Climate Change and Health in Sub-Saharan Africa: The Case of Uganda

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Climate Change Adaptation Innovation

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Foreword

Parties to the United Nations Framework Convention on Climate Change (UNFCCC), in their differentiated national circumstances, have obligations to fulfil commitments under the Convention, and its related instruments, to contribute to the global efforts to reduce the emissions of human-induced greenhouse gases (GHGs) in the atmosphere that lead to global warming and hence climate change. The establishment of the Climate Investment Funds (CIF) for scaled-up climate finance reflects the international effort to enhance the provision of the means of delivery (i.e., finance, technology, and capacity building) of actions to address the causes of climate change and its impacts.

Climate change talks in the early 1990s, at the onset of work under the Convention, did not consider health-related impacts of climate change, for the obvious reason that work under the health sector was not visualized and understood as a key source of GHGs threatening our common atmosphere.

Both the pre- and post-Paris climate change negotiations embraced climate change and health. Since climate change-related actions emanate from decisions of the Conference of the Parties to the UNFCCC (COP), anchored in the Climate Change Convention, the entry of health-related work into climate change actions decades after the onset of the Convention is, perhaps, understandable. Climate change actions in the run-up to the 2015 climate change talks in Paris were a milestone for the entry of the health sector into climate change discourse. Countries pronounced their nationally determined contributions (NDCs) towards holding the global average temperature increase to well below 2^0C above pre-industrial levels and pursuing efforts to limit temperature increases to 1.5^0C above pre-industrial levels, through sector-specific actions.

The 2019 World Health Organization review of *Health in NDCs* shows that, as of December 2019, 70% of NDCs (129 out of 184) included the health sector. Evidently, the NDC process has been a key trigger and vehicle for entry of the health sector into climate change action, particularly in the Least Developed Countries (LDCs), including Uganda. Uganda, in its NDC commitment is focusing on a 22% reduction of national GHG emissions by the year 2030, compared to business as usual, through mitigation and adaptation actions, as well as policies in eight key sectors including health. The specific adaptation actions in Uganda's NDC related to the health sector include "improvement in early warning systems for disease outbreaks". While the need for early warning systems and predictive tools that are readily applicable spans beyond health, the response to climate change impacts calls for participation of not only state but also non-state actors, as has been demonstrated in this innovative piece of work.

The commissioning of this study, therefore, by the Climate Investment Fund (CIF) Evaluation and Learning (E&L) Initiative is not only a commendable fulfilment of the CIF's mandate but also a demonstration of international solidarity in responding to climate change impacts, be it extreme events or slow-onset events. In addition, the collaborative designing and execution of the work leading to this innovation by the many individuals and institutions is highly commendable.

The digital predictive tool developed by the study for forecasting the occurrence of diseases, based on historical weather and health data, will strengthen the capacity of Uganda's health system to prepare for and respond to the impacts of climate change on health. The Climate Change Department will engage the Ministry of Health to explore possible mechanisms of institutionalizing the predictive tool with the Ministry's health information services.

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Disclaimer

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List of Acronyms and Abbreviations

CBD	Convention on Biological Diversity
CBO	Community Based Organizations
CCD	Climate Change Department
CHAI	Climate Change Adaptation Innovation
CHASA	Climate Change and Health in Sub-Saharan Africa
CIF	Climate Investment Funds
COP	Conference of the Parties
CSO	Civil Society Organization
DHIS 2	District Health Information System
E&L	Evaluation and Learning
EW	Early Warning
EWS	Early Warning System
FBO	Faith Based Organization
GDP	Gross Domestic Product
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GoU	Government of Uganda
HMIS	Health Management Information System
HTTPS	Hypertext Transfer Protocol Secure
ID	Identity
IPCC	Intergovernmental Panel on Climate Change
MAAIF	Ministry of Agriculture, Animal Industry, and Fisheries
MDAs	Ministries, Departments and Agencies
MLE	Maximum Likelihood Estimation
MoFPED	Ministry of Finance, Planning and Economic Development
MoH	Ministry of Health
MoLG	Ministry of Local Government
MWE	Ministry of Water and Environment
NAPA	National Adaptation Programme of Action
NAPs	National Adaptation Plans
NDC	Nationally Determined Contribution
NECOC	National Emergency Coordination Operations Centre
NGOs	Non-Government Organizations
OPM	Office of the Prime Minister
PFCC	Parliamentary Forum on Climate Change
RUWASS	Reform of the Urban Water and Sanitation Sector Reform Program
SSA	Sub-Saharan Africa
TAHMO	Trans-Africa Hydro-Meteorological Observatory
UNFCCC	United Nations Framework Convention on Climate Change
UNMA	Uganda National Meteorological Authority
UNOSSC	United Nations Office for South-South Cooperation
WHO	World Health Organization

Executive Summary

Climate change is a global threat to stability. With its impacts in the form of extreme weather events and rising water body levels, climate change exposes present and future generations to lifelong health and livelihood harm, particularly in regions with low adaptive capacity, such as Africa. In Uganda, a country with huge dependence on natural resources, the increased frequency and intensity of severe weather, such as flooding and drought, causes tormenting risks, as the occurrences of water-borne and vector-borne diseases and malnutrition-related illnesses are aggravated.

To enhance the ability of the national health systems to prepare for and cope with rising needs for treating climate-sensitive diseases, Uganda has put in place a range of measures, including a health sector development plan that reflects the need for "early warning systems and dissemination of weather forecasts to help health managers to improve preparedness and response" (GoU, 2015). Despite the successful introduction of policy measures, to-date, the country has not introduced a system capable of predicting the anticipated occurrence of climate sensitive diseases based on changes in weather conditions (such as temperature and rainfall). This would help prepare the health system to respond to increased occurrences of climate-sensitive diseases. This study addresses this gap by developing a digital solution that predicts the occurrence of climate-sensitive diseases based on historical and current weather and health data.

This *Climate Change and Health in Sub-Saharan Africa: The Case of Uganda* (CHASA) project aimed to fill this gap by: (i) identifying, ranking and documenting key climate-sensitive diseases, including analysis of the correlations between climate factors and disease risks; (ii) developing a forecast model on climate change and disease risks that runs as a web and smartphone application for use by health facilities, health managers and planners; (iii) documenting and sharing learning on the linkages between climate and weather changes and health risks; and (iv) developing key recommendations for improving the national health system to improve the detection and response to climate-sensitive diseases.

The study's project area in the "cattle corridor" was selected based on three major criteria: (i) prevalence of climate change and variability; (ii) representation of different ecosystems; and (iii) availability of functioning weather stations in close proximity to health facilities (considered for the predictive modeling). The cattle corridor is characterized by erratic rains, frequent prolonged droughts and flooding. A total of nine study districts were selected, these are: Butambala, Gulu, Kampala, Kitgum, Nakaseke, Nakasongola Sembabule Soroti and Wakiso

To achieve the above-mentioned objectives, the study undertook a literature review, stakeholder consultations to gather evidence on how climate change affects human health in Uganda and predictive modeling to project the potential changes in the prevalence of climate-sensitive diseases due to changes in climatic drivers. The study used a "supervised learning" approach of machine learning that involved the use of historical weather and health data (2014 – 2019) for the training and testing of the model. The predictive modeling was developed in the R statistical computing environment using a negative-binomial linear regression algorithm. A prediction model of disease risks based on weather parameters was

developed that runs as a web and mobile application for use by health facilities, managers and planners at the Ministry of Health.

The study found that the diseases most sensitive to climate in Uganda include Asthma, cholera, dysentery, fever, guinea worm, malaria, skin diseases, typhoid and yellow fever. The literature review and stakeholders' discussions conducted by the project show that climate change affects the environmental and social determinants of health and that the stakeholders have observed and experienced changes in the occurrence of the identified climate-sensitive diseases because of changing climate. The project recommends the integration of the digital predictive model as a strategy to improve the country's preparedness and response capabilities and enable the health system to respond to increased occurrence of climate-sensitive diseases due to changing climate. The project recommends for the use of the predictive tool at all levels of the health system ranging from health facilities up to the national health planners and emergency response coordination offices such as the Office of the Prime Minister.

In order to improve the detection and response to climate-sensitive diseases, the study found the importance of linking weather and climate institutions and officials to those in the health sector, and to operationalize what is in the strategic documents. Harnessing the digital solutions is another recommendation that would bring great results.

The Ministry of Health's Department of Environmental Health and the Division of Health Information have been engaged throughout the development process of the predictive tool and have expressed their desire to institutionalize the tool within the health system. The Ministry of Health recognizes the predictive tool's potential to enhance the current early warning capacity, risk reduction and management of national health risks of climate-related morbidity, mortality and economic loss. A key recommendation of the study is to expand the scope of the predictive tool from the nine districts considered for the study to cover all districts in the country. Such efforts may be hampered by the lack of weather stations covering all parts of the country and gaps in the availability of health data; however, an incremental approach can be taken by including health facilities that can be paired with a functioning weather station.

1. Introduction

The Climate Investment Funds (CIF) were founded with the mandate to serve as a learning laboratory for scaled-up climate finance. The CIF Evaluation and Learning (E&L) Initiative is helping to fulfill this mandate through a range of strategic and demand-driven evaluations covering some of the most important and pressing challenges facing climate finance funders and practitioners. Drawing on experience from across the CIF portfolio of investments in clean energy, forests and resilience in 72 developing countries, the E&L Initiative uses evaluation to enable learning that is relevant, timely and used to inform decisions and strategies, for both the CIF and the wider climate finance sector. This report was commissioned by CIF's E&L Initiative and presents the results of a study focusing on the link between changing climate and the incidence of climate-sensitive disease in Uganda, and a digital predictive tool driven by weather and health data.

1.1 Context

There is a global consensus that climate change is becoming a tenacious threat to various aspects of global stability of the 21st century (Russell, 2009; Freeman, 2010; Dafermos, 2018; Sellers, 2019). Its impacts are felt worldwide in the form of extreme weather conditions and rising sea levels posing unprecedented threats to the security and wellbeing of the population and future generations (Dafermos, 2018; Sellers, 2019). The fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) asserts that due to its high exposure to climatic hazards and low adaptive capacity, Africa continues to be one of the most vulnerable continents to climate variability and change (IPCC, 2014; Niang et al., 2014; Filho et al., 2015). The IPCC assessment notes with high confidence that climate change will intensify existing water stress in Africa and will continue to be a key impediment to the continent's economic development. Weak adaptive capacity throughout the region is aggravated by the interaction of multiple challenges occurring at various levels such as poverty, rapid population growth, complex governance and institutional aspects, and ecosystem degradation that in turn contribute to the continent's vulnerability to climate change (Serdeczny et al., 2015).

