Vulnerability to the Health Impacts of Climate Change in Kenya

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THESIS

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To my past, present and future self.

The best bet you can make is on yourself.

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LIST OF ABBREVIATIONS

CC	Climate Change
UNFCC	United Nations Framework Convention on Climate Change
NAP	National Adaptation Plans
HNAP	Health – National Adaptation Plan
LMIC	Low- and middle-income Country
IPCC	Intergovernmental Panel on Climate Change
AR5	Assessment Report 5
CIDP	County Integrated Development Plan
SCHRI	Social, Climate and Health Risk Index
SSA	Sub-Saharan Africa
ASAL	Arid and Semi-Arid Lands
WHO	World Health Organization
AC	Adaptive Capacity
S	Sensitivity
H	Hazard
E	Exposure
R	Risk
CHA	Climate and Health Adaptation
KNCCRS	Kenya National Climate Change Response Strategy
ACCAPAHS	Adaptation to Climate Change in Africa Plan of Action for the Health Sector
WASH	Water, Sanitation and Hygiene
KMD	Kenya Meteorological Department
KNBS	Kenya National Bureau of Statistics
LVRB	Lake Victoria Region Economic Block
FAO	Food and Agriculture Organization
IRR	Incidence Rate Ratio
CI	Confidence Interval
GHG	Green House Gases

LIST OF ABBREVIATIONS (Continued)

KHIS	Kenya Health Information System
eCHIS	Electronic Community Health Information System

SUMMARY

The health impacts of climate change are not homogenous across low- and middle-income countries (LMICs) and as a result vulnerable communities need to be identified for resource allocation to support climate change adaptation initiatives. The Intergovernmental Panel on Climate Change (IPCC) has addressed this need by developing a framework of risk for the impacts of climate change. Additionally, in 2014, the World Health Organization (WHO) developed guidelines for the Health National Adaptation Plans (HNAPs) for adaptation to climate change in LMICs.

Kenya is experiencing the effects of climate change nationwide, but the biggest threats are rising temperature, sea level rise, increased rainfall and floods in some areas, and droughts in others (Bauer and Mburu 2017, 74-79, Harison, Boitt, and Imwati 2017, Public Health & Environment Department World Health Organization 2010, Talisuna et al. 2020). Floods are projected to increase in frequency and intensity, posing a substantial risk to human life in Kenya (World Bank Group 2020, Romanello et al. 2021). In fact, every year since 2000, Kenya has experienced prolonged droughts and intense flooding (Thornton 2010). Additionally, riverine flooding in Kenya is projected to impact an additional 75,100 people by 2030, compared to impacting 29,600 people in 2010, with a high level of risk in Western Kenya (World Health Organization 2016, World Bank Group 2020). The Kenyan government considers waterborne diseases to be among the greatest health threats in the country in the near to long term future (World Bank Group 2020). It has been well documented that flooding and higher than average rainfall was associated with increases in the incidence of diarrheal diseases (Levy et al. 2016). Flooding and extreme rainfall can increase the already high burden of diarrheal disease in Kenya.

Health National Adaptation Plans were promoted by the World Health Organization (WHO) to increase the capacity of LMICs to adapt to impacts of climate change on the health sector. Climate and its health impacts vary locally, yet frameworks for evaluating the adaptive capacity of health systems on the subnational scale are lacking. This is problematic, as the health impacts of climate change and climate change hazards vary considerably within many countries. In Kenya, counties prepare County Integrated Development Plans (CIDPs), which contain information that might support evaluations of the extent to which counties are planning climate change adaptation for health. This research aimed to develop and apply a framework for evaluating plans for public health adaptation to climate change at the county level in Kenya. While nearly all Kenyan CIDPs note climate change in the context of development, only about half mention health related to climate change. This suggests that some counties are planning for the health impacts of climate change while others do not appear to be making such plans.

Currently, no risk index following the IPCC AR5 framework has been developed to address the association between weather and diarrheal disease. This is concerning, as diarrheal disease in children – which has been linked to recent rainfall – has substantial health and economic consequences. Prior indices have not included the system that is exposed, in this case the population that is exposed, and therefore do not take a systems-based approach to estimating risk. Additionally, health data is hard to obtain in low resource settings, but demographic and social data are more readily available. The IPCC did not provide guidance about how the AR5 risk index should be operationalized. For example, the types of data to be used and the ways that the index should be calculated were not spelled out, though researchers have developed their own approaches to this task, mainly driven by data availability. The aim of this research is to develop a risk index following the IPCC AR5 framework for the impact of climate change on diarrheal disease in Western Kenya for relatively small administrative units (sub-counties). Based on the literature and the IPCC framework, social and environmental factors that potentially relate climate change to diarrheal diseases were identified and principal component analysis was applied. The risk index of sub-county vulnerability varies on a subnational scale and does not follow a spatial gradient. The estimated local risks of diarrheal disease in the sub-counties should be useful to policymakers and health officials in Kenya. Moreover, our approach to implementing a risk index can be applied by climate and health researchers globally.

Risk indices are useful tools to identify spatial regions highly vulnerable to the impacts of climate change to guide resource allocation and prioritization. Although a variety of vulnerability indices and a small number of risk indices have been created for climate change in LMICs, very few have been validated with epidemiological data. Assessing the predictive capabilities of vulnerability indices on the association between extreme rainfall and health impacts is relatively novel. The final aim of this research is to evaluate the predicted risk levels of weather-associated diarrheal disease to observed rates of weather-associated diarrheal disease in children. The risk index developed using the IPCC risk AR5 framework predicts diarrheal disease in children under 5, as do season and weather variables, though the correspondence between observed and modeled risk is limited. Surprisingly, high temperatures were directly associated with risk while precipitation was inversely associated with risk. These findings demonstrate the potential of the application of the IPCC risk framework to predict the future burden of climate-sensitive disease. Such information should be useful for policymakers and health officials in Kenya to prioritize efforts to prepare communities for health impacts of climate change.

I. INTRODUCTION

A. General Background

Climate change defined by the United Nations Framework Convention on Climate Change (UNFCCC) is "a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods" (Begum, Lempert, Ali, Benjaminsen, Bernauer, Cramer, Cui, Mach, Nagy, Stenseth, Sukumar, and Wester 2022). As a result of climate change, global temperatures have increased by 1.2 degrees Celsius since the pre-industrial period, with the hottest seven years on record being 2015 to 2021 (Romanello et al. 2021). Sea level rise has been increasing, on average the sea level rose by 4.4mm per year from 2013 to 2021, two times the annual increase from 1993 to 2002 (World Meteorological Organization 2021). Additionally, in any given month from 2010 to 2019, up to 22% of global land surface was experiencing an extreme drought, almost double the maximum of 13% from 1950 to 1959 (Romanello et al. 2021). Fifty-one million people were affected by floods, droughts, and storms in a single 6-month period of 2020 (Romanello et al. 2021). The impacts of climate change are increasing in both frequency and severity and in 2020, climate change was identified by the WHO as one of the thirteen most urgent global health challenges of the next decade.

Climate change impacts human health by altering the system in which individuals live, specifically by changing exposure to various environmental hazards (Romanello et al. 2021). Exposure to climate change induced hazards have both direct and indirect impacts on human health. As seen in Figure 1, climate- sensitive health conditions range from injuries and deaths to non-communicable diseases. Storms, floods, and droughts account for 39%, 34%, and 16%, respectively, of global disaster related deaths (Ebi and Prats 2015). Extreme heat also directly impacts human health through increases in incidence of heat related illnesses or exacerbation of underlying chronic health conditions, such as cardiovascular and respiratory disease (Ebi and Prats 2015). Another direct impact of climate change on health is increased burden of mental health illnesses, such as post-traumatic stress disorder, depression, and anxiety (Ebi, and Prats 2015, Suhr and Steinert 2022). Finally, climate change disasters impact food and water supply globally increasing the burden of malnutrition and stunting, defined as height-for-age more than 2 standard deviations below the WHO Child Growth Standards median – with an estimated 7.5 million additional children expected to be stunted globally in 2030 due to climate change (Suhr and Steinert 2022, Wright et al. 2021). This increase in stunting is expected to result in an additional 95,000 childhood deaths (Wright et al. 2021).

Changes to the environment because of climate change indirectly impact human health by increasing exposure to infectious, vector-borne, water-borne, and food-borne diseases. It is well established that transmission of most vector-borne diseases follows a seasonal pattern (Wright et al. 2021). Therefore, climate change alters the normal seasonal and spatial distribution of vector-borne diseases (Wright et al. 2021, Suhr and Steinert 2022). Some vector-borne diseases that are projected to increase with climate change include malaria, dengue, west Nile virus, and yellow fever. In fact, it is estimated that an additional 520 million people will be at risk of contracting dengue in 2050 (Wright et al. 2021). Increases in temperature and rainfall drastically alter transmission of diarrheal disease, resulting in an estimated 48,000 excess deaths in children under 15 from diarrheal disease in 2030 (Wright et al. 2021). The health impacts of climate change are global and severe, but they are distributed unevenly across regions and populations.

