2	36	F	1
182		A	1	73	F	1
183		B	2	48	F	1
184		B	1	36	M	1
185		A	1	36	F	2
186		B	2	24	F	1
187		B	1	73	F	2
188		A	1	24	M	2
189		B	2	36	M	3
190		B	1	24	F	2
191		A	1	73	F	2
192		B	1	36	M	3
193		A	2	24	F	3
194		B	1	36	M	1
195		A	1	73	F	3
196		B	1	36	F	2
197		A	1	36	M	3
198		B	2	24	M	2
199		A	1	72	F	3
200		B	1	36	M	3
201		B	1	24	M	2
202		B	2	48	F	3
203		B	2	48	F	3
204		A	1	36	M	3
205		B	1	48	F	3
206		B	2	48	M	3
207		B	1	36	M	3
208		A	1	72	M	3
209		B	1	48	M	3
210		B	1	36	F	3
211	Shagari	B	1	48	M	1
212		B	2	36	F	2
213		A	1	48	F	1
214		B	2	48	F	2
215		B	1	36	M	2
216		A	1	24	F	3
217		B	2	24	F	3
218		B	1	23	F	1
219		A	2	74	M	3
220		B	2	36	M	3
221		A	1	24	F	3
222		B	1	73	F	3
223		B	1	36	M	2
224		B	2	24	F	1
225		B	1	36	M	3

226		A	1	73	F	3
227		B	1	36	F	2
228		A	1	36	M	3
229		B	2	24	M	3
230		A	1	72	F	2
231		B	1	36	M	2
232		B	1	24	M	3
233		A	1	72	F	2
234		B	2	48	F	3
235		B	1	36	M	2
236		B	1	48	F	3
237		B	2	48	M	3
238		B	1	36	M	2
239		A	1	72	M	2
240		B	1	48	M	3
241	Dange shuni	B	1	36	F	1
242		B	1	48	M	2
243		B	2	36	F	2
244		B	1	48	F	3
245		B	2	48	F	1
246		A	1	36	M	2
247		A	1	48	F	2
248		B	2	24	F	3
249		B	1	73	F	3
250		B	2	24	M	3
251		B	2	36	M	3
252		A	1	24	F	3
253		A	1	73	F	3
254		B	1	36	M	2
255		B	2	24	F	1
256		B	1	36	M	3
257		A	1	73	F	3
258		B	1	36	F	1
259		A	1	36	M	3
260		B	2	24	M	2
261		A	1	72	F	3
262		B	1	36	M	3
263		B	1	24	M	3
264		A	1	72	F	3
265		B	2	48	F	1
266		B	1	36	M	3
267		B	1	48	F	3
268		B	2	48	M	3
269		B	1	36	M	3
270		B	1	72	M	1

271	Rabah	A	1	48	M	1
272		B	1	36	F	2
273		B	1	48	M	1
274		B	2	36	F	2
275		B	1	48	F	3
276		B	2	48	F	1
277		B	1	36	M	2
278		A	1	73	F	2
279		B	2	24	F	1
280		B	1	73	F	3
281		B	2	24	M	2
282		B	2	36	M	1
283		A	1	24	F	2
284		A	1	73	F	3
285		B	1	36	M	3
286		B	2	24	F	1
287		B	1	36	M	3
288		A	1	73	F	2
289		B	1	36	F	3
290		A	1	36	M	3
291		B	2	24	M	1
292		A	1	72	F	3
293		B	1	36	M	3
294		B	1	24	M	2
295		A	1	72	F	3
296		B	2	48	F	3
297		A	1	36	M	3
298		B	1	48	F	3
299		B	2	48	M	3
300		A	1	36	M	3

Table A-27 Practices of cattle management and fascioliasis infection

ID	Provinces	F.Infection	herd acquisition	grazing areas	water source	Tribe
1	Gudu	A	1	3	2	B
2		B	1	3	2	A
3		B	1	3	1	B
4		B	1	2	1	A
5		B	2	2	2	B
6		B	2	2	1	A
7		A	1	2	1	B
8		B	3	3	2	A
9		B	2	2	1	A
10		B	1	2	1	A
11		A	2	2	2	B