The impacts of climate change are manifested in multiple ways. The major climate change-related risks in Africa include stress on water resources, reduced crop productivity, flooding, and changes in the incidence and geographic range of vector- and water-borne diseases (IPCC, 2014). The health risks range from direct threats of extreme temperatures and severe storms and floods, to less apparent impacts affecting the survival and distribution of mosquitoes and rodents that carry West Nile virus or lyme disease (Sellers, 2019).

In Uganda, climate change poses great risks to the well-being of the population. Changes in climate are threatening Uganda's ecosystems and the livelihoods of those that depend on them; and are increasing the frequency and intensity of severe weather events such as droughts and floods (Uganda NDC, 2018). Uganda's Nationally Determined Contribution (NDC) Partnership Plan established that climate variability and climatic changes are evident in the country in the form of escalating droughts and floods; and altered seasonal variations, especially changes in the onset and cessation of rains (Uganda NDC, 2018). Past studies that investigated the impacts of climate change on agriculture, health, and water in Uganda found that the country experienced seven droughts between 1991 and 2000 (Magrath, 2008). In

2010/11, Uganda was affected by a severe drought that resulted in a loss of US $1.2 billion, equivalent to 7.5% of its Gross Domestic Product (GDP) (OPM, 2012). In 2016, drought had a devastating effect in crop production resulting in food shortages for over 1.3 million households in Northern Uganda (Ojambo, 2016). These recorded droughts are part of a documented regional pattern of ongoing dry weather in the East African region that will only get worse over time according to the available climate change model (Choi, 2018). Since 1960, mean annual temperatures in Uganda increased by 1.3ºC, rainfall became more unpredictable, and extreme events such as droughts and floods increased in frequency and intensity (Uganda NDC, 2018).

Studies show that, in Uganda, climate change is aggravating the occurrences of water-borne diseases such as dysentery, cholera, hepatitis E; vector-borne diseases especially malaria; respiratory diseases; and malnutrition-related illnesses (GoU, 2014; WHO, 2015). To enhance the health system's ability to prepare for, and cope with rising needs for treating climate-sensitive diseases Uganda has approved a national health adaptation plan. Uganda's fourth Health Sector Development Plan indicates the importance of developing "early warning systems and dissemination of weather forecasts to help health managers to improve preparedness and response" (MoH, 2015). However, to-date, there are no digital tools that predict the occurrences of climate-sensitive diseases because of changes in weather conditions such as temperature and rainfall. The ability to predict future occurrences of diseases affected by climate will help the health system be prepared in advance and minimize morbidity and mortality. The Climate Change and Health in Sub-Saharan Africa (CHASA) project, with a focus on Uganda, aimed to fill this gap by first assessing the link between changing climatic conditions and the changing patterns of climate-sensitive disease incidences; and second by developing a digital solution for predicting the occurrence of climate-sensitive diseases based on weather conditions.

1.2 Specific Objectives

The ultimate objective of the CHASA project is to develop recommendations for enhancing Uganda's health system so that it can support the health and wellbeing of the population in a changing climate.

The specific objectives are to:

i. **Identify, rank and document key climate-sensitive diseases**, including analysis of the correlations between climate factors and disease risks;
ii. **Develop a forecast model on climate change and disease risks** that runs as a smartphone application for use by local communities;
iii. **Document and share learning on the linkages between climate and weather changes and health risks**; and
iv. **Develop key recommendations for improving the national health surveillance systems** to improve detection and response to climate-sensitive diseases.

1.3 Project Area

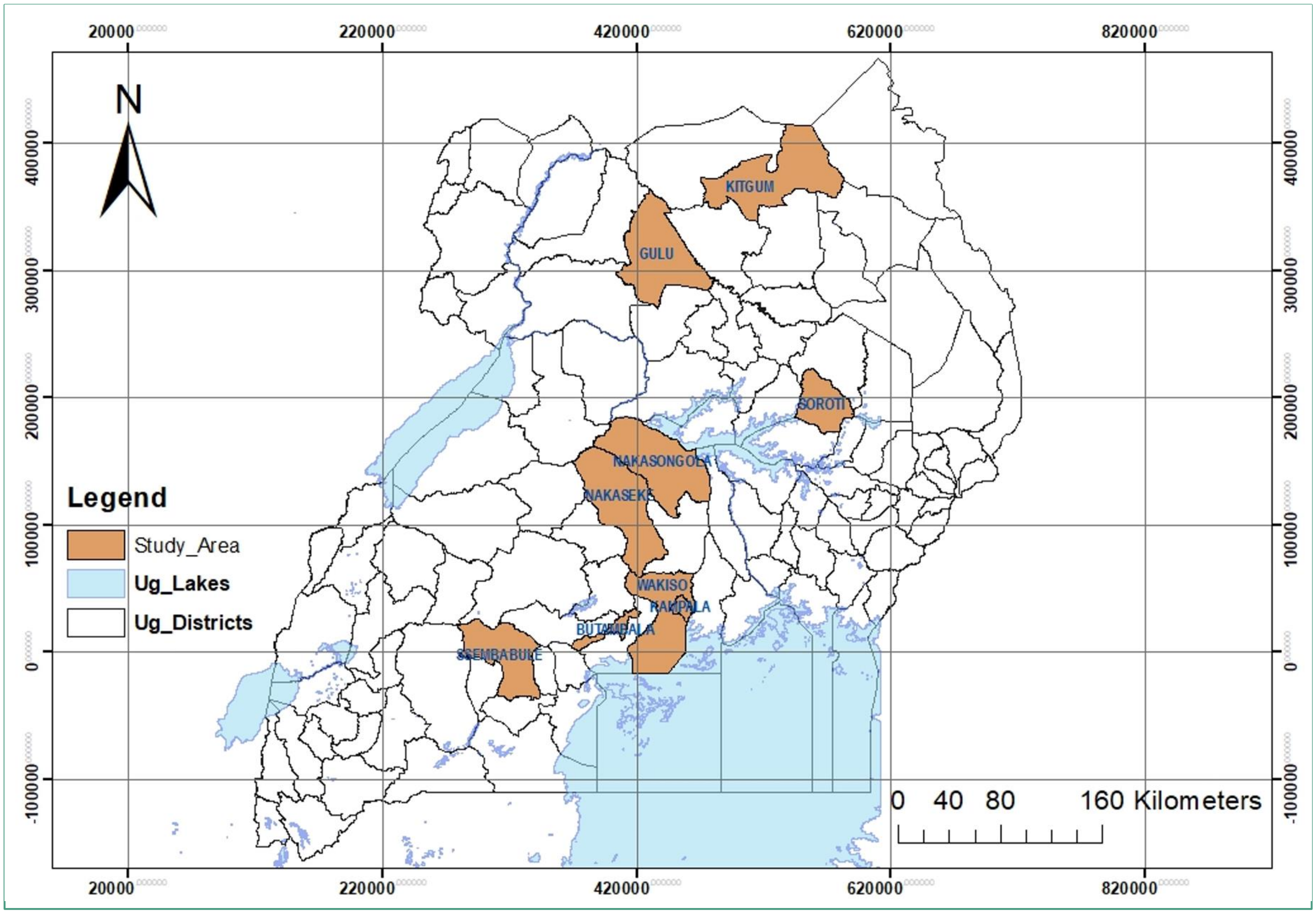
The project area included purposefully selected nine districts from the different climatic zones in Uganda. Most of the study districts were selected from the “cattle corridor”, a semi-arid ecosystem that covers 40% of Uganda’s land and is characterized by erratic rains, frequent and prolonged droughts, and flooding. The area is one of the most ecologically fragile parts in Uganda (Lufafa, 2006), vulnerable to climate change (GoU, 2007) and experiences higher proportions of droughts than other parts of the country.

The nine CHASA study districts were Nakasongola, Nakaseke, Soroti, Gulu, Kitgum, Sembabule, Butambala, Kampala and Wakiso (**Figure 1**). The selection of the districts was made during stakeholder consultation and engagement meetings with the following selection criteria:

- **Districts experiencing climate change and variability**: The selected districts lie in the cattle corridor which constitutes one of the most fragile areas in the country and where climate change impacts are evident.
- **Districts representing different ecosystems**: The selected districts lie in different ecosystems, specifically in arid, semi-arid, lowland and highlands.
- **Availability of climate and health data:** A total of nine health facilities spread over the nine districts were selected based on the availability of a functioning weather station within a radius of 40 kilometers.

The selected districts represent a range of hydro-climatic, climatologic, and agro-ecological conditions. This helps to ensure that the study investigated diverse settings to make the findings of the research more representative of the national situation.

Figure 1: CHASA Study Districts



2. Project Design and Methodology

The design of the study involved a *literature review* and *stakeholder engagement* to gather evidence on how climate change affects human health in Uganda, as well as *predictive modeling* to project the potential changes in the prevalence of climate sensitive diseases due to changes in climatic drivers. The approaches for the literature review, stakeholder engagement and predictive modeling were as follows.

2.1 Literature Review

The literature review was conducted to understand the current state of research on how climate conditions affect the incidences of diseases, current government policies, guidelines and understandings related to the human health threats posed by climate change and the actions (or inaction) by the government. Among others, the review included examining which national policy documents mention the link between climate change and health and what policy provisions are provided to strengthen the health system to respond to anticipated increases in the burden of diseases.

A growing body of research shows that climate change adversely affects human health (Sellers, 2019). It profoundly affects the key determinants of health, such as clean air and water, sufficient food and adequate shelter. The World Health Organization (WHO) estimates that about 150,000 deaths/year in low-income countries are due to the adverse effects of climate change (WHO, 2010). Climate change also brings new challenges relating to the control of infectious diseases since many of the major killer diseases are highly sensitive to climatic conditions, especially temperature and patterns of rainfall. Climate change, together with other natural and human-made health stressors, threatens human health and wellbeing in multiple ways. According to the IPCC Fifth Assessment Report, climate change has altered the distribution of some disease vectors. For example, the WHO's *Climate Change and Human Health* publication (McMichael et al., 2003; WHO, 2015) notes that temperature and precipitation are the most important factors for the survival and reproduction of vectors[1], pathogens[2] and hosts[3] (Wu et al., 2016). The changes in temperature and precipitation will thus impact the occurrence of infectious and other vector-borne diseases such as malaria.