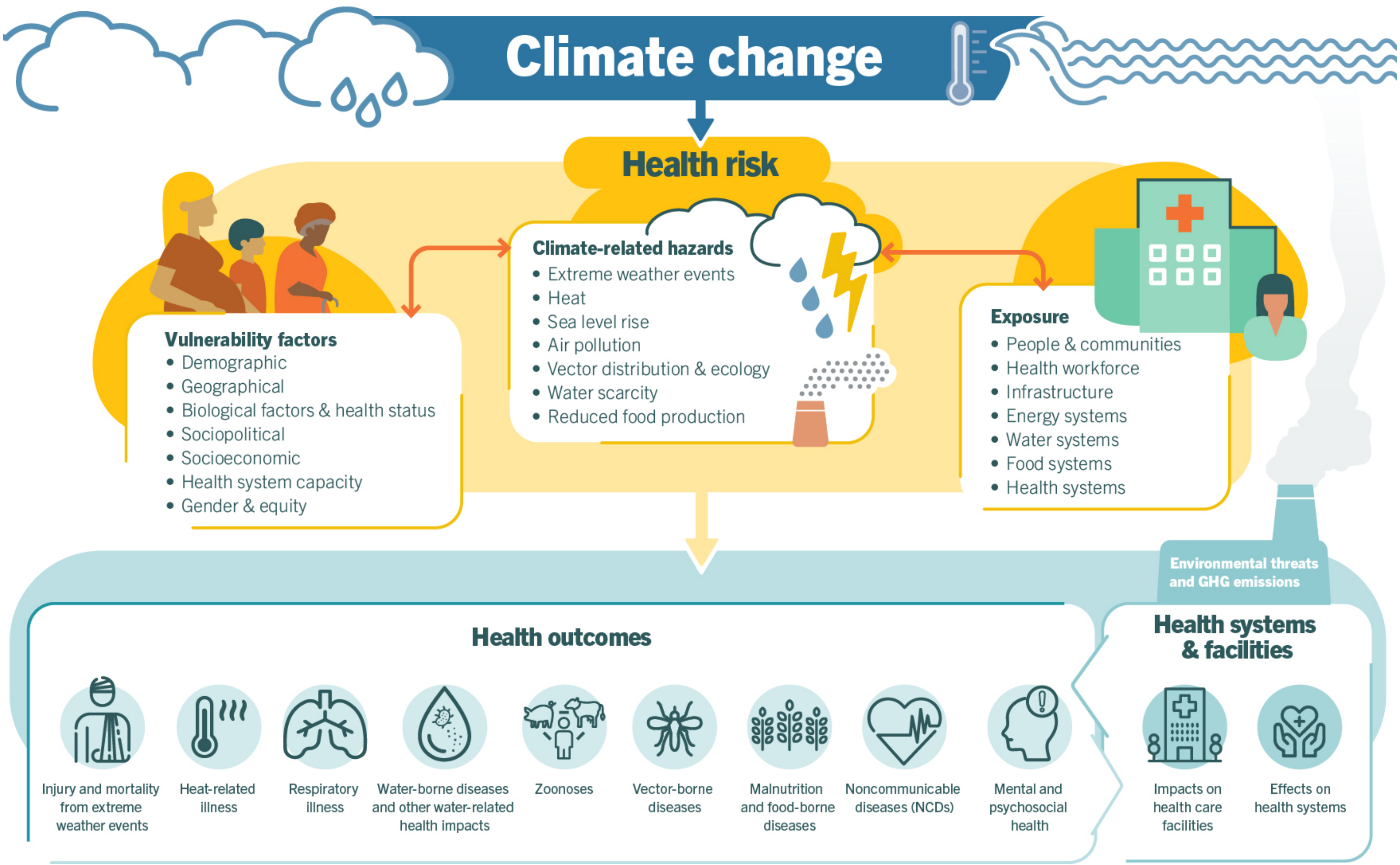

Figure 1. Overview of climate change impacts on health

B. Specific Aims

Climate change is one of the greatest global health threats of our time and disproportionately impacts low- and middle-income countries (LMICs) such as Kenya (Wright et al. 2021). Due to the impact of climate change on the upstream drivers of disease, the health risk of and preparedness for climate change varies on a subnational level. At the international level, Health National Adaptation Plans (HNAPs) have been evaluated. Additionally, research in Botswana, Madagascar, Dominica, Brazil, and Kenya has been conducted to estimate vulnerability to climate change on a subnational level.

While there is a framework for evaluating HNAPs, only five nations currently have an HNAP, thus calling for a need to develop a framework of evaluation for existing subnational plans in Kenya. To date, most research in LMICs on vulnerability to the health impacts of climate change, has been based on the Intergovernmental Panel on Climate Change (IPCC) Assessment Report (AR) 4 framework of vulnerability. The most up-to-date framework by the IPCC, AR 5, is a framework of risk to a system and takes a more systems-based approach to understanding climate change and health risk on a subnational scale. For example, a research team in the Indian Bengal Delta compared the AR4 and AR5 framework on a subnational level and found that the AR5 framework was a better estimate of risk regarding climate change (Das et al. 2020). Additionally, the two climate change vulnerability assessments in Kenya do not assess vulnerability to the health impacts of climate change nor do they focus on a specific climate hazard or climate-sensitive health outcome. The goal of this research is to develop a risk index of the impact of climate change on waterborne disease on a subnational level in Kenya. Thus, my specific aims, are:

1. **Specific Aim 1: Assess the extent to which climate change and health are addressed in county-level integrated development plans in Kenya**

   County-level integrated development plans (CIDPs) will be manually evaluated based on the presence or absence of the connection of climate change and health in the four sections of the CIDPs.

2. **Specific Aim 2: Develop and evaluate a Risk Index for risk of diarrheal disease as a result of extreme weather at the sub-county level**

   Following the IPCC AR5 framework of risk, the risk index will estimate the risk of diarrheal disease from extreme weather at the subcounty level in the Lake Victoria Regional Economic Block of Kenya. The risk index will be a function of exposure, hazard, and vulnerability. Vulnerability as defined by the IPCC is a function of adaptive capacity and sensitivity. These components will be calculated from secondary sub-county level data and weighted using PCA analysis.

3. **Specific Aim 3: Validation of the Risk Index with Historical Diarrheal Disease Data**

   The purpose of this aim is to validate the risk index developed in aim 2. This will be done using epidemiological data on the sub-county level in western Kenya from 2014 to 2022. Utilizing health outcome data and meteorological data, we will be able to run a Poisson regression that includes risk index as a predictor variable of diarrheal disease cases.

C. Review of Related Literature

The health impacts of climate change disproportionately impact LMICs (Wright et al. 2021). Within LMICs, vulnerable populations, such as children, are hit the hardest. Children under the age of 5 are disproportionately impacted by diarrheal diseases because of climate change. For example, for every 1-degree Celsius increase in temperature in Peru there was a 3.8% increase in childhood clinic visits for diarrhea (Delahoy et al. 2021). Similarly, in Nepal a 1-degree increase in temperature was found to be associated with a 4.4% increased incidence of diarrheal disease in children (Dhimal et al. 2022). In addition to an association with temperature, diarrheal disease incidence is associated with rainfall. For example, for every 1 cm increase in rainfall diarrheal disease incidence in Nepalese children increases by 0.4 to 0.8% (Dhimal et al. 2022). With changes in rainfall comes the risk of floods, droughts, and other natural disasters. In Cambodia, diarrheal disease in children has been identified as the biggest health hazard following severe flooding (Davies et al. 2015). The demonstrated association between climate hazards and diarrheal disease and its impact on vulnerable communities calls for the need to identify vulnerable communities on a sub national level in LMICs.