12		B	1	1	1	A
13		B	2	2	2	B
14		B	3	1	1	A
15		A	3	1	1	B
16		B	2	2	2	A
17		B	1	3	1	B
18		B	3	1	1	A
19		A	3	1	1	B
20		B	2	2	1	B
21		B	3	1	1	A
22		A	3	1	1	B
23		B	3	1	2	A
24		B	2	2	1	A
25		B	3	1	1	B
26		B	3	1	2	A
27		B	3	1	1	B
28		B	2	2	1	A
29		B	3	1	1	B
30		B	3	1	2	B
31	Goronyo	A	3	2	2	A
32		A	2	2	1	B
33		B	1	2	2	A
34		B	2	2	1	B
35		B	3	1	1	A
36		A	2	2	1	B
37		B	2	2	2	A
38		B	3	1	1	B
39		B	3	1	2	A
40		A	3	2	2	B
41		B	1	2	1	A
42		B	3	1	1	B
43		B	3	1	1	A
44		A	1	3	1	B
45		B	1	1	1	A
46		B	2	2	2	B
47		A	2	2	1	A
48		A	1	1	1	B
49		B	3	1	1	A
50		B	3	1	1	B
51		A	3	1	2	A
52		B	3	1	1	B
53		B	1	3	1	B
54		A	3	1	1	A
55		B	2	2	2	B
56		B	3	1	1	A
57		B	2	2	1	A

58		A	3	1	1	B
59		B	1	3	1	A
60		B	2	2	1	B
61	Gada	A	1	3	1	B
62		B	1	1	2	B
63		A	3	2	1	B
64		B	2	2	1	A
65		B	1	2	2	B
66		B	3	1	1	A
67		B	1	2	2	B
68		B	2	2	1	B
69		B	3	1	1	B
70		B	3	3	2	A
71		A	1	3	1	B
72		B	3	1	1	B
73		B	2	2	1	A
74		B	1	1	1	A
75		A	3	1	1	B
76		B	1	2	2	B
77		B	3	1	1	A
78		A	3	1	2	B
79		B	3	1	1	A
80		B	1	3	1	B
81		B	3	1	1	A
82		B	3	1	1	B
83		B	1	3	1	A
84		A	3	1	1	B
85		B	3	1	2	A
86		B	1	2	1	B
87		B	3	1	1	A
88		B	3	1	1	B
89		A	3	1	2	B
90		B	3	1	1	A
91	Wurno	B	3	1	2	A
92		A	3	1	1	B
93		B	1	3	1	A
94		B	2	2	1	B
95		B	1	3	1	A
96		B	2	2	1	B
97		B	1	3	2	A
98		B	1	3	1	B
99		B	2	2	1	A
100		B	1	3	2	B
101		B	3	1	1	A
102		A	2	1	1	B
103		B	1	3	1	A

104		B	3	1	1	B
105		B	3	1	1	A
106		A	3	1	1	B
107		B	1	3	1	B
108		B	3	1	1	A
109		A	3	1	1	A
110		A	3	1	1	B
111		B	3	1	2	A
112		B	3	1	1	B
113		A	3	1	1	B
114		B	3	1	2	A
115		A	3	1	1	B
116		B	3	1	1	A
117		B	3	1	2	B
118		B	1	3	1	A
119		B	3	1	2	B
120		A	3	1	1	A
121	Sokoto north	A	1	3	1	B
122		B	2	2	1	A
123		A	1	1	1	B
124		B	2	2	1	A
125		B	3	1	1	A
126		A	2	1	1	B
127		B	1	2	2	A
128		B	1	2	1	B
129		A	3	1	1	A
130		B	3	1	1	B
131		B	3	1	2	B
132		B	1	2	1	B
133		A	3	1	1	B
134		B	3	1	1	A
135		A	3	1	1	B
136		B	1	1	2	A
137		A	3	3	1	B
138		B	3	1	1	B
139		B	3	1	1	A
140		A	3	1	1	B
141		A	3	1	1	A
142		B	3	1	2	B
143		B	3	1	1	B
144		A	3	1	2	B
145		B	3	1	1	B
146		A	3	1	1	B
147		A	3	1	1	B
148		B	3	1	1	A