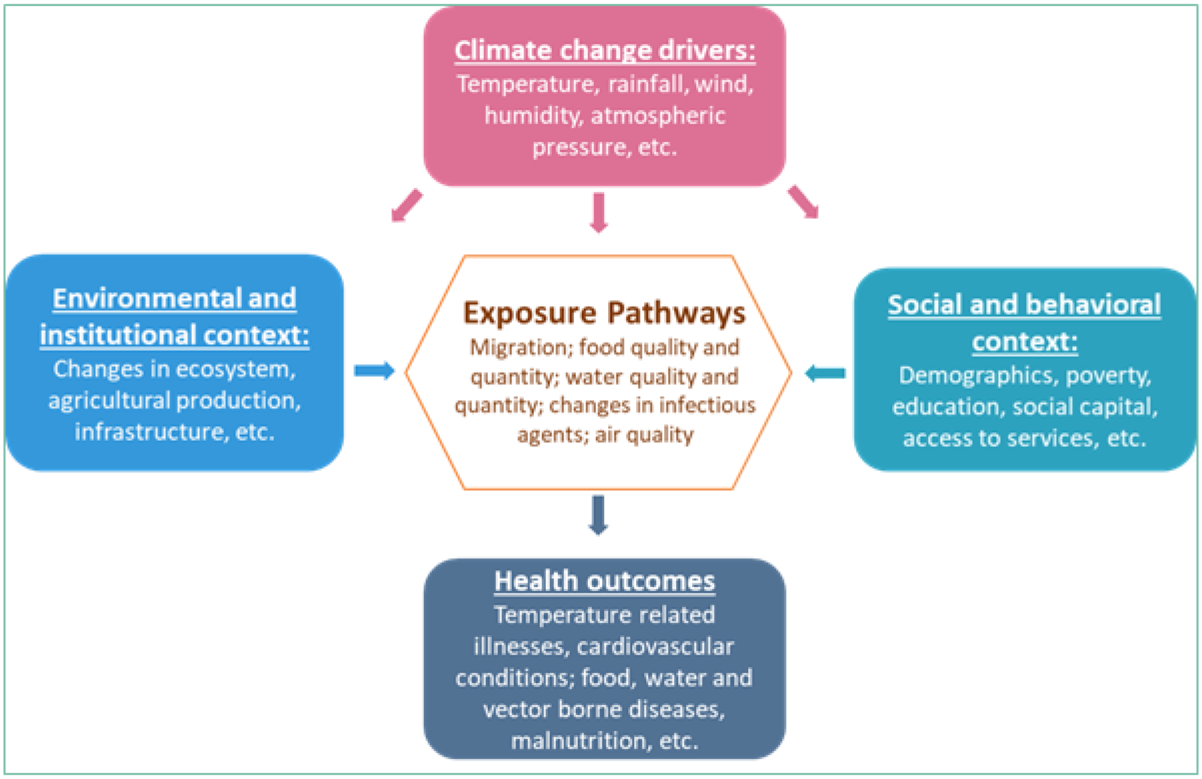
A useful approach to understand how climate change affects human health is to consider the specific exposure pathways and how they can lead to diseases affecting humans. Exposure pathways are context-specific, depending on the timing, location and affected population. The severity of the health risks will depend on the ability of health systems to prepare for and address the changing threats, including factors that determine the vulnerability of individuals and communities. **Figure 2** illustrates the conceptual framework of the exposure pathways through which climate change affects human health.

1 Vector: A carrier that transfers an infective agent from one host (which can include itself) to another.

2 Pathogen: Organism capable of causing disease.

3 Host: Person or other organism that harbors an infectious agent under natural conditions.

Figure 2: Conceptual Framework for CHASA project (Adopted from Balbus et al., 2016)



Changes in climatic variables (*climate change drivers* in **Figure 2**) such as variations in temperature, precipitation, atmospheric pressure, wind speed and direction affect the survival and reproduction of various vectors, pathogens and hosts. For example, statistical modeling on the relationship between temperature and malaria shows that a global temperature increase of 2 to 3ºC would increase the number of people who would be at risk of malaria by 3 – 5% (Martens et al., 2002). More recent estimates show that there will be an increase in mortality due to climate change as a result of various exposures by 2030 (Phalkey et al., 2016). The climate change drivers affect disease *exposure pathways*, such as the diminishing quality of food, water and air and exacerbate climate-induced migration of people and animals. However, the exposure pathways are not solely affected by climate change drivers. Exposure pathways are also influenced by *environmental*, *institutional*, *social and behavioral* contexts that negatively or positively affect human health. For example, from an environmental and institutional context, during heavy rains, storm water has been known to breech existing toilet facilities. These breeches lead to an increase in the fecal content of water around the shores of water bodies and are associated with various water-borne diseases which become a public health hazard.

Climate change has adverse effects on human health, economic development and growth in Sub-Saharan Africa (SSA), and studies show that the SSA region is particularly vulnerable due to its exposure to multiple stressors including high variability of climate, low adaptive capacity and high rates of poverty (Niang et al., 2014; Costello et al., 2009).

As in many other SSA countries, in Uganda, climate change is resulting in increased droughts, increased frequency and severity of extreme weather events, unpredictability in the onset and cessation of rainfall, and shifts in seasons. As a Party to the United Nations Framework Convention on Climate Change (UNFCCC), Uganda, working with the WHO, has helped the Least Developed Countries (LDC) Expert Group (LEG) integrate health into National Adaptation Plans (NAPs) (UNFCCC, 2020). At the national level, a study conducted to investigate the impacts of climate variability on health in South-Western Uganda showed that the area faces increased risks in the occurrence of malaria and gastrointestinal illnesses due to climate variability and change (Lebbe et al., 2016).

Uganda's *Second National Communication to the UNFCCC* notes that climate change and variability have a profound effect in diminishing the health status of the population and that the major climate-sensitive diseases include cholera, hepatitis-E, dysentery, malaria, schistosomiasis and diarrheal diseases (GoU, 2014). In addition, Uganda government documents note the importance of developing an early warning system and sharing weather forecasts with health managers to improve preparedness and responses to increased illnesses due to climate change and variability (GoU, 2014; GoU, 2015). However, to-date, the country has not introduced a system capable of predicting the anticipated occurrence of climate-sensitive diseases and to help prepare the health system to respond to increased occurrences of the diseases. This study addresses this gap by developing a digital solution that predicts the occurrence of climate-sensitive diseases based on historical and current weather and health data.

2.2 Stakeholder Engagement

The objective of the stakeholder engagement was to gather different points of view and lay the basis for buy-in from the stakeholders so that the outcome of the project, a digital predictive tool for predicting the occurrence of climate-sensitive diseases based on weather and health data, would be owned and taken forward by them. Stakeholders in this activity were defined as person(s), groups, or organizations that affect or will be affected by the project outcome; and may have positive or negative influence on the project. Considered stakeholders included: (i) entities that may serve as source of information for the project; (ii) possible consumers of knowledge products emanating from the project; and (iii) well-positioned entities to influence policy action based on project outcomes. The stakeholder engagement process involved a review of climate change-related reports to identify stakeholders, as well as discussions with Ministry of Water and Environment's (MWE) Climate Change Department (CCD) to obtain the list of entities involved in climate change activities within the country. As the implementing agency for the project, the consultations began with the MWE. This resulted in the permanent secretary of the MWE writing a letter to the permanent secretary of the Ministry of Health (MoH) inviting them to participate in the study. The permanent secretary of the MoH then cascaded the invitation to other departments and authorities within a ministry. A semi-structured discussion guide was developed to identify the key climate-sensitive diseases from the perspectives of the stakeholders, to investigate the stakeholders' understanding of the link between climate change and health and investigate if there is a forecast model in use in Uganda for predicting occurrence of diseases based on weather conditions. Information gathered from the stakeholders using semi-structured discussion guides was then analyzed to generate a synthesis of perceptions and recommendations. The outcomes of the stakeholder engagement are provided under the "Key Results" section of this report.

The project engaged national and district level government entities, community-based organizations (CBO), non-governmental organizations (NGO) and donor agencies interested in climate change and health. The stakeholder engagement and consultations aimed to understand the perceptions of the different actors regarding the link between climate change and health. This also allowed for their enhanced participation in the implementation of the project. The summary of stakeholder perceptions on the climate change and health nexus are presented in **Table 1** below.

Table 1: Key Findings from Stakeholder Consultations

Stakeholders Consulted	*Ministries, Departments and Agencies (MDAs) stakeholders:* MWE, MoH, Office of the Prime Minister (OPM), Ministry of Local Government (MoLG), Ministry of Finance, Planning and Economic Development (MoFPED), Parliamentary Forum on Climate Change (PFCC), Climate Change Department of the MWE and the Uganda National Meteorological Authority (UNMA). *Non-state stakeholders:* Media: The New Vision Civil Society: Climate Action Network – Uganda (CAN-U) Cultural Institutions: Buganda Kingdom, Buruli Cultural Institution Faith Based: Interreligious Council of Uganda
Key Findings from Consultations	
Climate-sensitive Diseases	Asthma, cholera, dysentery, fever, guinea worm, malaria, skin diseases, typhoid and yellow fever. The stakeholders identified these diseases based on experience and expert knowledge. The stakeholders have observed and experienced an increase in the occurrence of droughts and damaging rainfall both in terms of frequency and intensity and concomitant increases in the occurrence of the identified climate-sensitive diseases.
Pathways to Climate-induced Health Hazards	The stakeholders identified pathways that expose individuals and communities to climate-induced health hazards. These include droughts that affect the availability of safe and adequate water supply for domestic consumption, as well as floods that contaminate water sources with disease-causing pollutants which result in water-related diseases such as typhoid and cholera. In addition, heavy rainfall that results in the proliferation of stagnant water increases the breeding of vectors, such as mosquitoes, which increases the prevalence of vector-borne diseases, such as malaria. The discussions showed that women and children are more exposed to climatic hazards and health issues since they are responsible for farm and off-farm activities. Direct impacts of climate change and variability on human health were cited as the disappearance of herbal medicines, loss of biodiversity that leads to malnutrition, proliferation of pests

	and vectors due to favorable conditions for their reproduction and concomitant increases in water and vector-borne diseases.
Existing Policies, Instruments and Strategies Addressing Climate Change Impacts on Human Health	Uganda's *National Adaptation Programs of Action* (NAPA) submitted in 2007, the *Second National Communication* (2014), and the *Third National Communication* (2020 under production), as well as the NDC, all include health as one of the key sectors affected by climate change. Uganda has an approved *National Health Adaptation Strategy*, the *National Biodiversity Strategy and Action Plan* (2015-2025), *National Climate Change Policy*, *National Action Plans* (NAPs), and the *National Strategy for Climate Change Mitigation* that considers the implications of mitigation actions on human health. Lack of resources is hampering effective concerted research on climate change and health, but climate change budget tagging which is taking place across sectors will impose mandatory budgetary allocation of resources for climate change action in every sector including health.
Priorities to Enhance Climate Resilience of the Health System	The stakeholders recommended increasing efforts to support climate change adaptation actions to better understand climate health risks, early warning, and reduction of infectious and vector-borne diseases, and increase resilience of health facilities and systems.