The health impacts of climate change are not homogenous across LMICs and as a result vulnerable communities need to be identified for resource allocation. For example, a study in Brazil focused on how the determinants of health were associated with increased burden of dengue through spatial clustering (Do Carmo et al. 2020). Population density, low levels of education, housing, and social vulnerabilities were found to contribute to an increased burden of dengue in the community (Do Carmo et al. 2020). These results pointed to the need to develop a climate change vulnerability index in Brazil, thus the Human Vulnerability Index was developed in the state of Minas Gerais, Brazil (Quintão et al. 2017). This vulnerability index was a function of exposure, sensitivity, and adaptive capacity, where sensitivity was comprised of the following components: endemic diseases, sociodemographic information, and poverty (Quintão et al. 2017). Similarly, vulnerability assessment based on WHO framework in Dominica, identified infants and children under age 5 as one of the vulnerable groups for food- and water-related diseases; specifically, this group is disproportionately affected by gastroenteritis (Schnitter et al. 2018). Since the number of gastroenteritis cases in Dominica has increased over the last 15 years and it is projected to increase further, this is a very important finding for resource allocation in Dominica (Schnitter et al. 2018). It is clear from the above-mentioned vulnerability assessments that social factors play a role in vulnerability to the adverse health impacts of climate change in LMICs and need to continue to be studied.

Sub-Saharan Africa (SSA) is expected to bear the greatest burden of mortality attributable to climate change in 2030 (Wright et al. 2021, WHO 2014a). Flood exposure in SSA nations has led to increased incidence of various infectious diseases such as, cholera, scabies, malaria, taeniasis, Rhodesian sleeping sickness, and alpha- and flaviviruses (Suhr and Steinert 2022, Okaka and Odhiambo 2018). According to systematic reviews, half of the studies on floods and health in SSA are focused on malaria, while this attention is deserved, it is also crucial to address the other adverse health outcomes associated with floods (Suhr and Steinert 2022). There are a variety of mechanisms by which floods impact human health including, damaging infrastructure, loss of homes, overcrowding, displacement, overflow of sanitation systems, increases in human-to-human contact, and the contamination of the environment and water sources (Suhr and Steinert 2022). Another major concern in SSA is heat related morbidity and mortality (Pasquini et al. 2020). This is of particular concern for communities living in informal settlements, such as unplanned urban slums, where there is high population density and poor infrastructure, such as housing and sanitation services (Pasquini et al. 2020). In relation to heat, a study in Uganda found that temperatures above the 95th percentile were associated with an increase in same-day hospital admissions (Bishop-Williams et al. 2018). While SSA is disproportionately impacted by the health effects of climate change, it is also clear that the impacts vary on a subnational level.

To date, there has been limited research on social vulnerability to the impacts of climate change in SSA with only 4.3% of studies being done in Africa (Li, Toll, and Bentley 2023). In Botswana, a research team developed a social vulnerability index for natural hazards (Dintwa et al. 2019). This research found that social vulnerability was driven by size of household, disability, level of education, age, people receiving social security, employment status, household status, and poverty level (Dintwa et al. 2019). Additionally, it was found that having a higher percentage of the population under 5 increased the likelihood that the population was highly vulnerable. While the Botswana study did not consider health, a vulnerability index in Madagascar did address the health sector. In Madagascar a vulnerability index for the climate change impacts on the health sector was developed and found that the population overall and health sector – system of providers, infrastructure, and health care services - is highly vulnerable to the impacts of climate change (Rakotoarison et al. 2018). This assessment found that the 22 regions in Madagascar have very different levels of vulnerability with poverty and literacy rates playing a large role in regional vulnerability(Rakotoarison et al. 2018). These vulnerability studies demonstrate how indicators of vulnerability are country and sector specific.

Kenya is a lower middle-income nation in Eastern SSA with a population of 52.6 million people (World Bank Group 2021). Approximately 60% of Kenyans living in urban areas live in informal settlements, such as slums, and as of 2021 38.6% of the population was classified as poor (United Nations Habitat 2023, Kenya National Bureau of Statistics 2023). Additionally, only 34% of households have access to piped water and 8.2% of households do not have access to a sanitation facility (Kenya National Bureau of Statistics 2019a). As of 2019, the life expectancy at birth in Kenya is 66.7, a drastic improvement from 50 years in 2000 (World Bank Group 2021, Ministry of Health 2014). As of 2019, the top 4 leading causes of death in Kenya were, HIV/AIDs, lower respiratory infections, diarrheal disease, and neonatal disorders respectively (GBD 2019 Diseases and Injuries Collaborators 2020, Ministry of Health 2014). As the climate change impacts increase in intensity and severity in Kenya, the burden of disease will only increase thus putting a strain on the healthcare sector.

The healthcare workforce in Kenya has been growing in recent years but is still under performing compared to the WHO-recommendations, with an average of 20.7 doctors and 159.3 nurses for every 100,000 people in 2014 (Ministry of Health 2014). Additionally, health facilities are not evenly distributed across the 47 counties in the nation, with some counties having as few as 0.4 hospitals per 100,000 people and others having 3.1 hospitals per 100,000 people (Ministry of Health 2014). As a result, in 2013, the Kenyan government shifted to a decentralized health system (Masaba et al. 2020). Under this new system, the 47 county governments are responsible for community health, primary health care, and county referral services and the national government (the Ministry of Health) is responsible for national referral services (Masaba et al. 2020). Within each county, sub-counties are responsible for community health and primary care services (Ministry of Health 2014). Community health services include promotion of healthy lifestyles, personal hygiene, treatment of minor ailments, and improving community awareness of services. Primary care services include basic outpatient diagnostic, ambulatory services, medical, surgical, and rehabilitative services. On the county level referral health services for the sub-counties include inpatient diagnostics, specialized outpatient services, reproductive health services, and funeral management. Finally on the national level, national referral services provide specialized services not available at the county level.

Kenya is experiencing the effects of climate change nationwide. Some of biggest climate change threats to Kenya include rising temperature, sea level rise, increased rainfall and floods in some areas, and droughts in others (Bauer and Mburu 2017, Harison, Boitt, and Imwati 2017, Public Health & Environment Department WHO 2010, Talisuna et al. 2020). Based on Global Climate Modeling it is estimated that the average temperature in Kenya will rise an additional 1.7°C by 2050 (Climate Action Tracker 2020, Government of the Republic of Kenya 2016b). Additionally, average rainfall is expected to increase, and extreme rainfall is expected to increase in frequency, intensity, and duration (Climate

Action Tracker 2020). Mombasa, a coastal city in Kenya, is very vulnerable to sea level rise, an estimated 17% of the city will be submerged if sea-level rises 0.3 meters (Bauer and Mburu 2017, 74-79, Climate Action Tracker 2020). While sea level rise is a hazard of concern on the coast, floods and droughts are the hazards of greatest concern nationally (Government of the Republic of Kenya 2018b). In fact, every year since 2000, has seen prolonged droughts and intense flooding in Kenya (Thornton 2010). Riverine flooding in Kenya is projected to impact an additional 75,100 people by 2030, compared to impacting 29,600 people in 2010 (World Health Organization 2016). Arid and semi-arid lands (ASAL) are the most vulnerable regions to the most adverse impacts of droughts (Climate Action Tracker 2020). Droughts are particularly concerning since 88% of the land in Kenya is considered ASAL and 18 of the 20 poorest counties in the country are designated ASALs (Climate Action Tracker 2020, Harison, Boitt, and Imwati 2017). Floods are projected to increase in frequency and intensity, posing a substantial risk to human life in Kenya (Climate Action Tracker 2020, Romanello et al. 2021). According to the World Bank, the most vulnerable counties to increased flood risk include: Baringo, West Pokot, Kisumu, and Laikipia (Climate Action Tracker 2020).

The incidence of diseases such as heat-related illnesses, asthma, infectious diseases, vector –, water -, food-borne diseases, and diarrheal diseases are projected to increase (World Bank Group 2020). Heat-related deaths are particularly concerning in Kenya. In a high greenhouse gas emissions scenario, it is projected that heat-related deaths in the elderly will increase to 45 deaths per 100,000 by 2080, a massive increase from 2 deaths per 100,000 annually from 1961 to 1990 (World Bank Group 2020). It is projected that by 2055 there will be a south to north shift of anthrax risk in Kenya compared to current areas of risk (Otieno et al. 2021). The most prominent health impacts of climate change for Kenya in the near to long-term future include malnutrition, vector-borne diseases, and water-borne diseases.

As of 2010, approximately 30% of children under 5 years old were stunted in Kenya (Grace et al. 2012). Malnutrition has been declining in Kenya on a national scale but is not improving in ASAL regions of the country (Grace et al. 2012). These areas of the country tend to have few resources, high levels of poverty, frequent droughts, and suffer from acute food shortages (Grace et al. 2012). A recent study focused on five counties in the northern region of Rift Valley to determine and model causal factors of malnutrition in children under five (Grace et al. 2012). As a result, it was found that vegetation index, poverty, drinking water, literacy rate, place of delivery and temperature are significantly associated with malnutrition (Grace et al. 2012). Additionally, studies have shown that drought is a strong indicator of malnutrition, when using a robust measure of drought such as, Normalized Difference Vegetation Index (NDVI) (Bauer and Mburu 2017). Specifically, in the Marsabit district of Kenya, it was found that there is a positive association between NDVI and childhood stunting (Bauer and Mburu 2017). The increase in malnutrition due to climate change will not be distributed equally across Kenya, thus the subnational vulnerability to malnutrition needs to be characterized.