149		B	3	1	1	B
150		B	3	1	1	B
151	Kebbe	B	1	2	1	B
152		B	3	1	2	A
153		B	2	2	1	B
154		A	1	1	1	B
155		B	3	1	2	A
156		A	2	1	1	B
157		A	3	1	1	B
158		B	2	2	1	B
159		B	1	2	1	B
160		A	3	3	1	B
161		B	2	2	1	B
162		B	3	1	2	B
163		B	3	1	1	A
164		A	3	1	1	B
165		B	3	1	2	B
166		A	3	1	1	B
167		B	3	1	1	A
168		A	3	1	1	B
169		B	3	1	1	A
170		A	3	1	1	B
171		A	3	1	1	B
172		B	3	1	2	A
173		B	3	1	2	B
174		A	3	1	1	A
175		B	3	1	1	B
176		B	3	1	1	B
177		A	3	1	1	B
178		B	3	1	1	A
179		B	3	1	1	A
180		A	3	1	1	B
181	Shagari	B	1	2	2	B
182		A	1	3	1	A
183		B	1	2	1	B
184		B	1	2	1	A
185		A	2	2	1	B
186		B	1	1	1	A
187		B	2	2	2	B
188		A	2	1	1	B
189		B	3	1	1	A
190		B	1	1	2	A
191		A	3	1	1	B
192		B	3	1	1	A
193		A	3	1	1	B
194		B	1	1	1	A

195		A	3	1	2	B
196		B	1	1	1	A
197		A	3	1	1	B
198		B	2	1	2	A
199		A	3	1	1	B
200		B	3	1	1	A
201		B	1	1	1	B
202		B	3	1	2	A
203		B	3	1	1	B
204		A	3	1	1	B
205		B	3	1	2	A
206		B	3	1	1	B
207		B	3	1	1	B
208		A	3	1	1	B
209		B	3	1	1	A
210		B	3	1	2	A
211	Silame	B	1	3	1	B
212		B	2	1	2	A
213		A	1	3	1	B
214		B	1	1	1	A
215		B	1	1	1	B
216		A	3	1	1	B
217		B	3	1	2	A
218		B	1	3	1	A
219		A	3	3	1	B
220		B	3	3	2	B
221		A	3	3	1	A
222		B	3	3	1	B
223		B	1	1	1	A
224		B	1	1	1	B
225		B	3	3	1	A
226		A	3	1	2	B
227		B	2	1	1	A
228		A	3	1	1	B
229		B	3	1	2	B
230		A	2	1	1	B
231		B	2	1	1	A
232		B	3	3	1	A
233		A	3	1	1	B
234		B	3	1	2	A
235		B	2	1	1	B
236		B	3	1	2	B
237		B	3	1	1	A
238		B	1	3	1	B
239		A	2	1	1	B
240		B	3	1	1	A

241	Dange shuni	B	1	1	1	A
242		B	2	1	1	B
243		B	1	1	1	A
244		B	3	3	1	B
245		B	1	1	1	A
246		A	3	1	1	B
247		A	2	1	1	A
248		B	3	1	2	B
249		B	3	1	1	B
250		B	3	1	1	A
251		B	3	3	1	B
252		A	3	1	1	A
253		A	3	1	1	A
254		B	1	1	1	B
255		B	1	3	1	B
256		B	3	1	1	A
257		A	3	1	1	A
258		B	1	1	2	B
259		A	3	1	1	A
260		B	1	1	1	B
261		A	3	1	1	A
262		B	3	3	1	B
263		B	3	1	1	A
264		A	3	1	1	A
265		B	1	1	1	A
266		B	3	1	1	B
267		B	3	3	1	B
268		B	3	1	1	A
269		B	3	1	1	B
270		B	1	1	1	A
271	Rabah	A	1	1	1	A
272		B	1	1	1	A
273		B	1	3	2	B
274		B	1	1	1	A
275		B	3	3	1	A
276		B	1	1	1	B
277		B	2	1	1	A
278		A	2	1	2	B
279		B	1	1	1	A
280		B	3	1	1	A
281		B	1	1	2	B
282		B	1	1	1	A
283		A	3	1	1	A
284		A	3	1	1	A
285		B	3	1	1	B

286	B	1	3	1	A
287	B	1	1	1	B
288	A	3	1	1	A
289	B	3	1	1	B
290	A	3	1	1	A
291	B	1	3	1	A
292	A	3	1	1	A
293	B	1	1	1	B
294	B	1	1	1	A
295	A	3	1	1	A
296	B	1	1	1	B
297	A	3	1	1	A
298	B	1	1	1	B
299	B	1	1	1	A
300	A	3	1	1	A