2.3 Predictive Modeling

The study designed a model for predicting the occurrence of climate-sensitive diseases through machine learning using weather information obtained from weather stations and health data from the national Health Information Management System (HMIS) database (DHIS2). The findings from the stakeholder consultations on climate-sensitive diseases in study districts informed the selection of the diseases considered in the predictive modeling analyses. During the analysis, disease incidence diagnosis from health facilities within the study area was matched to the corresponding study area's monthly climate data from the nearby weather stations. The study used a "supervised learning" approach of machine learning, where historical weather and health data (between 2014-2019) were provided to train the model in order to predict the occurrence of climate-sensitive diseases based on variations of climatic drivers. The predictive modeling was developed in the R version 3.6.2 statistical computing environment using a negative binomial hierarchical regression algorithm in the Brms package[4]. The selection of a hierarchical Bayesian method using a negative binomial distribution was informed by the following considerations: (i) focus on modeling all the variables together as part of a prediction model as opposed to obtaining an independent estimate of the effect of each variable on the outcome; (ii) to account for prior information given the study's small sample size setting (Duran, 2009; Fu, 2015; Heudtlass, 2018); (iii) simulation studies have shown that the Bayesian methodology performs better than classical Maximum Likelihood Estimation (MLE) (Duran, 2009; Fu, 2015); and (iv) the cluster (district) level

[4] The brms package implements Bayesian multilevel models in R using the probabilistic programming language Stan.

output of Bayesian modeling makes for easier communication to diverse audiences (Heudtlass, 2018). In view of sparse health and weather data available for modeling, use of a Bayesian approach has advantages over more commonly used frequentist approaches. In addition, the Bayesian approach offers a formal and transparent way of combining new data with existing data and expert knowledge to improve decision-making (Heudtlass, 2018).

Historical weather data for rainfall, temperature (maximum, minimum and mean), humidity, solar radiation, wind gust and atmospheric pressure were retrieved from the Uganda National Meteorological Authority (UNMA) and Trans-Africa Hydro-Meteorological Observatory (TAHMO) databases for the period 2014 to 2019. The data for the weather parameters were obtained as monthly averages. Likewise, historical health data for asthma, cholera, dysentery, malaria, skin disease and typhoid were obtained from the national DHIS2 database of the participating hospitals and health facilities. A total of 1,168 records each containing monthly disease diagnosis records paired with historical weather data were obtained. Each record was assessed for completeness to ensure data contains all the weather parameters and health conditions identified for the study. Of the 1,168 records, 436 that were found with no missing information and were used as an input for the predictive modeling. The records used for the modeling are available online as a Figshare archive (Munabi et al, 2020).

The modeling focused on developing a predictive model to establish the associations between the relevant climate parameters climate-related data and the incidence of diseases at study sites. Prior to modeling three records, one corresponding to the diagnosis of Guinea worm and the other two for yellow fever were removed. This final dataset containing the 433 complete weather and disease count data records was split in half to make two sub-data sets, one for training the model and the other for testing. Prior to modeling correlations were made on the climate data to identify strongly correlated variables. The modeling was done using the R-3.6.2 Statistical computing environment brms package (Bürkner, 2017) for a hierarchical model, with the formula summarized in following box.

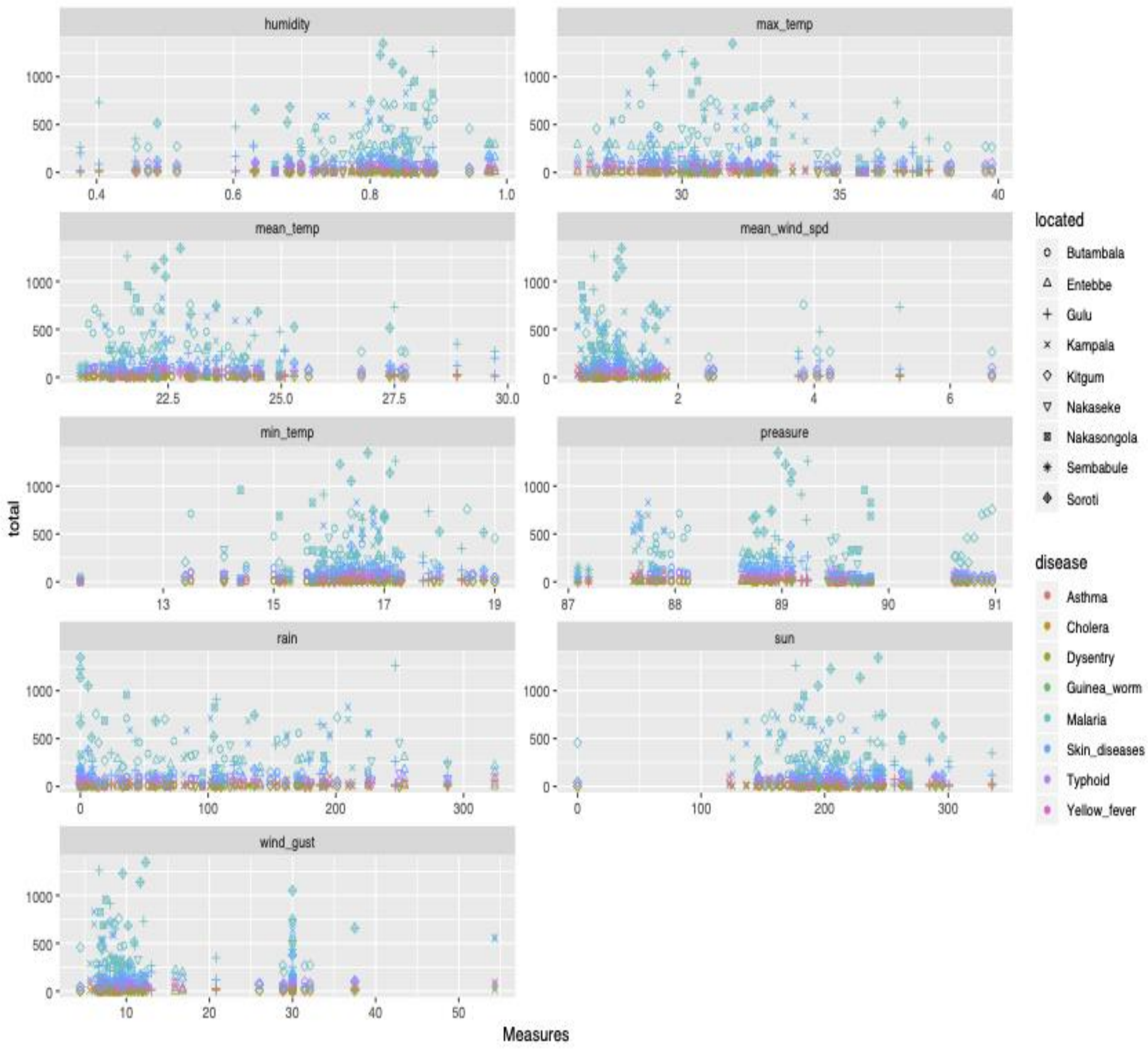
Disease Count ~ Location weather information + Disease name + Location + (1 | Location)

The above formula indicates that disease count is a function of each of the weather parameters at a given location, the type of disease, the location and is conditioned on the location. The *location weather information* corresponds to the monthly weather-related information for each site. This was matched to the monthly aggregate disease incidence data to generate an observation record represented by the record identifier (ID) in the dataset from each site. The “*disease name*” is the list of all disease names. The training dataset was used to create a regression model using the negative binomial distribution family for the following parameters: chains = 6, cores = 3, sampling iterations per chain= 10,000, prior = prior (Cauchy (0,2.5)), thin=1 on a 2017 i7 MacBook-air computer. The output from the modeling process was subjected to a series of diagnostic tests that included: various visualizations, estimation of autocorrelation and calculating the “leave-one-out” (LOO) statistic for the model. The coefficients from the modeling process were then used for an out of sample prediction with new data contained in the second test dataset. Comparisons of the original and predicted counts were made using the students paired t-test, Wilcoxon paired ranking and visualization to identify significant differences in counts for the different modeled disease groups. In the regression reporting for categorical variables like disease, the default first category in alphabetical order was used as the reference. During the analysis the cut-off for statistical significance was set at 0.05 for all observations.

3. Key Results from the Predictive Model

Figure 3 provides a summary of the comparisons of the different disease counts from the various study locations relative to the difference weather parameters used in the modeling.

<u>Figure 3: Comparisons of disease counts and weather observations</u>



A correlation matrix (summarized in **Table 2**) was generated to identify strongly correlated (>0.7) measurements. The value of 0.7 was selected because it would indicate that this observation explains more than 50% of the variation in the variable.

Table 2: Correlations between Weather Measurements

	Pressure	Rain	Sun	Humidity	Mean_Temp	Max_Temp	Min_Temp	Wind_Gust
Pressure								
Rain	-0.19							
Sun	0.06	-0.11						
Humidity	-0.11	0.46	-0.55					
Mean_Temp	0.28	-0.37	0.61	**-0.87**				
Max_Temp	0.39	-0.40	0.49	**-0.79**	**0.85**			
Min_Temp	0.06	0.02	0.08	-0.13	0.29	0.11		
Wind_Gust	<-0.01	-0.07	0.17	-0.28	0.26	0.33	0.02	
Mean_Wind_Spd	0.34	-0.39	0.15	-0.66	0.65	0.59	0.16	0.28

In the above table, the following observations had very large correlations (>0.7): humidity with mean temperature, humidity with maximum temperature and mean temperature with maximum temperature. Such high correlations are associated with multicollinearity (Paul, 2006) and can lead to overfitting of the model, both of which are associated with poor predictive performance. To reduce the effects of this strong correlation, the study team: (a) selected to focus on the model as opposed to the effects of each variable on the outcome; (b) selected a Bayesian hierarchical regression model that doesn't overfit or underfit data (Graham, 2003); (c) standardized the data in the modeling process using the scale function in base R before modeling; and (d) used the out of sample prediction after modeling as a final strategy to reduce the effect of over-fitting.

3.1 The Model

The modeling dataset of 433 records was split into half using a randomly generated set of numbers to create a training dataset with 217 observations and a testing dataset with 216 observations (Martin, 2018). **Table 3** provides a summary of the population level effects of the various modeled parameters on the disease counts based on 60,000 samples. In this table, only the mean estimate difference for the intercept, maximum temperature and all diseases were compared to the reference disease (asthma) that were significant. The reference disease is automatically picked by the modeling software based on the alphabetical order. The intercept for the random variable corresponding to the site from which the health records originated was significant (estimate = 0.636, 95% CI 0.235 to 1.403). Also, the use of the negative binomial family was significant (shape estimate = 1.942, 95% CI 1.570 to 2.2.363). In **Table 3**, items in bold font were significant and Rhat is the potential scale reduction factor (at convergence, Rhat=1).