Mosquito-borne diseases, such as malaria, dengue, and rift valley fever, are endemic to Kenya and thus the impacts of climate change on them are of great concern. A recent study on the impact of extreme rainfall and temperature on mosquito abundance found a positive association between flooding and extreme rainfall and increase mosquito abundance (Nosrat et al. 2021). Additionally, it has been shown that dengue and mosquito abundance have a non-linear relationship due to the extrinsic incubation period, the time in between a vector acquiring an infectious agent and being able to transmit the infectious agent (Tjaden et al. 2013, Nosrat et al. 2021). Extrinsic incubation periods speed up at higher temperatures, therefore as rainfall and temperature increase in Kenya the burden of dengue fever will increase (Nosrat et al. 2021). It has also been well documented that flooding and increases in rainfall are associated with increased incidence of malaria and rift valley fever (Olubulyera

2021). Specifically, quantitative modeling has shown an association between rainfall and high temperature and an increase in inpatient malaria cases in the following 3 -4 months (Githeko, Ndegwa, and Ndegwa 2001). Thus, increases in temperature and rainfall in Kenya due to climate change may increase the burden of malaria in Kenya.

Flooding has played and continues to play a key role in infectious disease outbreaks in Kenya (Olubulyera 2021). Specifically, flooding causes increases in water-borne and mosquito-borne diseases (Olubulyera 2021). The main cause of waterborne diseases during flooding is the contamination of drinking water sources (Okaka and Odhiambo 2018, Olubulyera 2021). It has been well documented that flooding is associated with increased incidence of cholera and higher than average rainfall was associated with increases in incidence of diarrheal disease (Olubulyera 2021). For example, flooding in Mombasa in 2006 led to a cholera outbreak resulting in 94 suspected cases, 13 confirmed cases, and 2 deaths (Awuor, Orindi, and Adwera 2008). A study in Malindi, Kenya found a strong positive correlation between increased rainfall and cases of childhood diarrhea (Saidi et al. 1997). Additionally, a study in Malawi found that moderate rainfall is associated with an increased relative risk of invasive non-typhoidal salmonella (Thindwa et al. 2019). Specifically, it has been found that the estimated lag between peak rainfall and increased salmonella cases is 15.46 weeks (Gauld et al. 2022). A recent study in Ethiopia found that for every one-millimeter increase in rainfall the cases of diarrheal disease under 5 increased by approximately 0.17%, although this association demonstrated spatial variability across districts (Alemayehu et al. 2020). Additionally, there is a positive association between diarrheal disease and flooding, with many studies showing increased detection of *Escherichia coli* and *Vibrio cholera* during or after floods (Levy et al. 2016). Temperature has also been shown to have a strong positive association with diarrheal disease (Levy et al. 2016). For example, on the district level in Ethiopia, the warm dry season was associated with increased cases of diarrheal disease under 5 and for every one degree Celsius increased, cases increased by approximately 16.6% (Alemayehu et al. 2020). Flooding and extreme rainfall can increase the already high burden of diarrheal disease in Kenya, but to date there has been limited research on vulnerability to diarrheal disease in Kenya.

Given the above-noted anticipated increases in climate sensitive diarrheal disease in Kenya, the health care sector may need to adapt to the anticipated increase in clinic visits and hospitalizations on both a local and regional scale. On a national level in Kenya there is a variety of policies that address climate change preparedness and another set of policies that address planning in the health sector. Relevant policies regarding health include Health Policy 2017, Kenya Health Policy 2014-2030, Kenya Community Health Strategy 2020-2025, Kenya Health Sector Strategic Plan 2018-2023, and Universal Health Coverage plans as presented as a part of the Big Four Agenda in 2018 (Ministry of Health Kenya 2021, Ministry of Health Kenya 2020, Government of the Republic of Kenya 2018, Government of the Republic of Kenya 2018b). Relevant policies regarding climate change include the Kenya National Climate Change Response Strategy (KCCRS) and the Climate Change Act of 2016 (Opemo et al. 2020, Government of the Republic of Kenya 2016a). In 2010 the KCCRS was developed, and it focuses on reducing GHG emissions, climate change mitigation, with only minimal content regarding adaptation plans for the health sector (Opemo et al. 2020). Health sector adaptation plans include recruitment of more technical staff, construction of nomadic clinics, health education campaigns and enhanced surveillance (Opemo et al. 2020). The KCCRS called for a national vulnerability assessment for the climate risk and impacts on health, but this has not been done (Opemo et al. 2020). The KCCRS also developed the Kenya climate change knowledge portal as a way of sharing climate change resources, but this portal does not have a health component (Opemo et al. 2020). The Climate Change Act of 2016 also moved the needle on climate change action in Kenya by establishing the climate change directorate, requiring the formation of the national climate change action plan, and establishing a climate change fund (Government of the Republic of Kenya 2016a). These recent – but separate - health and climate change policies on a national scale attest to the focus the Kenyan government has placed on climate change and health in recent years. However, climate change policy has little to say about the health consequences of climate change, and the health policies have little to say about the impacts of climate change on health.

The lack of integration of climate change and health policies in Kenya is very concerning, since climate change and health are intrinsically linked. Climate change impacts the upstream social determinants of health and impacts on human health are one of the many adverse impacts of climate change. Therefore, if climate change and health were connected in policies, then cross sector collaboration could increase, resulting in better preparedness, increased international funding, reduced future vulnerability, and a decreased gap between climate change risk awareness and preparedness (Ebi and Prats 2015, Public Health & Environment Department WHO 2010). Given the separate climate change and health policies in Kenya it is important to analyze the policies to see where connections already exist. While there are policies on the national level the hazards and impacts of climate change are not homogenous across the nation and therefore evaluation of the intersection of climate change and health on a subnational level is essential.

A high-quality climate change vulnerability index would allow the national and county governments of Kenya to allocate limited adaptation resources to communities that are most vulnerable to the health impacts of climate change. There have been two climate change vulnerability indices created for Kenya that followed the 4th Assessment Report (AR4) of the IPCC framework of vulnerability, focusing on exposure, sensitivity, and adaptation. The first vulnerability index was nationwide at the county level, as seen in Table I (Marigi 2017). The exposure parameters of this index included: mean annual total rainfall, mean coefficient of annual rainfall variability, mean annual rainfall trend, and mean annual decadal rainfall changes, mean annual standardized precipitation index (Marigi 2017). The sensitivity parameter included: county population densities, county poverty indices, county population access to improved sanitation (Marigi 2017). Finally, the adaptive parameter included: county literacy levels, and county population access to healthcare facilities (Marigi 2017). This analysis found that the northern region of Kenya is the most vulnerable to climate change (Marigi 2017).

Another vulnerability index was created for Kitui County, Kenya on the subcounty level, as seen in Table II (Mwangi et al. 2020). The exposure component includes precipitation change, temperature change, poverty, and malaria susceptibility. The sensitivity component includes soil health, population, housing, and water access. Finally, the adaptive capacity component included access to market services and female literacy (Mwangi et al. 2020). As a result of this vulnerability assessment, it was discovered that climate change vulnerability in Kitui county follows a west to east gradient, with the most vulnerable sub-counties being those in the eastern region of the county. Both climate change vulnerability indices created for Kenya found differences in vulnerability to climate change on a sub-national level but did not account for the health impacts of climate change.

D. Critical Knowledge Gaps

Climate change is one of the greatest global health threats of our time. Due to the impacts of climate change on the upstream drivers of disease, LMICs such as Kenya are disproportionately impacted. To date, climate change and health research has disproportionately been focused on high-income countries and has not characterized the differences in risk on a subnational level in Kenya. To identify the most vulnerable communities to the impact of climate change in Kenya, the spatial distribution of climate change and health risk must be understood.