Table A-28 Climatic/environmental factors and fascioliasis infection

ID	Provinces	F_Infection	temperature	NDVI	Rainfall	soil moisture	Elevation
1	Goronyo	A	34	0.2	730	198	300
2		B	34	0.2	730	198	300
3		B	34	0.2	730	198	300
4		B	34	0.2	730	198	300
5		B	34	0.2	730	198	300
6		B	34	0.2	730	198	300
7		A	34	0.2	730	198	300
8		B	34	0.2	730	198	300
9		B	34	0.2	730	198	300
10		B	34	0.2	730	198	300
11		A	34	0.2	730	198	300
12		B	34	0.2	730	198	300
13		B	34	0.2	730	198	300
14		B	34	0.2	730	198	300
15		A	34	0.2	730	198	300
16		B	34	0.2	730	198	300
17		B	34	0.2	730	198	300
18		B	34	0.2	730	198	300
19		A	34	0.2	730	198	300
20		B	34	0.2	730	198	300
21		B	34	0.2	730	198	300
22		A	34	0.2	730	198	300
23		B	34	0.2	730	198	300
24		B	34	0.2	730	198	300
25		B	34	0.2	730	198	300

26		B	34	0.2	730	198	300
27		B	34	0.2	730	198	300
28		B	34	0.2	730	198	300
29		B	34	0.2	730	198	300
30		B	34	0.4	1088	230	300
31	Kebbe	A	32	0.4	1088	230	300
32		A	32	0.4	1088	230	300
33		B	32	0.4	1088	230	300
34		B	32	0.4	1088	230	300
35		B	32	0.4	1088	230	300
36		A	32	0.4	1088	230	300
37		B	32	0.4	1088	230	300
38		B	32	0.4	1088	230	300
39		B	32	0.4	1088	230	300
40		A	32	0.4	1088	230	300
41		B	32	0.4	1088	230	300
42		B	32	0.4	1088	230	300
43		B	32	0.4	1088	230	300
44		A	32	0.4	1088	230	300
45		B	32	0.4	1088	230	300
46		B	32	0.4	1088	230	300
47		A	32	0.4	1088	230	300
48		A	32	0.4	1088	230	300
49		B	32	0.4	1088	230	300
50		B	32	0.4	1088	230	300
51		A	32	0.4	1088	230	300
52		B	32	0.4	1088	230	300
53		B	32	0.4	1088	230	300
54		A	32	0.4	1088	230	300
55		B	32	0.4	1088	230	300
56		B	32	0.4	1088	230	300
57		B	32	0.4	1088	230	300
58		A	32	0.4	1088	230	300
59		B	32	0.4	1088	230	300
60		B	32	0.4	1088	230	300
61	Wurno	A	33	0.3	717	195	300
62		B	33	0.3	717	195	300
63		A	33	0.3	717	195	300
64		B	33	0.3	717	195	300
65		B	33	0.3	717	195	300
66		B	33	0.3	717	195	300
67		B	33	0.3	717	195	300
68		B	33	0.3	717	195	300
69		B	33	0.3	717	195	300
70		B	33	0.3	717	195	300
71		A	33	0.3	717	195	300

72		B	33	0.3	717	195	300
73		B	33	0.3	717	195	300
74		B	33	0.3	717	195	300
75		A	33	0.3	717	195	300
76		B	33	0.3	717	195	300
77		B	33	0.3	717	195	300
78		A	33	0.3	717	195	300
79		B	33	0.3	717	195	300
80		B	33	0.3	717	195	300
81		B	33	0.3	717	195	300
82		B	33	0.3	717	195	300
83		B	33	0.3	717	195	300
84		A	33	0.3	717	195	300
85		B	33	0.3	717	195	300
86		B	33	0.3	717	195	300
87		B	33	0.3	717	195	300
88		B	33	0.3	717	195	300
89		A	33	0.3	717	195	300
90		B	33	0.3	717	195	300
91	Gada	B	34	0.2	730	199	300
92		A	34	0.2	730	199	300
93		B	34	0.2	730	199	300
94		B	34	0.2	730	199	300
95		B	34	0.2	730	199	300
96		B	34	0.2	730	199	300
97		B	34	0.2	730	199	300
98		B	34	0.2	730	199	300
99		B	34	0.2	730	199	300
100		B	34	0.2	730	199	300
101		B	34	0.2	730	199	300
102		A	34	0.2	730	199	300
103		B	34	0.2	730	199	300
104		B	34	0.2	730	199	300
105		B	34	0.2	730	199	300
106		A	34	0.2	730	199	300
107		B	34	0.2	730	199	300
108		B	34	0.2	730	199	300
109		A	34	0.2	730	199	300
110		A	34	0.2	730	199	300
111		B	34	0.2	730	199	300
112		B	34	0.2	730	199	300
113		A	34	0.2	730	199	300
114		B	34	0.2	730	199	300
115		A	34	0.2	730	199	300
116		B	34	0.2	730	199	300
117		B	34	0.2	730	199	300