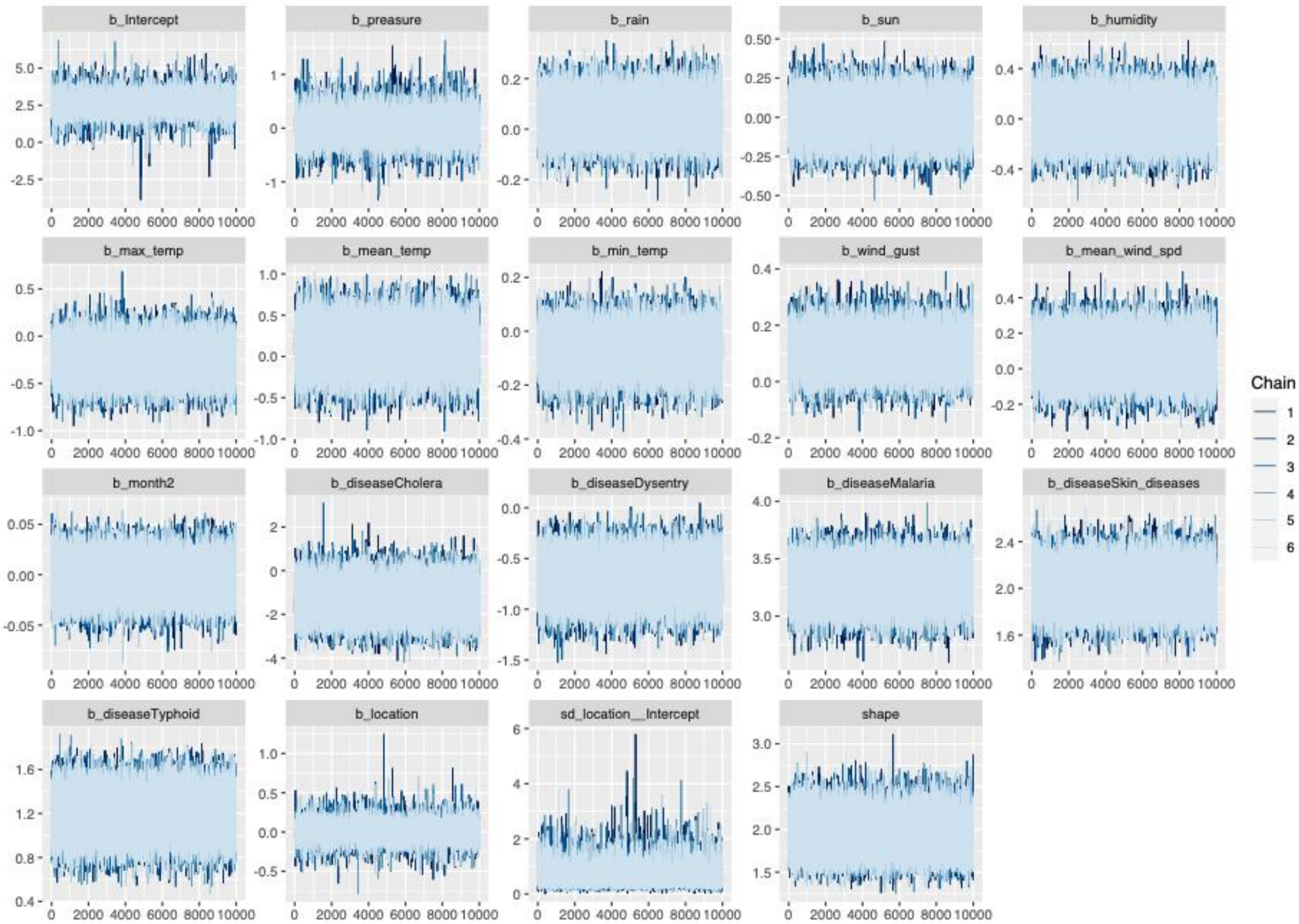
Table 3: Modeled Population-Level Effects

	Estimate	Est. Error	95% Credible Interval (CI)	Rhat
Intercept	2.594	0.550	**1.495 to 3.713**	1.000
Pressure	0.003	0.225	-0.404 to 0.487	1.000
Rain	0.053	0.072	-0.088 to 0.194	1.000
Sun	0.001	0.115	-0.226 to 0.224	1.000
Humidity	0.006	0.146	-0.280 to 0.293	1.000
Max_temp	-0.246	0.171	-0.578 to 0.091	1.000
Mean_temp	0.135	0.245	-0.354 to 0.613	1.000
Min_temp	-0.071	0.069	-0.207 to 0.064	1.000
Wind_gust	0.106	0.064	-0.016 to 0.232	1.000
Mean_wind_spd	0.065	0.107	-0.142 to 0.277	1.000
Month	-0.002	0.017	-0.037 to 0.032	1.000
Asthma	Reference disease			
Cholera	-1.359	0.695	-2.667 to 0.068	1.000
Dysentery	-0.709	0.185	**-1.070 to -0.347**	1.000
Malaria	3.276	0.159	**2.962 to 3.586**	1.000
Skin diseases	2.018	0.161	**1.701 to 2.332**	1.000
Typhoid	1.185	0.176	**0.841 to 1.531**	1.000
Location	0.027	0.096	-0.175 to 0.212	1.000

3.2 Model Diagnostics

There was complete mixing of the runs on the different chains, which is confirmed by the Rhat values in **Table 3** that were all less than 1.01. This indicates that the estimation algorithm doesn't show divergence (such as Rhat >1.1) and that there was adequate mixing of the chains throughout modeling (**Figure 3**). All the other diagnostic information for the model were within acceptable ranges. The additional diagnostic information from the model can be obtained by running the code for the model and the web application are available online (CHAI, 2020).

__Figure 4: Model Trace Diagnostics__



3.3 Out of Sample Model Prediction and Validation

Table 4 shows comparisons of both the actual and predicted disease counts from the f sample model prediction on the test dataset. In **Table 4**, note that the difference between the maximum and minimum values was less for the predicted disease counts compared with the actual disease counts. This is known as *shrinkage*, an essential feature of multilevel modeling that leads to better estimations and acts as a safeguard against overfitting (Nalborczyk, 2019)

Table 4: Comparing the Out of Sample Model Prediction Disease Counts

	Comparisons											
	Actual disease counts						Predicted disease counts					
Disease	Mean	SD	Min.	Max.	Median	N	Mean	SD	Min.	Max.	Median	N
Asthma	25.5	27.0	1	104	14.0	34	18.9	8.3	7.1	46.2	17.1	34
Cholera	3.7	2.3	1	5	5.0	3	7.7	0.4	7.3	8.0	7.6	3
Dysentery	8.6	6.5	1	28	7.0	49	9.2	3.9	3.5	22.6	8.3	49
Malaria	410.3	311.3	46	1261	287.0	42	463.7	202.6	188.3	947.0	417.6	42
Skin disease	163.5	160.1	35	635	112.0	45	133.1	51.0	54.3	271.4	124.1	45
Typhoid	47.3	30.4	2	140	40.5	44	58.8	24.8	23.6	150.5	54.1	44

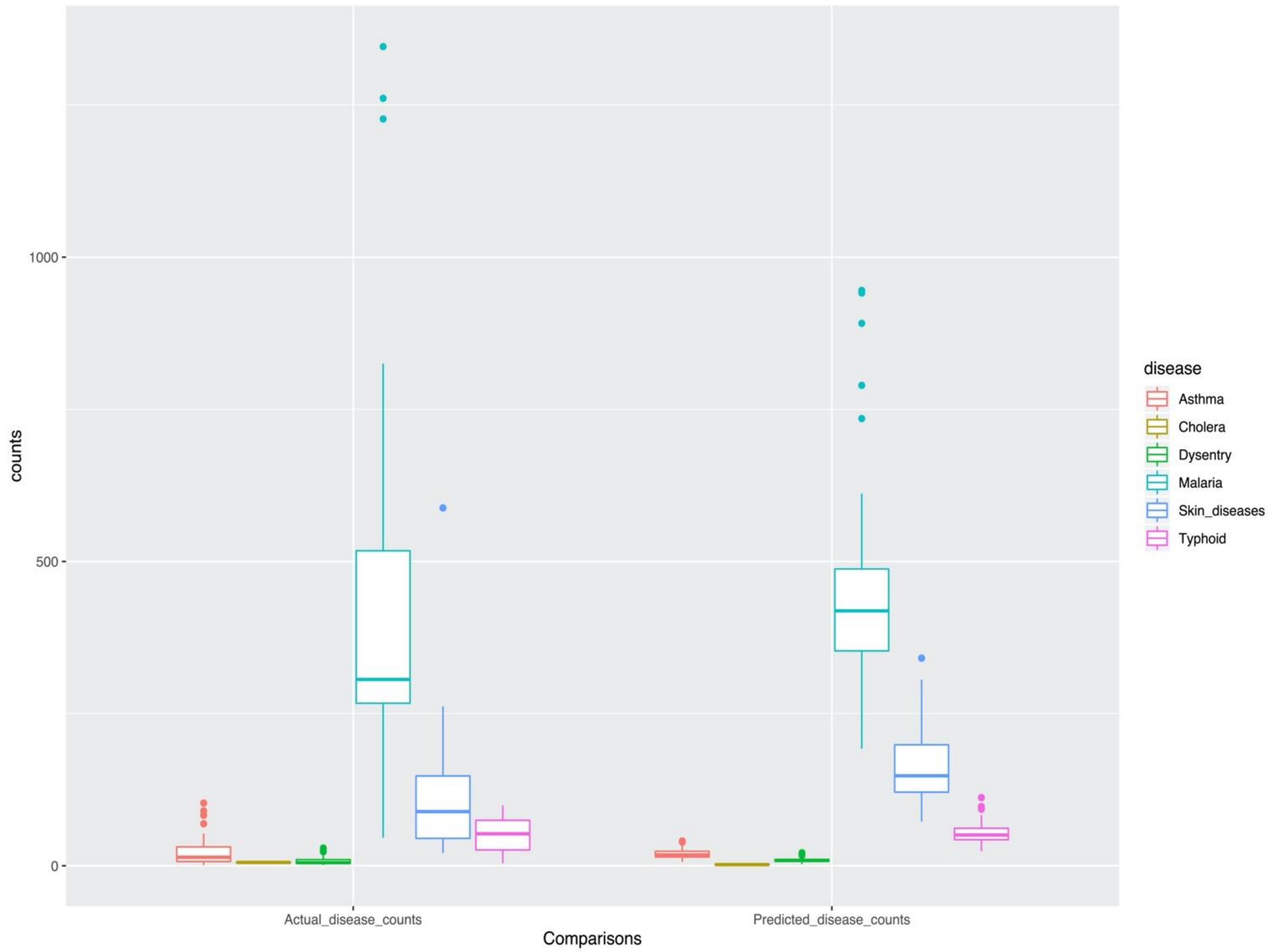
Overall, the diseases with more records wound up with smaller differences between the predicted estimate and the actual counts. This is confirmed by the paired sample Wilcoxon signed rank test output (**Table 5**) comparing the original counts against the model's out of sample estimate.