TABLE I. CLIMATE CHANGE VULNERABILITY INDEX FOR KENYA

SVI Component	Indicator	Specific Variables	Data Source	Spatial Resolution
Exposure	Mean annual total rainfall	Point rainfall data from 1960 to 2014	Kenya Meteorological Department (KMD)	County
	Mean coefficient of annual rainfall variability		KMD	County
	Mean annual rainfall trend		KMD	County
	Mean annual decadal rainfall changes		KMD	County
	Mean annual standardized precipitation index		KMD	County
Sensitivity	County population densities		Commission on Revenue Allocation	County
	County poverty indices			County
	County population access to improved sanitation			County
Adaptive Capacity	Literacy Level			County
	County population access to healthcare facilities			County

TABLE II. CLIMATE CHANGE VULNERABILITY INDEX FOR KITUI COUNTY, KENYA

SVI Component	**Indicator**	**Specific Variables**	**Data Source**	**Spatial Resolution**
Exposure	Precipitation Change	Long term average, long term trend, long term coefficient of variation	CHIRPS enhanced precipitation, 1983-2016	.05x.05 degrees
	Temperature Change	Long term average, long term trend	CHIRPS enhanced precipitation, 1983-2016	05x.05 degrees
	Poverty	Poverty index (%)	KNBS 2016	Subcounty
	Malaria Susceptibility	Malaria susceptibility index	Malaria Atlas Project, 2010	
Sensitivity	Soil Health	Soil organic carbon stock	FAO-ISRIC Soil Grids, 2017	
	Population	Population count	KNBS 2010	Subcounty
	Housing	House wall type index	KNBS 2013	Subcounty
	Water Access	Access to safe drinking water	KNBS 2015	Subcounty
Adaptive Capacity	Markets	Access to market services (travel time)	KNBS 2015	Subcounty
	Literacy Level	Female literacy	KNBS 2013	Subcounty

This spatial distribution of vulnerability is currently under-studied and represents a major information gap faced by those responsible for preparing communities for the health impacts of climate change in Kenya.

The IPCC AR5 risk framework is only a conceptual framework and has not been widely implemented. The types of data to use and how to analyze the data is still unclear. The operationalization of this risk framework regarding climate-sensitive diarrheal disease aims to address this knowledge gap. The findings of this research should be useful to other climate and health researchers regarding the development and implementation of the IPCC AR5 risk framework for climate-sensitive health outcomes in a variety of settings.

The aims of this research intend to explore adaptive capacity, sensitivity, and climate hazards at a subnational level in a region of Kenya. Through these aims numerous public health tools at the county level will be developed and evaluated. These include a framework of CIDP evaluation, a Risk Index, and modeling diarrheal disease cases by risk. The results of each of the aims will be beneficial to the Kenyan government, specifically in helping them identify the most vulnerable counties to the health impacts of climate change. Additionally, these tools can be utilized to measure growth and improvement in climate change preparedness on the county level for the years to come. These tools are not intended to test a hypothesis, but instead, aim to describe the political adaptive capacity, climate change and health risk, and understand the predictive ability of risk indices regarding diarrheal disease on a subnational scale in Kenya. This is not a novel concept; similar descriptive focused research has been done in Madagascar and the Indian Bengal Delta in recent years. Such descriptive research is instrumental in driving meaningful policy change and thus the hoped use of these aims is to impact climate change and health policies in Kenya.

E. Innovation

A recent paper by Semenza et al., notes that "Climate effects can have far-reaching implications for public health through inherent societal vulnerabilities that can magnify the impacts of cascading risk pathways" (Semenza, Rocklöv, and Ebi 2022). Recent global events, such as COVID-19, have shown the importance of identifying vulnerable communities and addressing the upstream drivers of disease (Sheehan and Fox 2020).

Vulnerability, as defined by the 2007 IPCC, is the degree to which geophysical, biological, and socio-economic systems are susceptible to climate change and includes the concepts of exposure, sensitivity, and adaptive capacity. Components of vulnerability are summarized in in Table III (Intergovernmental Panel on Climate Change 2007). In 2014, the Fifth Assessment Report (AR5) of the IPCC updated the framework of vulnerability to be a component of the risk of climate change impacts. Yet to date, the only climate change vulnerability indices for Kenya have followed the AR4 framework, thus they do not address risk (the AR5 approach) on a county level in Kenya. A study done in the Indian Bengal Delta found that the AR4 vulnerability index and AR5 risk framework changed the relative ranking of the subdistricts potentially providing a better predictor of risk (Das et al. 2020). The AR5 framework is also a more systems driven approach allowing it to be better able to identify vulnerable communities (Begum, Lempert, Ali, Benjaminsen, Bernauer, Cramer, Cui, Mach, Nagy, Stenseth, Sukumar, and Wester 2022, Das et al. 2020, Intergovernmental Panel on Climate Change 2014). While it is well understood that sub-Saharan Africa is disproportionately adversely affected by climate change, the risk that climate change poses to systems on a local level is not well understood. Therefore, this research will give a better understanding of how the county level system in Kenya is could be impacted by climate change.

TABLE III. AR4 AND AR5 CLIMATE CHANGE FRAMEWORKS

AR4 Vulnerability Framework (Intergovernmental Panel on Climate Change 2007)		**AR5 Risk Framework** (Intergovernmental Panel on Climate Change 2014)	
Components	**Definition**	**Components**	**Definition**
Exposure	The magnitude and duration of climate-related stress	Exposure	The presence of people, livelihoods, species or ecosystems, environmental functions, services and resources, infrastructure, or economic, social or cultural assets in places and settings that could be adversely affected
Sensitivity	The degree to which a system is affected, either adversely or beneficially by climate variability or climate change	Vulnerability	The propensity or predisposition to be adversely affected, a function of sensitivity and adaptive capacity as defined in AR4
Adaptive Capacity	The whole of capabilities, resources and institutions of a country or region to implement effective adaptation measures.	Hazard	The potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources.

Climate change is causing more extreme weather in Kenya and will do so for the foreseeable future, with 70% of natural hazards attributable to extreme events (World Bank Group 2020). Since the current leading cause of death in Kenya is diarrheal disease and the literature has showed a positive correlation between extreme weather and waterborne disease, aims 2 and 3 will focus on this relationship. Specifically, aim 2 will focus on estimating the predictors of the risk of diarrheal disease. Then aim 3 will explore the association between rates of diarrheal disease, extreme weather, and risk. Understanding the true impact of Hazard, Exposure, Sensitivity, and Adaptive Capacity on risk of waterborne diseases will allow the Kenyan government to focus their resources on the correct area of the system. Doing this estimation of risk for numerous sub-counties in Kenya will also provide the Kenyan government critical information on which sub-counties are the most at risk.

II. A FRAMEWORK FOR EVALUATING LOCAL ADAPTIVE CAPACITY TO HEALTH IMPACTS OF CLIMATE CHANGE: USE OF KENYA'S COUNTY-LEVEL INTEGRATED DEVELOPMENT PLANS

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A. Background

1. Adaptive Capacity, Climate Change, and Health

Climate change is a threat to global health due to increasing exposure to climate-sensitive health hazards: heat, drought, flooding, sea-level rise, and distribution of vector-borne diseases. Changes in burden of disease due to these health hazards depend on both the adaptive capacity and sensitivity of a community. This concept is vulnerability, or predisposition to be adversely impacted, and is a function of sensitivity and adaptive capacity (Trisos et al. 2022). Adaptive capacity is the ability of a system, such as the healthcare system, to reduce the adverse impacts of a stressor – such as climate change (Trisos et al. 2022). Sensitivity is the degree to which a system is affected by climate change, or susceptible to harm (Trisos et al. 2022). Consider the two communities in Figure 2, both facing the same climate hazards and having comparable sensitivity to those hazards. The community with health care and public health systems that can withstand the impacts of the climate hazard, overall, will have lower vulnerability to the health effects of climate change. We refer to these as 'health systems', which are the network of hospitals, public health offices, emergency response systems, outpatient care facilities, and pharmacies. For example, in 2012 Superstorm Sandy demonstrated the low level of adaptive capacity in New York City health systems due to flooding (Teperman 2013). Superstorm Sandy hit the northeastern United States on October 29, 2012, resulting in 65 deaths, 8.5 million people without power, a shutdown of all mass transit, and six hospital closures (Teperman 2013, Smith et al. 2016). These conditions led to patient surges in emergency departments, failures of backup generators, displacement of patients, loss of healthcare services, and damage to healthcare infrastructure (Teperman 2013). While healthcare systems in high income countries may have resources to rebuild following a climate disaster, healthcare systems in LMICs may not. To reduce the vulnerability of populations in LMIC to the health effects of climate change, it is essential to increase adaptive capacity of healthcare systems in those countries. That can be accomplished through actions such as strengthening primary care services (to keep patients well), develop early warning systems for disasters, establish multisectoral collaboration, educate the health workforce about climate-sensitive health conditions, and build climate resilient infrastructure, such as electrical grids, water infrastructure, and health care facilities (Lokotola et al. 2023).