118		B	34	0.2	730	199	300
119		B	34	0.2	730	199	300
120		A	34	0.2	730	199	300
121	Sokoto N.	A	35	0.3	739	213	289
122		B	35	0.3	739	213	289
123		A	35	0.3	739	213	289
124		B	35	0.3	739	213	289
125		B	35	0.3	739	213	289
126		A	35	0.3	739	213	289
127		B	35	0.3	739	213	289
128		B	35	0.3	739	213	289
129		A	35	0.3	739	213	289
130		B	35	0.3	739	213	289
131		B	35	0.3	739	213	289
132		B	35	0.3	739	213	289
133		A	35	0.3	739	213	289
134		B	35	0.3	739	213	289
135		A	35	0.3	739	213	289
136		B	35	0.3	739	213	289
137		A	35	0.3	739	213	289
138		B	35	0.3	739	213	289
139		B	35	0.3	739	213	289
140		A	35	0.3	739	213	289
141		A	35	0.3	739	213	289
142		B	35	0.3	739	213	289
143		B	35	0.3	739	213	289
144		A	35	0.3	739	213	289
145		B	35	0.3	739	213	289
146		A	35	0.3	739	213	289
147		A	35	0.3	739	213	289
148		B	35	0.3	739	213	289
149		B	35	0.3	739	213	289
150		B	35	0.3	739	213	289
151	Gudu	B	36	0.3	715	199	289
152		B	36	0.3	715	199	279
153		B	36	0.3	715	199	279
154		A	36	0.3	715	199	279
155		B	36	0.3	715	199	279
156		A	36	0.3	715	199	279
157		A	36	0.3	715	199	279
158		B	36	0.3	715	199	279
159		B	36	0.3	715	199	279
160		A	36	0.3	715	199	279
161		B	36	0.3	715	199	279
162		B	36	0.3	715	199	279

163		B	36	0.3	715	199	279
164		A	36	0.3	715	199	279
165		B	36	0.3	715	199	279
166		A	36	0.3	715	199	279
167		B	36	0.3	715	199	279
168		A	36	0.3	715	199	279
169		B	36	0.3	715	199	279
170		A	36	0.3	715	199	279
171		A	36	0.3	715	199	279
172		B	36	0.3	715	199	279
173		B	36	0.3	715	199	279
174		A	36	0.3	715	199	279
175		B	36	0.3	715	199	279
176		B	36	0.3	715	199	279
177		A	36	0.3	715	199	279
178		B	36	0.3	715	199	279
179		B	36	0.3	715	199	279
180		A	36	0.3	715	199	279
181	Silame	B	35	0.3	706	215	248
182		A	35	0.3	706	215	248
183		B	35	0.3	706	215	248
184		B	35	0.3	706	215	248
185		A	35	0.3	706	215	248
186		B	35	0.3	706	215	248
187		B	35	0.3	706	215	248
188		A	35	0.3	706	215	248
189		B	35	0.3	706	215	248
190		B	35	0.3	706	215	248
191		A	35	0.3	706	215	248
192		B	35	0.3	706	215	248
193		A	35	0.3	706	215	248
194		B	35	0.3	706	215	248
195		A	35	0.3	706	215	248
196		B	35	0.3	706	215	248
197		A	35	0.3	706	215	248
198		B	35	0.3	706	215	248
199		A	35	0.3	706	215	248
200		B	35	0.3	706	215	248
201		B	35	0.3	706	215	248
202		B	35	0.3	706	215	248
203		B	35	0.3	706	215	248
204		A	35	0.3	706	215	248
205		B	35	0.3	706	215	248
206		B	35	0.3	706	215	248
207		B	35	0.3	706	215	248
208		A	35	0.3	706	215	248