Table 5: Paired Wilcoxon rank and t-tests

Disease	statistic	P.value	Method	Effect size
Asthma	283	0.813	Wilcoxon signed rank test	0.701
Cholera	6	0.250	Wilcoxon signed rank test	0.701
Dysentery	790	0.078	Wilcoxon signed rank test	-0.701
Malaria	589	0.087	Wilcoxon signed rank test	-0.701
Skin diseases	543	0.780	Wilcoxon signed rank test	-0.701
Typhoid	695	0.020	Wilcoxon signed rank test	0.701
Asthma	-1.836	0.075	Paired t-test	
Cholera	2.986	0.096	Paired t-test	
Dysentery	0.671	0.505	Paired t-test	
Malaria	1.137	0.262	Paired t-test	
Skin diseases	-1.561	0.125	Paired t-test	
Typhoid	2.264	0.029	Paired t-test	

Table 5 above shows that on both the non-parametric paired Wilcoxon signed ranking test and paired t-test, there were only significant difference in ranks observed with typhoid. For all the diseases, the effect size for the computation was plus or minus 0.701. Looking at **Figure 4** below, which gives a visual comparison of the actual and predicted estimated counts, the distributions of all the other diseases were within the range of the actual counts. This is explained by shrinkage in estimated values obtained from Bayesian modeling as shown in **Figure 4**.

Figure 5: Visual Comparisons Between the Actual and Predicted Disease Counts

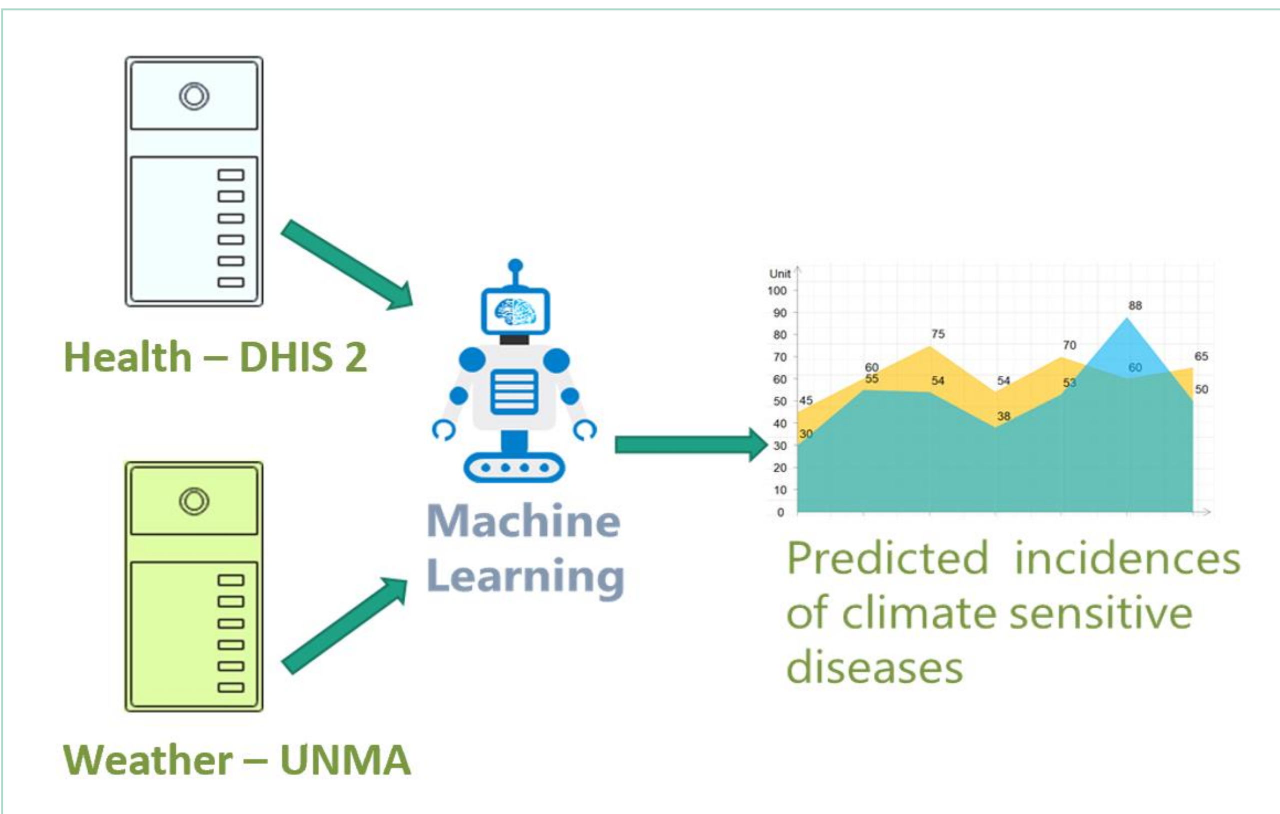


In summary, from the modeling, it was found that it was possible to predict the occurrence of climate-sensitive diseases based on weather and health data. The predicted disease counts were within the range of the actual disease counts in the historical data. This demonstrates that it is possible to use historical and current weather and health data for the development of reasonably accurate prediction models for estimate future occurrences of climate sensitive diseases.

4. Model Application Software

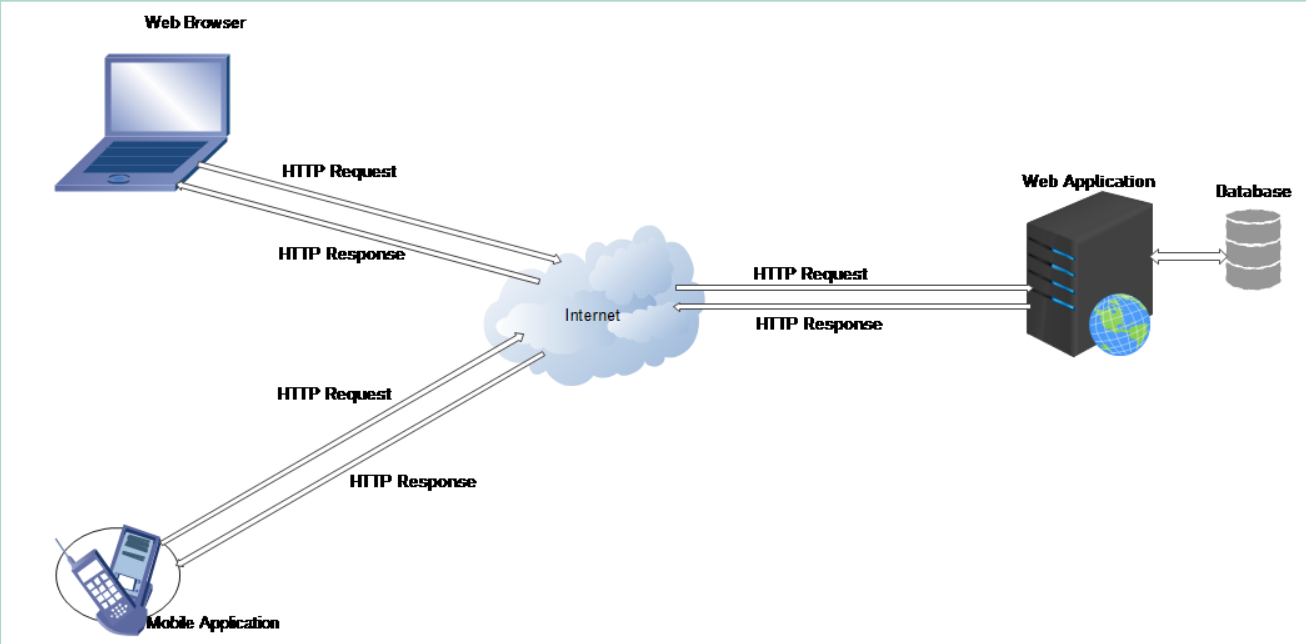
As part of this study, a forecasting model of disease risks based on weather and health parameters was developed, that runs as both a web and mobile application for use by health facilities, managers and planners at the MoH and other stakeholders involved in early warning, such as the Office of the Prime Minister (OPM). The web application can be accessed by users through any web browser, and the mobile app can be accessed on Android or iOS devices. The web and mobile apps automatically capture weather data from the Uganda National Meteorological Authority (UNMA) database as input data for the predictive model. The application provides, as an output, the estimated number of occurrences of the climate sensitive diseases included in the predictive model (i.e. Asthma, cholera, dysentery, fever, guinea worm, malaria, skin diseases, typhoid and yellow fever. In order to iteratively improve the match between predicted and actual disease counts, the model is designed to be retrained with the latest historical data at six month intervals by automatically extracting disease data from the national District Health Information System (DHIS 2) instance and weather data from the UNMA database through API integration (**Figure 5**).

Figure 6: Machine Learning Powered Predictive Analytics of CHASA project



The interaction between the end user interfaces (web or mobile app), server applications and databases are made through Hypertext Transfer Protocol Secure (HTTPS) (**Figure 6**).

Figure 7: High Level Architecture of the Web and Mobile Application



The web application is where all the business logic such as validation, analysis and prediction are implemented. A user sends a request to the web application via a web browser or mobile app and the web application processes the request and provides the predicted disease counts for the selected location. The web application provides the following functionalities:

1. ***Register a health facility***: Health facility staff, district and national-level health workers, managers or planners register a health facility for which they require the predicted occurrence of climate sensitive diseases. This is done only once per user.
2. ***Register a weather station***: The closest weather station to the selected health facility are displayed, and the user confirms the selection. Health facilities and weather stations are paired through these steps.
3. ***Extract weather data***: The web application extracts daily weather data from automatic weather stations through Application Programming Interface (API) integration. User action is not needed to trigger this function.
4. ***Predict disease counts based on weather data***: The web application automatically runs the model and generates predicted monthly disease counts based on monthly average weather data obtained from UNMA. The monthly average weather data are obtained from the daily records of UNMA's weather stations and the calculated average from each station is used as an input to the model.
5. ***Re-train the model***: To enhance the accuracy of predicted disease counts, the web application automatically extracts recent health data from the national DHIS2 database every six months and retrains the model.

5. Discussion

As previously mentioned, the overarching goal of this study was to develop recommendations for enhancing Uganda's health system to support the health and wellbeing of the population in a changing climate. To achieve this, the study aimed to achieve the following four objectives: i) identify, rank and document key climate-sensitive diseases; ii) document and share learning on the linkages between climate and weather changes and health risks; iii) develop recommendations for improving the national health surveillance systems; and iv) develop a forecast model on climate change and disease risks. The key findings on these four objectives are summarized below.