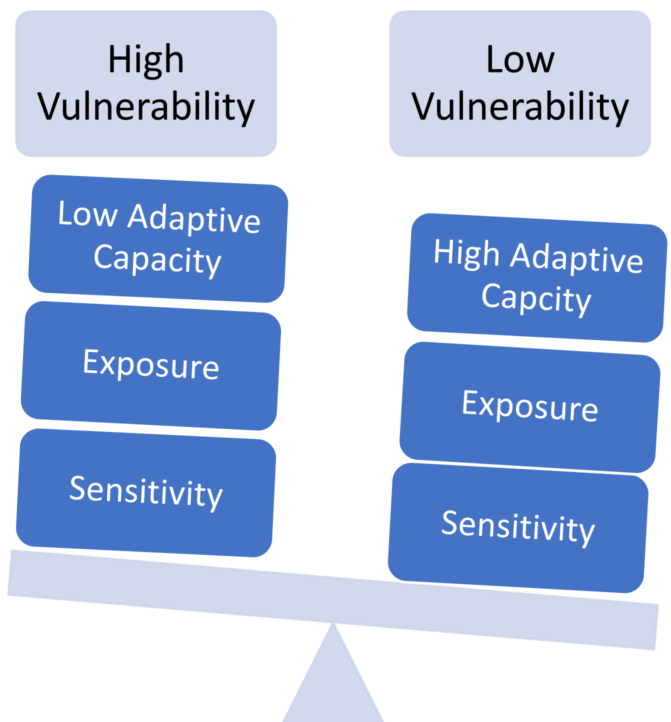

Figure 2. Impacts of adaptive capacity on vulnerability, for a given exposure and a degree of sensitivity

2. National Adaptation Plans

A framework for climate change adaptation has been developed by the United Nations Framework Convention on Climate Change (UNFCCC)(UNFCCC LDC Expert Group 2021, Least Developed Countries Expert Group 2012). That framework, the National Adaptation Plan (NAP), has two main objectives: to reduce vulnerability to climate change at the national level, and to facilitate the integration of climate change adaptation into new and existing policies in low- and middle-income countries (Least Developed Countries Expert Group 2012). The NAP process is intended to be iterative and specific to the needs of a country. The four main steps in the NAP process are: laying the groundwork and addressing gaps; preparatory elements; implementation strategies; and reporting, monitoring, and review (Least Developed Countries Expert Group 2012). The initial NAP guidance did not emphasize health impacts of climate change or health sector adaptation in the context of climate change (Least Developed Countries Expert Group 2012).

3. WHO National Adaptation Frameworks for the Health Sector

In 2014 the World Health Organization (WHO) filled this gap by developing guidelines for the Health National Adaptation Plans (HNAPs) (World Health Organization 2014b). HNAPs consider the physical, social, and biological determinants of health and follow the same steps used in NAP development (Ebi and Prats 2015). The objectives of an HNAP are to reduce vulnerability, build adaptive capacity and resilience, and to facilitate integration of climate change adaptation into new and existing policies in LMIC (World Health Organization 2021a). HNAP guidance is intended to ensure that health risks of climate change are integrated into the overall NAP (World Health Organization 2021a). HNAPs should also ensure that climate-sensitive health outcomes are addressed, and that the health sector can access adaptation funds. The HNAP process is meant to be country driven, collaborative, evidence-based, and built on existing national efforts. HNAPs should integrate health adaptation to climate change into national health systems (World Health Organization 2014b, World Health Organization 2021b). Though NAPs have been submitted by 19 countries, only 4 countries have submitted HNAPs to the WHO: Ethiopia, Brazil, Fiji, and Kiribati (World Health Organization 2021b). As a result, in 2021, the WHO conducted an evaluation of 19 NAPs submitted to UNFCCC to examine the extent to which health was considered in climate change adaptation (World Health Organization 2021b). That evaluation framework found that all 19 NAPs identified the health sector as being vulnerable to climate change. Importantly, the WHO evaluation noted that, "The conduct of health vulnerability assessments and the use of findings could be strengthened in many NAPs, such as through using context-specific local data, establishing baselines and projections, using a clear methodology, and establishing a clear link between the vulnerability assessment findings and proposed adaptation actions."

4. The Framework for Climate Change Adaptation for the Health Sector in Africa

Prior to the WHO's development of HNAP's, the WHO Regional Committee for Africa adopted the Adaptation to Climate Change in Africa Plan of Action for the Health Sector 2012-2016 (ACCAPAHS) (World Health Organization Regional Office for Africa 2012). The objectives of ACCAPAHS are to identify country-specific climate-sensitive health risks in Africa, strengthen national health systems, facilitate implementation of public health and environmental interventions, facilitate research on local health adaptation, and to facilitate implementation of adaptation strategies in other relevant sectors (World Health Organization Regional Office for Africa 2012).

These adaptation frameworks – NAPs, HNAPs, and ACCAPAHS – share many similarities, specifically in being country owned, country-driven, evidence-based, interdisciplinary, and iterative in nature. Additionally, the frameworks call for a comprehensive assessment of vulnerability and adaptive capacity to climate change while considering the disproportionate burden of climate-sensitive health outcomes on vulnerable populations (World Health Organization 2021b). However, how adaptive capacity of LMIC health systems should be assessed has not been specified. One of the aims of this research is to address that knowledge gap using information that has already been compiled by government agencies.

5. Subnational Variability in Climate Change Vulnerability

While national health adaptation frameworks are important to preparing for climate change, the three elements of climate change vulnerability – hazard, sensitivity, and adaptive capacity - can vary widely within national borders. A given country might include coastal, grassland, desert, mountainous, tundra, and/or wetland regions. Climate change may make some regions more arid and prone to drought and wildfires, while other regions of the same country become more prone to flooding. Similarly, the current distribution of climate-sensitive health outcomes (such as heat stress illness and vector borne disease) varies on a subnational level. The variability of these factors on subnational scales are unlikely to be characterized or addressed in national climate assessments. A second aim of this research is to evaluate variability in climate change adaptation for health systems at the subnational scale. Furthermore, because socioeconomic factors are major determinants of health, we also evaluate whether subnational variability in health system adaptive capacity regarding climate change is associated with subnational metrics of poverty.

6. Climate Change Policy in Kenya

Kenya is a lower middle-income nation in Eastern sub-Saharan Africa with a population of 52.6 million people (World Bank Group 2020). Kenya is experiencing the effects of climate change nationwide, include rising temperature, sea level rise, increased rainfall and floods in some areas, and droughts in others (Government of the Republic of Kenya 2016b, Bauer and Mburu 2017, Harison, Boitt, and Imwati 2017, Public Health & Environment Department WHO 2010, Talisuna et al. 2020). These climate change impacts lead to increases in malnutrition, vector-borne diseases (such as malaria and Rift Valley Fever), and water borne diseases in the near to long-term future (National Environment Management Authority 2015). As of 2010, approximately 30% of children under 5 years old were stunted in Kenya, this is expected to increase and with increases in frequency and duration of droughts (Grace et al. 2012). Malaria and Rift Valley fever are associated with both flooding and increases in rainfall (Olubulyera 2021). Flooding is also associated with increased incidence of cholera and higher than average rainfall was associated with increases in incidence of diarrheal disease (Levy et al. 2016).

In its most recent NAP, the Kenyan government addressed health in the context of climate change, including proposed short- and medium-term actions to address health (Government of the Republic of Kenya 2016b). Those include the development of climate change and health vulnerability assessments, increasing public awareness of the connection between climate change and health, the need for climate change-related interventions for the health sector, and beginning or enhancing surveillance of climate change-related diseases (Government of the Republic of Kenya 2016b). In addition to addressing health in the NAP, a variety of Kenyan policies address planning in the health sector and climate change preparedness. Among those health policies are Health Policy 2017, Kenya Health Policy 2014-2030, Kenya Community Health Strategy 2020-2025, Kenya Health Sector Strategic Plan 2018-2023, and Universal Health Coverage plans as presented as a part of the Big Four Agenda in 2018 (Government of the Republic of Kenya 2018a, Ministry of Health Kenya 2021, Government of the Republic of Kenya 2016b, Government of the Republic of Kenya 2018b, Ministry of Health Kenya 2020, Ministry of Health Kenya 2014). Relevant policies regarding climate change include the Kenya National

Climate Change Response Strategy (KNCCRS) and the Climate Change Act of 2016 (Opemo et al. 2020, Wambua 2019). In 2010 the KNCCRS was developed, and it focuses on reducing GHG emissions, climate change mitigation, and adaptation plans for the health sector (Opemo et al. 2020). Health sector adaptation plans for climate change include recruitment of more technical staff, construction of mobile clinics, health education campaigns and enhanced surveillance (Opemo et al. 2020). These recent – but separate - policies for health (the Big Four Agenda) and climate (Climate Change Act of 2016) on a national scale attest to the focus the Kenyan government has placed on climate change and health in recent years. The lack of joint consideration of climate change and health on a subnational scale is a critical issue, as Kenya is experiencing the effects of climate change nationwide, include rising temperature, sea level rise, increased rainfall and floods in some areas, and droughts in others (Government of the Republic of Kenya 2016a, Bauer and Mburu 2017, Harison, Boitt, and Imwati 2017, Public Health & Environment Department WHO 2010, Talisuna et al. 2020).