209		B	35	0.3	706	215	248
210		B	35	0.3	706	215	248
211	Shagari	B	34	0.4	866	220	300
212		B	34	0.4	866	220	300
213		A	34	0.4	866	220	300
214		B	34	0.4	866	220	300
215		B	34	0.4	866	220	300
216		A	34	0.4	866	220	300
217		B	34	0.4	866	220	300
218		B	34	0.4	866	220	300
219		A	34	0.4	866	220	300
220		B	34	0.4	866	220	300
221		A	34	0.4	866	220	300
222		B	34	0.4	866	220	300
223		B	34	0.4	866	220	300
224		B	34	0.4	866	220	300
225		B	34	0.4	866	220	300
226		A	34	0.4	866	220	300
227		B	34	0.4	866	220	300
228		A	34	0.4	866	220	300
229		B	34	0.4	866	220	300
230		A	34	0.4	866	220	300
231		B	34	0.4	866	220	300
232		B	34	0.4	866	220	300
233		A	34	0.4	866	220	300
234		B	34	0.4	866	220	300
235		B	34	0.4	866	220	300
236		B	34	0.4	866	220	300
237		B	34	0.4	866	220	300
238		B	34	0.4	866	220	300
239		A	34	0.4	866	220	300
240		B	34	0.4	866	220	300
241	Dange S.	B	34	0.2	866	221	311
242		B	34	0.2	866	221	311
243		B	34	0.2	866	221	311
244		B	34	0.2	866	221	311
245		B	34	0.2	866	221	311
246		A	34	0.2	866	221	311
247		A	34	0.2	866	221	311
248		B	34	0.2	866	221	311
249		B	34	0.2	866	221	311
250		B	34	0.2	866	221	311
251		B	34	0.2	866	221	311
252		A	34	0.2	866	221	311
253		A	34	0.2	866	221	311
254		B	34	0.2	866	221	311

255		B	34	0.2	866	221	311
256		B	34	0.2	866	221	311
257		A	34	0.2	866	221	311
258		B	34	0.2	866	221	311
259		A	34	0.2	866	221	311
260		B	34	0.2	866	221	311
261		A	34	0.2	866	221	311
262		B	34	0.2	866	221	311
263		B	34	0.2	866	221	311
264		A	34	0.2	866	221	311
265		B	34	0.2	866	221	311
266		B	34	0.2	866	221	311
267		B	34	0.2	866	221	311
268		B	34	0.2	866	221	311
269		B	34	0.2	866	221	311
270		B	34	0.2	866	221	311
271	Rabah	A	34	0.3	873	228	311
272		B	34	0.3	873	228	277
273		B	34	0.3	873	228	277
274		B	34	0.3	873	228	277
275		B	34	0.3	873	228	277
276		B	34	0.3	873	228	277
277		B	34	0.3	873	228	277
278		A	34	0.3	873	228	277
279		B	34	0.3	873	228	277
280		B	34	0.3	873	228	277
281		B	34	0.3	873	228	277
282		B	34	0.3	873	228	277
283		A	34	0.3	873	228	277
284		A	34	0.3	873	228	277
285		B	34	0.3	873	228	277
286		B	34	0.3	873	228	277
287		B	34	0.3	873	228	277
288		A	34	0.3	873	228	277
289		B	34	0.3	873	228	277
290		A	34	0.3	873	228	277
291		B	34	0.3	873	228	277
292		A	34	0.3	873	228	277
293		B	34	0.3	873	228	277
294		B	34	0.3	873	228	277
295		A	34	0.3	873	228	277
296		B	34	0.3	873	228	277
297		A	34	0.3	873	228	277
298		B	34	0.3	873	228	277
299		B	34	0.3	873	228	277
300		A	34	0.3	873	228	277

Figure A-58 Field work 2016 interviewing slaughtered cattle holder

Figure A-59 Recording data on biological characteristics of slaughtered cattle at Sokoto abattoir.

Figure A-60Goronyo slaughter slabs (field work 2016)

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