5.1 Key Climate-sensitive Diseases

The study found that the key climate sensitive diseases in Uganda are Asthma, cholera, dysentery, fever, guinea worm, malaria, skin diseases, typhoid and yellow fever. The project worked with subject matter experts to rank the diseases based on their importance, severity, and frequency of occurrence. The use of a panel of experts is a recognized initial step in the identification of relevant areas for intervention or change in practice within a given social cultural context (Marshall, 2003). In addition, engaging these stakeholders at the beginning of the study was an important step towards securing buy-in that is key for later adoption of the digital predictive tool for supporting the health system's ability to predict and prepare for the increased occurrence of climate-sensitive diseases. The list of disease though not exhaustive, offers a critical starting point for the stakeholders to learn together as they use this information to guide future health related response and planning for climate change variations in disease occurrence.

5.2 Linkages Between Climate, Weather and Health

The linkages between climate, weather and health have previously been described in detail by various authors (Russell, 2009; Freeman, 2010; Dafermos, 2018; Sellers, 2019). Each of these papers allude to the indirect link between health and climate change, that manifests as increased incidence of disease as summarized in our conceptual model (Figure 2). The increased incidence may also manifest as variations in disease patterns (Ramin, 2009), and is likely to get worse according to the projected climate scenarios for sub Saharan Africa (Déqué, 2017). In Table 3, we note that with the exception of the maximum and minimum temperatures all the other weather parameters were associated with an increase in disease counts keeping all the other parameters constant. These associations, though not significant, confirm the above-mentioned trends towards increased disease incidence due to weather for Uganda as a country and the African continent. These changes in disease patterns have created an urgent need for early warning aids or models to enhance the sub-Saharan health system's ability to prepare for, and cope with escalations in treatment needs of climate sensitive diseases (Nhamo, 2019). The absence of prediction models remains one of the recognized gaps in the use of prediction data for planning and guiding the health response to climate change on the African continent (Benjamin 2017; Guarner 2019; Nhamo, 2019; Scheerens, 2020).

5.3 Improving the National Health Surveillance Systems

The modeling tested in this study demonstrates that it is possible to predict the occurrence of climate-sensitive diseases based on weather and health data in settings where there is limited historical weather and health data. The predicted disease counts were within the range of the actual disease counts in the historical data. This demonstrates that it is possible to use the available health and weather data for the development of reasonably accurate disease prediction models. This modeling effort has the potential to address the need for automated early warning models to enhance the sub-Saharan Africa health system's ability to prepare for, and cope with escalations in treatment needs of climate sensitive diseases (Nhamo, 2019). Previous attempts of such modeling in Africa exist in literature for single diseases such as for cholera in Tanzania (Leo, 2019) and vector-borne diseases (Carvalho, 2017; Gh, 2019; Guarner, 2019). It is important to note that most of the previous modeling efforts have concentrated on agriculture to ensure access to food (Benjamin, 2017). The current model differs from the above cited examples in that the modeling focused on multiple diseases at the same time with a focus on prediction for communication with for key stakeholders. The lack of such tools is a recognized gap in the use of prediction data for planning and action Sub-Saharan Africa that this model seeks to address (Benjamin, 2017; Gh, 2019; Nhamo, 2019; Scheerens, 2020). Our model represents an opportunity for potential furthering of the collaboration between the climate change department represented by the Uganda Ministry of Water and Energy and Uganda Ministry of Health to address climate change related challenges to the national health system. This model of collaboration can be replicated in other countries within the region that are similarly challenged by the adverse effects of climate change.

5.4 Caveats

The current modeling has been implemented in the R statistical computing environment that uses a mature statistical programming language. The base version of the R statistical computing environment is known for being inefficient in its use of memory which may become a limitation with larger than memory datasets as is expected with this kind of data. Future iterations of the model will include additional code to allow the use of memory saving features/packages that enable the parsing of data through memory during analysis (Nguyen, 2019). As has been reported by several other studies, when modeling climate change and health outcomes (Benjamin, 2017; Carvalho, 2017; Déqué, 2017; Gh, 2019; Leo, 2019; Ramin, 2009; Scheerens, 2020), access to quality weather and health data was a major limitation. This was overcome in this study in part using the hierarchical Bayesian modeling method that has proved to be especially effective in such small sample size scenarios (Duran, 2009; Fu, 2015; Heudtlass, 2018). Even though the weather data is available in real time, the monthly health aggregates limited the sensitivity of the model to monthly periods. With the wide adoption of electronic health records, future attempts at such modeling will hopefully improve with more data points (Liang, 2018; Uganda National eHealth policy, 2016). The other limitation was the absence of socio-economic data in the model. Socio-economic data has been identified as an important modifier of disease outcomes in Sub-Saharan Africa and its impacts can affect modeling (Benjamin, 2017). Future efforts to further localize the modeling must innovatively include available socio-economic data (Bedford, 2019). Overall, despite the limitations, the use of machine learning with the recommended out of sample prediction of the model was acceptable (Bedford, 2019; Benjamin, 2017). The final limitation to this and future attempts to automate the modeling process is the non-uniform data formats in the DHIS2 repository. The ongoing efforts by the MoH to develop data standards and an interoperability layer to support health information exchange will support the automation of the modeling process, meanwhile, some level of human intervention to clean DHIS 2 data might be required. This may require data cleaning prior to future updating of the model implying that there will be some level of human intervention to run the model. This will be solved when the country fully adopts the implementation of electronic health records, enforces data standards and operationalizes the use of an interoperability layer to facilitate health information exchange.

6. Conclusion

The overarching objective of the project was to develop recommendations for strengthening Uganda's health system so that it can support the health and wellbeing of the population in a changing climate. To achieve this objective, the project developed a digital predictive model for estimating the occurrence of climate-sensitive diseases based on historical weather and health data. The model uses monthly average weather data obtained from UNMA for predicting the occurrence of monthly climate-sensitive diseases. The digital predictive tool developed by the project has the potential to enhance the current early warning capacity, risk reduction and management of national and global health risks of climate-related morbidity, mortality and economic loss. While Uganda has a national health adaptation strategy that recognizes the link between climate change and health and the imperative to develop a mechanism that would inform the health system to prepare for anticipated increased burden of climate-sensitive diseases, to date, no such tool has been developed. Therefore, the predictive tool developed by this study is an initial step towards filling this gap.

The machine learning-based predictive model developed by the Climate Change Adaptation Innovation (CHAI) through CIF Evaluation and Learning (E&L) funding will be available for use by the Uganda Ministry of Health (MoH) to predict trends of disease occurrence as a result of changes in climatic variables. The current modeling in this report is limited to the selected nine districts. Extrapolation of the study findings to the other districts and diseases will require updating the model with additional data from these sites to provide a more nationally representative picture. Such efforts may be hampered by the lack of weather stations covering all parts of the country and gaps in the availability of health data. However, an incremental approach can be taken by including health facilities that can be paired with a functioning weather station.

To explore mechanisms of institutionalizing the predictive tool, discussions between CHAI and the different stakeholders (MWE and MoH) began in 2018 when the Ministry of Water and Environment (MWE) wrote to the Ministry of Health (MoH) introducing the CHASA project. Since then, the MoH was involved in the identification of study districts, health facilities and provided health data for the model. The web and mobile applications were demonstrated to pertinent MoH personnel and they expressed satisfaction on the outcomes of the model. As a way forward, the CHAI team will continue working with the Ministries of Health (MoH) and Water and Environment (MWE) to enhance the system and institutionalize it with the MoH, in order to enhance the preparedness of the Ugandan health system to respond to expected increased occurrences of climate-sensitive diseases.

The project recommends the integration of the digital predictive tool as a strategy to improve the country's preparedness and response capabilities and enable the health system to respond to increased occurrence of climate-sensitive diseases due to changing climate. The project recommends for the use of the predictive tool at all levels of the health system ranging from health facilities up to the national health planners and emergency response coordination offices such as the Office of the Prime Minister. As the facility level, the predictive tool can provide an insight about the anticipated occurrence of climate-sensitive diseases within the areas served by the health facility. At the district-level, the district health officers can use the tool to estimate anticipate burden of climate-sensitive disease and use the information to inform their plans. Likewise, at the national level, the predictive tool can inform lanners and policy makers the anticipated burden of pertinent diseases and inform their preparedness and response plans.

References

Balbus, J., A. Crimmins, J.L. Gamble, D.R. Easterling, K.E. Kunkel, S. Saha, and M.C. Sarofim, (2016): Ch. 1: Introduction: Climate Change and Human Health. The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment. U.S. Global Change Research Program, Washington, DC, 25–42. http://dx.doi.org/10.7930/J0VX0DFW

Bedford, J., Farrar, J., Ihekweazu, C., Kang, G., Koopmans, M., & Nkengasong, J. (2019). A new twenty-first century science for effective epidemic response. Nature, 575(7781), 130-136. doi:10.1038/s41586-019-1717-y

Benjamin, F. Z. (2017). Climate and Health across Africa. In: Oxford University Press.

Bürkner, P.-C. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. Journal of Statistical Software, 80(1), 1--28.

Carvalho, B. M., Rangel, E. F., & Vale, M. M. (2017). Evaluation of the impacts of climate change on disease vectors through ecological niche modeling. Bull Entomol Res, 107(4), 419-430. doi:10.1017/S0007485316001097

Climate Change Adaptation Innovation (CHAI) (2020). CHASA Predictive Model. GitHub: https://github.com/CHAIUGA/chasa-model.git

Climate Change Adaptation Innovation (CHAI) (2020). CHASA Web Application. GitHub: https://github.com/CHAIUGA/chasa-webapp.git

Choi, T. (2018). A Severe Drought Study in the Eastern Horn of Africa (HOA) using Decadal MODIS Data (Doctoral dissertation, George Mason University).

Costello A, Abbas M, Allen A (2009) Managing the health effects of climate change. (vol 373, pg 1693, 2009). Lancet 373:2200–2200

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate change, financial stability and monetary policy. Ecological Economics, 152, 219-234.

Déqué, M., Calmanti, S., Christensen, O. B., Dell Aquila, A., Maule, C. F., Haensler, A., et al., Teichmann, C. (2017). A multi-model climate response over tropical Africa at +2°C. Climate Services, 7, 87-95. doi:https://doi.org/10.1016/j.cliser.2016.06.002

Duran Pacheco, G., Hattendorf, J., Colford, J. M., Jr., Mausezahl, D., & Smith, T. (2009). Performance of analytical methods for overdispersed counts in cluster randomized trials: sample size, degree of clustering and imbalance. Stat Med, 28(24), 2989-3011. doi:10.1002/sim.3681

Filho, W.L., Rao, K.P.C., Esilaba, A.O. and Sridhar, G. (2015). Adapting African agriculture to climate change: Transforming rural livelihoods. Springer., Switzerland. DOI: 10.1007/978-3-319-13000-2.