7. Kenya: Subnational Vulnerability to Climate Change

Kenya has several distinct climate zones, including coastal areas, arid lands, tropical areas, and highlands, which present different health hazards (World Bank Group 2020). For example, Mombasa, a city of 700,000 people on Kenya's Indian Ocean coastline, is very vulnerable to sea level rise, where an estimated 17% of the city will be submerged when sea-level rises 0.3 meters (Awuor, Orindi, and Adwera 2008). While sea level rise is a hazard of concern on the coast, floods and droughts are the hazards of greatest concern nationally (World Bank Group 2020). Arid and semi-arid lands (ASAL), accounting for 88% of the land in Kenya, are the most vulnerable regions to the most adverse impacts of droughts (Harison, Mark, and Imwati 2017). Additionally, in ASAL regions of Kenya, precipitation level has a significant effect on child stunting with households that rely on surface water having a higher incidence of stunting (Grace et al. 2012). Floods are projected to increase in frequency and intensity, posing a substantial risk to human life in Kenya, with the most vulnerable counties to increased flood risk include: Baringo, West Pokot, Kisumu, and Laikipia (Romanello et al. 2021). Climate-sensitive health impacts also vary on a subnational scale, for example, anthrax risk is projected to make a northward shift across Kenya by 2055 (Otieno et al. 2021). If this shift in anthrax risk was not considered in health sector planning, then these areas may not be equipped to deal with this new health problem. In addition to climate and climate-sensitive health impacts varying across the subnational scale the vulnerability to the impacts of climate change also varies. A vulnerability analysis of counties in Kenya that used sociodemographic data as well as 55 years of historical weather data found that the northern region of Kenya is the most vulnerable to climate change and has the lowest adaptive capacity (Marigi 2017). Given the substantial variability within Kenyan of climate, climate sensitive health conditions, and vulnerability due to social factors, it is important to know the extent to which at the subnational level planning accounts for health sector preparedness for climate change.

8. County Integrated Development Plans

Following the passage of the Public Finance Management Act in 2012, every county in Kenya is required to develop 5-year County Integrated Development Plan (CIDP) (Government of the Republic of Kenya 2019). CIDPs are intended to inform the county's budget, sectoral, spatial, city, and municipal plans and reflect the midterm priorities of the county government (Government of the Republic of Kenya 2019). CIDPs contain objectives, implementation plans, monitoring, and evaluation plans, and reporting mechanisms. Following the initial CIDP for 2013-2017, all 47 counties have completed their CIDPs for the 2018-2022 period (Government of the Republic of Kenya 2019). Given that climate change, health impacts, and sociodemographic characteristics vary at a subnational scale in Kenya, CIDPs provide an opportunity to evaluate the extent to which county officials address health in their preparations for climate change. Development at the county level and the health impacts of climate change at the county level overlap in important ways. Thus, the short to medium term goals as well as budgets spelled out in CIDPs are an opportunity to assess the extent to which climate change and health are being addressed jointly (Ebi, et al. 2018). Additionally, the Kenyan NAP for 2015 to 2030 specified mainstreaming climate change adaptation into CIDPs as a priority action (Government of the Republic of Kenya 2016b).

9. Knowledge Gap and Research Objectives

To date there is not a framework for evaluating the extent to which planning activities address climate change adaptation for the health sector. This research aims to develop and apply a framework for evaluating the extent to which subnational plans address specific actions and interventions related to health and climate change as put forth in national frameworks. Beyond evaluation of this assessment framework, this research aims to identify counties that are considering climate change and health in their planning and those that may need additional support to address this challenge.

B. Methods

1. Evaluating CIDPs

A literature review and internet search were conducted to identify frameworks for evaluating climate change adaptation plans for health. This literature review was done in Google Scholar using the following search terms, “health adaptation”, “adaptation plans to climate change”, “health adaptation to climate change”, “adaptation plans in Africa”. A title and abstract review of results was conducted, studies that did not include a framework of evaluation, specific guidelines for adaptation plans, climate-sensitive health impacts, or subnational frameworks were excluded. Similarly, grey literature searches on policies in Kenya were conducting using the Kenya Institute for Public Policy Research and Analysis – Public Policy Repository using key words such as “health” and “climate change”. Given the lack of an existing framework for governments to evaluate climate change adaptation planning for the health sector, international frameworks and Kenya-specific policies listed in **Error! Reference source not found.** were examined to develop such a framework to be used in assessing County planning through the examination of CIDPs.

TABLE IV. KEY FRAMEWORKS AND POLICIES REGARDING ADAPTATION TO CLIMATE CHANGE

UNFCCC Framework
• National Adaptation Plans
WHO Frameworks
• Health in National Adaptation Plans
• Quality Health National Adaptation Plans
• Framework for Public Health Adaptation to Climate Change
African Framework
• African Framework for Public Health Adaptation to Climate Change
Kenyan Policies
• Kenya National Adaptation Plan: 2015 to 2030
• Kenya National Climate Change Response Strategy (KNCCRS)
• Climate Change Act 2016

County Integrated Development Plans have four main sections (County General Information, Links to other Plans, Review of Previous CIDPs, and County Development Priorities and Strategies) within which sub-sections address sectors such as health, agriculture, tourism, and the environment. The four sections of the CIDP were evaluated regarding the degree to which the joint consideration of climate change and health is present. Table V lists the evaluation elements developed for evaluating the CIDPs. The joint consideration of climate change and health was evaluated in multiple ways within each section of the CIDPs.

Data from each section of each CIDP were abstracted into a spreadsheet based on the evaluation elements and the protocol in appendix A. Once this was completed for all 47 counties, descriptive statistics were run to summarize the extent to which counties jointly considered climate change and health in their integrated development plans. In addition to summarizing this data, illustrative quotes from a subset of CIDPs were pulled to complement the presence/absence data.

2. Were ACCAPAHS Interventions Utilized in CIDP Adaptation Strategies?

Health sector programs planned for climate change adaptation were evaluated based on the extent to which they addressed the ACCAPAHS interventions. Table VI lists the ACCAPAHS interventions and the metrics used to assess planned programs noted in each CIDP.

3. Composite Score of CIDP and ACCAPAHS Evaluation

After the above assessments of CIDPs were complete, a climate and health adaptation (CHA) score for each county was calculated. CIDP and ACCAPAHS elements were given a score of 1 if present and 0 if absent except for a few CIDP elements. In section 4 of the CIDPs, counties were given a score of 0 if adaptive capacity was not mentioned, a score of 1 if adaptive capacity was mentioned but no programs addressed it, a score of 2 if there is an adaptive capacity sub-program and a score of 3 if there is a full program. The sum of scores from all evaluation elements was calculated. The lowest possible score of 0 and highest possible score of 23. Based on the distribution of the data, scores were assigned to three categories, low (≤ 5), medium ($5 < x < 11$) high (≥ 11) joint consideration of climate change and health in CIDPs. Each county was assigned to one of these groups based on their CHA score. The data on CHA scores was then applied to Kenyan shapefiles in ArcGIS to examine the geographic distribution of levels of joint consideration of climate change and health.

TABLE V. CIDP EVALUATION ELEMENTS

Section 1: County Description	Was climate change mentioned in the environmental sector? Was health mentioned in the context of climate change within the environmental sector? If so, how many specific climate-sensitive health conditions were noted?
Section 2: Links to Other Plans	Was Sustainable Development Goal 13 mentioned? Was Kenya Vision 2030 Medium Term Plan III Climate Change Goal mentioned?
Section 3: Review of previous CIDPs	Did the previous 5-year CIDP note adaptation for climate change in the health sector?
Section 4: Priorities and Strategies – Health Sector	Was building adaptive capacity for climate change mentioned in the health sector? Is a climate change adaptive capacity program planned? If so, is it a full- or sub-program? If any key program outputs are noted, what are they?
Section 4: Priorities and Strategies – Environment Sector	Was building adaptive capacity for climate change or mitigating climate change mentioned in the environment sector? To what extent is climate change prioritized? Is a climate change adaptive capacity program planned? If so, is it a full- or sub-program? If any key program outputs are noted, what are they?

4. Associations between County Poverty Rates and CHA Scores

To evaluate whether CHA scores are driven by other factors in the county, the relation between socio-economic status of the county and CHA scores was explored. Poverty rate is a proxy measure of socio-economic status therefore, county-level poverty rate data was obtained from the Kenya poverty report for 2021 by the Kenya National Bureau of Statistics (KNBS) (Kenya National Bureau of Statistics 2023). Because CHA scores and poverty rates were normally distributed, Pearson correlation analyses were conducted.