Freeman, D. (2010). The missing link: China, climate change and national security. Brussels Institute of Contemporary China Studies, Asia Paper Series, 5(8).

Fu, S. (2015). A hierarchical Bayesian approach to negative binomial regression. Methods and Applications of Analysis, 22(4), 409-428.

Gamble, J. (. (2008). Analyses of the effects of global change on human health and welfare and human systems. Washington DC: U.S. Environmental Protection Agency.

Gh, El Samra. (2019). CLIMATE CHANGE AND HUMAN INFECTIOUS DISEASES. Egyptian Journal of Occupational Medicine, 43(1), 33-56.

Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. Ecology, 84(11), 2809-2815.

Government of Uganda (2014). Uganda's Second National Communication to the United Nations Framework Convention on Climate Change. Climate Change Department. Retrieved from: https://unfccc.int/resource/docs/natc/uganc2.pdf

Guarner, J., & Hale, G. L. (2019). Four human diseases with significant public health impact caused by mosquito-borne flaviviruses: West Nile, Zika, dengue and yellow fever. Semin Diagn Pathol, 36(3), 170-176. doi:10.1053/j.semdp.2019.04.009

Held, I. &. (2006). Robust Responses of the Hydrological Cycle to Global Warming. Journal of Climate, 5686-5699.

Heudtlass, P., Guha-Sapir, D., & Speybroeck, N. (2018). A Bayesian hierarchical model for mortality data from cluster-sampling household surveys in humanitarian crises. Int J Epidemiol, 47(4), 1255-1263. doi:10.1093/ije/dyy088

IPCC (Intergovernmental Panel on Climate Change). (2014). Climate Change 2014: Impacts, Adaptation and Vulnerability. Chapter 22, Africa. Cambridge University Press, Cambridge, p.8.

Jia, P., Stein, A., James, P., Brownson, R. C., Wu, T., Xiao, Q., . . . Wang, Y. (2019). Earth Observation: Investigating Noncommunicable Diseases from Space. Annu Rev Public Health, 40, 85-104. doi:10.1146/annurev-publhealth-040218-043807

Kehs, A., McCloskey, P., Chelal, J., Morr, D., Amakove, S., Plimo, B., . . . Hughes, D. (2019). From village to globe: A dynamic real-time map of African fields through PlantVillage. In: bioRxiv.

Labbé, J., Ford, J.D., Berrang-Ford, L. et al. (2016). Vulnerability to the health effects of climate variability in rural southwestern Uganda. Mitig Adapt Strateg Glob Change 21, 931–953 (2016). https://doi.org/10.1007/s11027-015-9635-2

Leo, J., Luhanga, E., & Michael, K. (2019). Machine Learning Model for Imbalanced Cholera Dataset in Tanzania. Scientific World Journal, 9397578. doi:10.1155/2019/9397578

Liang, L., Wiens, M. O., Lubega, P., Spillman, I., & Mugisha, S. (2018). A Locally Developed Electronic Health Platform in Uganda: Development and Implementation of Stre@mline. JMIR formative research, 2(2), e20. https://doi.org/10.2196/formative.9658

Lufafa, A. (2006). Land use and climate change effects on terrestrial c stocks in Uganda's cattle corridor. End of project technical report submitted to start. Faculty of Agriculture, Makerere University

Magrath J, (2008). Turning up the Heat: Climate Change and Poverty in Uganda. Oxfam UK.

Mahmood Akhtar, M. U. (2018). A dynamic neural network model for predicting risk of Zika in real-time. bioRxiv, 1-40.

Marshall, M. N., Shekelle, P. G., McGlynn, E. A., Campbell, S., Brook, R. H., & Roland, M. O. (2003). Can health care quality indicators be transferred between countries?. BMJ Quality & Safety, 12(1), 8-12.

Martens WJM, R. J. (2002). Environmental Change, Climate and Health: Issues and Research Methods. In M. WJM, Environmental Change. pp. 197- 225. Cambridge: Cambridge University Press.

Martin, O., (2018). Bayesian Analysis with Python: Introduction to statistical modeling and probabilistic programming using PyMC3 and ArviZ. Packt Publishing Ltd.

McMichael A Campbell-Lendrum D Ebi K Githeko A Scheraga J Woodward A (2003). Climate change and human health: risks and responses. World Health Organization, Geneva

Ministry of Health, Uganda (2010). Health Sector Development Plan IV (2015 -2020). Retrieved from: http://npa.go.ug/wp-content/uploads/2016/08/Health-Sector-Development-Plan-2015-16-2019-20-1.pdf

Munabi Ian G., Kibaya Patrick, Gebru Berhane, Sserwadda George, Khaled Charlie, Rutabara Robert and Kaddu John Baptist (2020). Dataset for Modeling Climate Change and Health in Uganda-East Africa. http://dx.doi.org/10.6084/m9.figshare.12236957.v1

Nalborczyk, L., Batailler, C., Lœvenbruck, H., Vilain, A., & Bürkner, P. C. (2019). An introduction to Bayesian multilevel models using brms: A case study of gender effects on vowel variability in standard indonesian. Journal of Speech, Language, and Hearing Research, 62(5), 1225-1242.

Namanya D.B. (2009). An assessment of the impact of climate change on the health sector in Uganda: a case of malaria and cholera epidemics and how to improve planning for effective preparedness and response

Nhamo, G. and S. Muchuru (2019). "Climate adaptation in the public health sector in Africa: Evidence from United Nations Framework Convention on Climate Change National Communications." Jamba 11(1): 644.

Niang I, Ruppel OC, Abdrabo MA, Essel A, Lennard C, Padgham J, Urquhart P (2014) Africa. In: Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach KJ, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) Climate change 2014: impacts, adaptation, and vulnerability. Part B: regional aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp 1199–1265

Niang, I., Ruppel, O.C., Abdrabo, M.A., Essel, A., Lennard, C., Padgham, J., Urquhart, P. (2014) Africa. In: Climate change 2014: impacts, adaptation and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Office of the Prime Minister (OPM) (2012). The 2010-2011 integrated rainfall variability impacts needs assessment and drought risk management strategy. Department of Disaster Management-Office of the Prime Minister, Government of Uganda. Retrieved from https://gfdrr.org/sites/gfdrr/files/UGANDA_PDNA_Report_2012.pdf

Nguyen, G., Dlugolinsky, S., Bobák, M., Tran, V., García, Á.L., Heredia, I., Malík, P. and Hluchý, L., (2019). Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey. Artificial Intelligence Review, 52(1), pp.77-124.

Paul, R. K. (2006). Multicollinearity: Causes, effects and remedies. IASRI, New Delhi, 58-65.

Phalkey, R., Louis, V. (2016). Too hot to handle: How do we manage the simultaneous impacts of climate change and natural disasters on human health? Eur. Phys. J. Spec. Top. 225, 443–457 https://doi.org/10.1140/epjst/e2016-60071-y

Ramin, B. M., & McMichael, A. J. (2009). Climate change and health in sub-Saharan Africa: a case-based perspective. Ecohealth, 6(1), 52-57. doi:10.1007/s10393-009-0222-4

Republic of Uganda (2007). Climate Change: National Adaptation Programmes of Action (NAPA), Ministry of Water and Environment.

Republic of Uganda (2015). Health Sector Development Plan, 2015/16 – 2019/20. Ministry of Health.

Republic of Uganda (2018). Nationally Determined Contributions (NDC), Ministry of Water and Environment, Uganda.

Russell, J. A. (2009). Environmental security and regional stability in the Persian Gulf. Middle East Policy, 16(4), 90-101.

Sachin, D. (2019). an-illustrated-guide-to-the-poisson-regression-model. Retrieved from https://towardsdatascience.com: https://towardsdatascience.com/an-illustrated-guide-to-the-poisson-regression-model-50cccba15958

Scheerens, C., Ruyssen, I., Ray, S., De Sutter, A., Vanhove, W., Bekaert, E., . . . De Maeseneer, J. (2020). Tackling adverse health effects of climate change and migration through intersectoral capacity building in Sub-Saharan Africa. BJGP Open. doi:10.3399/bjgpopen20X101065

Sellers, S., Ebi, K. L., & Hess, J. (2019). Climate change, human health, and social stability: addressing interlinkages. Environmental health perspectives, 127(04), 045002.

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, W., Perrette, M. and Reinhardt, J. (2015). Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. Regional Environmental Change, Volume 15, No.8. DOI 10.1007/s10113-015-0910-2.

Uganda National eHealth policy (2016) (http://library.health.go.ug/download/file/fid/517)

United nations framework convention on climate change (2017). Human health and adaptation : understanding climate change impacts on health and opportunities for action. A synthesis paper by the Secretariat. FCCC/SBSTA/ 2017/2. Subsidiary Body for Scientific and Technological Advice, Forty-sixth session

United nations framework convention on climate change (UNFCC) (2020). Stocktaking meeting of the Least Developed Countries Expert Group (LEG) Madagascar . FCCC/SBI/2020/7 Subsidiary Body for Implementation .

United Nations. Economic Commission for Africa. In Climate Change and Health in Africa Issues and Options; ClimDev Africa (Policy brief); © UN. ECA: Addis Ababa, Ethiopia, 2013; No. 12; p. 3.

United Nations Office for South-South Cooperation (UNOSSC) and South Center (2017). Climate Partnerships for a Sustainable Future: An initial overview of South-South cooperation on climate change in the context of sustainable development and efforts to eradicate poverty. New York: United Nations Office for South-South Cooperation and the South Centre. Retrieved from: https://www.un.org/sustainabledevelopment/wp-content/uploads/2017/11/here.pdf

Word Health Organization (WHO) (2018). COP24 Special report: Health and climate change. Retrieved from https://reliefweb.int/sites/reliefweb.int/files/resources/9789241514972-eng.pdf

World Health Organization (WHO) (2015). Climate and Human Country Profile – Uganda. Retrieved from: https://apps.who.int/iris/bitstream/handle/10665/246136/WHO-FWC-PHE-EPE-15.30-eng.pdf;jsessionid=CC7B904F469D4F422AD53A2816300FE0?sequence=1

World Health Organization (WHO) (2015). Climate Change and Human Health. Retrieved from: https://www.who.int/globalchange/climate/summary/en/index5.html

World Health Organization (WHO) (2018). Health and climate change survey report: tracking global progress. Geneva: World Health Organization; 2019 (WHO/CED/PHE/EPE/19.11). Licence: CC BY-NC-SA 3.0 IGO.

Wu X., Li Y., Zhou S., Chen L., Xu B (2016). Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. Environ. Int. 2016; 86:14–23. doi: 10.1016/j.envint.2015.09.007

Yiou, P. &. (2017). A statistical framework for conditional extreme event attribution. Advances in Statistical Climatology, Meteorology and Oceanography (ASCMO), 3. 17-31. 10.5194/ascmo-3-17-2017.