All statistical analyses were conducted using SAS version 9.4 (SAS Institute, Cary, NC).

C. Results

1. County Level CIDPs: Climate Change and Health in "County Description" and "Links to Other Plans" Sections

As seen in Table VII, even though almost all counties in Kenya mention climate change in the county description, only half mention health in the context of climate change. Likewise, nearly all counties link their development plan to sustainable development goal 13, to adapt to and limit climate change, but only a third link to the climate change goal in Kenya Vision 2030 MTP III, to enhance climate action (Government of the Republic of Kenya 2018a). None of the CIDPs mentioned climate change in the context of health in previous CIDPs. Although climate change is noted in CIDPs of nearly all counties, the consideration of health in the climate change/environment section is far less common.

2. Analysis of "Priorities and Strategies" Section

Table VII summarizes key outputs, sub-programs, and full programs noted in the Priorities and Strategies section of CIDPs.

TABLE VI. COUNTY LEVEL INTERVENTIONS SPECIFIED BY ACCAPAHS MEASURED IN KENYAN CIDPS AND HOW THEY WERE MEASURED

Interventions	**Evaluation Metric: Does the CIDP address the following?**
1. Undertake baseline risk and capacity assessments	The need to undertake these assessments
2. Capacity building	Increasing number of healthcare workers, increasing hospital beds, strengthening healthcare infrastructure
3. Implement integrated environment and health surveillance	Action to increase data sharing/health surveillance
4. Undertake awareness raising and social mobilization	Specific action to increase awareness of climate-sensitive diseases among the public (such as communicable, vector etc)
5. Promote public-health oriented environmental management	Program or sub-program on health promotion
6. Scale up existing public health interventions	Scale up existing public health actions focused on environmental factors WASH, communicable and vector-borne diseases
7. Strengthen and operationalize the health components of disaster risk reduction.	Disaster preparedness in the health sector development priorities or cross-sectoral collaborations
8. Promote Research on Climate Change Impacts	Allocating funds for research in the health sector
9. Strengthen partnerships and intersectoral collaboration.	Cross-sectoral impacts relating to adaptation in the health sector

TABLE VII. SUMMARY OF FINDINGS REGARDING THE JOINT CONSIDERATION OF CLIMATE CHANGE AND HEALTH IN THE FIRST TWO SECTIONS OF CIDPS

Measure	**Yes**	**No**
Climate change is mentioned in the county description	45 (95.7%)	2 (4.3%)
Health is mentioned in the climate change/environment county description	23 (48.9%)	24 (51.1%)
Linked to Sustainable Development Goal 13	43 (91.5%)	4 (8.5%)
Linked to Kenya Vision 2030 Medium Term Plan III – Climate change goal	16 (34.0%)	31 (66.0%)

These results further demonstrate the stark contrast among counties based on their joint consideration of climate change and health. Over 50% of counties have a sub- or full program for building adaptive capacity to climate change, whereas there are no full programs on environmental health and only 45% of counties have a sub-program addressing environmental health. Additionally, only 12 of the 47 counties have both an environmental health and adaptive capacity sub-program.

The health sector was evaluated for the number of key outputs specified that would build adaptive capacity to climate change, such as having a back-up generator. As seen in Table IX, there is a strong association between the health sector mentioning adaptation strategies as key outcomes and mentioning one or more specific climate-sensitive health impacts. Compared to county CIDPs that did not note health sector adaptation strategies as key outcomes, those that did were more likely to also mention health impacts (odds ratio 3.11, 95% confidence interval 0.60 - 16.02).

3. Analysis of ACCAPAHS Specific Actions

Following the initial evaluation of all 47 CIDPs, we further analyzed the 24 counties that listed an environmental health subprogram or adaptation strategies in the health sector based on the specific ACCAPAHS actions that were addressed. As seen in Table X, these 24 counties prioritized capacity building, environment, and health surveillance, and scaling up existing public health interventions but are lacking in baseline risk and capacity assessments. Few counties addressed efforts to raise awareness or to mobilize the population of the county about climate change and health (7), to promote health components of disaster risk reduction (5), or to conduct research on climate change impacts (6).

4. Composite Scores of County-level Planning for Climate Change and Health

After evaluation of CIDPs based on the CIDP framework and the ACCAPAHS framework, a composite score was calculated with scores ranging from 1 to 15 (higher scores indicate greater attention to climate change impacts and adaptation in the health sector in CIDPs) out of a possible score of 23, with a median score of 8. Based on the distribution of the scores, counties were classified into low, medium, and high composite score groups. As seen in

Figure 3, composite scores vary drastically across the country and do not follow a gradient or regional pattern. Kilifi and Nakuru counties have the highest composite score of 15, and Uasin Gishu county has the lowest composite score of 1. The poverty rate ranged from 16.5% to 77.7% among the counties. Poverty rates were not significantly correlated with CHA scores (Pearson correlation coefficient of 0.255, p=0.08).

TABLE VIII. SUMMARY OF THE PRIORITY GIVEN THE CLIMATE CHANGE AND HEALTH IN TWO DEVELOPMENT PRIORITY SECTIONS OF CIDPS

		Environmental Health in Health Sector Development Priorities			
		Sub Program	***Mentioned***	***Not Mentioned***	***Total N (%)***
Climate Change Adaptive Capacity or Mitigation Goal in the Development Priorities	***Full Program***	1	0	4	5 (10.6%)
	Sub Program	12	2	8	22 (46.8%)
	Mentioned	5	1	3	9 (19.14%)
	Not Mentioned	3	0	8	11 (23.4%)
	Total N (%)	21 (44.7%)	3 (6.4%)	23 (48.9%)	47 (100%)

TABLE IX. CIDPS WITH HEALTH SECTOR ADAPTATION GOALS BY MENTIONING SPECIFIC CLIMATE-SENSITIVE HEALTH OUTCOMES IN THE BACKGROUND

		Priorities and Strategies for the Health Sector – Adaptation strategies as Key Outcomes		
		Not - mentioned	***Mentioned***	***Total***
Climate Sensitive Health Impacts in the Background	***Not- mentioned***	28	2	31 (66%)
	Mentioned	12	4	16 (34%)
	Total	40 (85.1%)	7 (14.9%)	47 100%)

D. Discussion

While nearly all counties in Kenya developed CIDPs that note climate change in the context of development, only half mention health in the context of climate change in the CIDP "County Description" section. Sixteen of the counties (34%) noted one or more specific climate-sensitive health outcomes in their discussions of the health impacts of climate change. In the Development Priorities section, 12 (25.3%) counties had a sub-program for both adaptive capacity to climate change and environmental health. Further, 24 (51%) counties prioritized an environmental health subprogram and/or adaptation strategies in the health sector. While all 24 of these counties specified capacity building and scaling up public health interventions in the health sector, none specified conducting baseline risk and capacity assessments, less than 30% specified increasing research on climate change, integrating health into disaster risk reduction, and raise awareness. CHA scores show no clear spatial pattern and were not correlated with county level poverty rates. This suggests that county-level socio-demographics may not drive the extent of climate change preparedness and that health departments of counties with low CHA scores should be prioritized for education, training, and support.

Variability in sub-national adaptive capacity has been seen in previous subnational vulnerability assessments, but unlike our results, they followed a south to north gradient (Marigi 2017). The measure of adaptive capacity by S.N. Marigi, was a function of literacy rates and poor health services and as a result was highly correlated with SES of the counties (Marigi 2017). Given that our CHA score did not include measures of SES and S.N. Marigi's adaptive capacity score did not include policy measures, the disconnect between findings is not surprising (Marigi 2017). Understanding the extent to which adaptive capacity is being addressed in subnational planning is essential to understanding county-level planning needs and to guide resource allocation.

TABLE X. EVALUATION OF ACCAPAHS ACTION PRESENCE IN THE HEALTH SECTOR DEVELOPMENT PRIORITIES FOR 24 KENYAN COUNTIES

ACCAPAHS Action	**Number (%) of Counties with This Action**
Undertake baseline risk and capacity assessments	0 (0)
Capacity building	24 (100)
Implement integrated environment and health surveillance	21 (87.5%)
Undertake awareness raising and social mobilization	7 (29.2%)
Promote public-health oriented environmental management	14 (58%)
Scale up existing public health interventions	24 (100)
Strengthen and operationalize the health components of disaster risk reduction.	5 (20.1%)
Promote Research on Climate Change Impacts	6 (25%)
Strengthen partnerships and intersectoral collaboration.	12 (50)

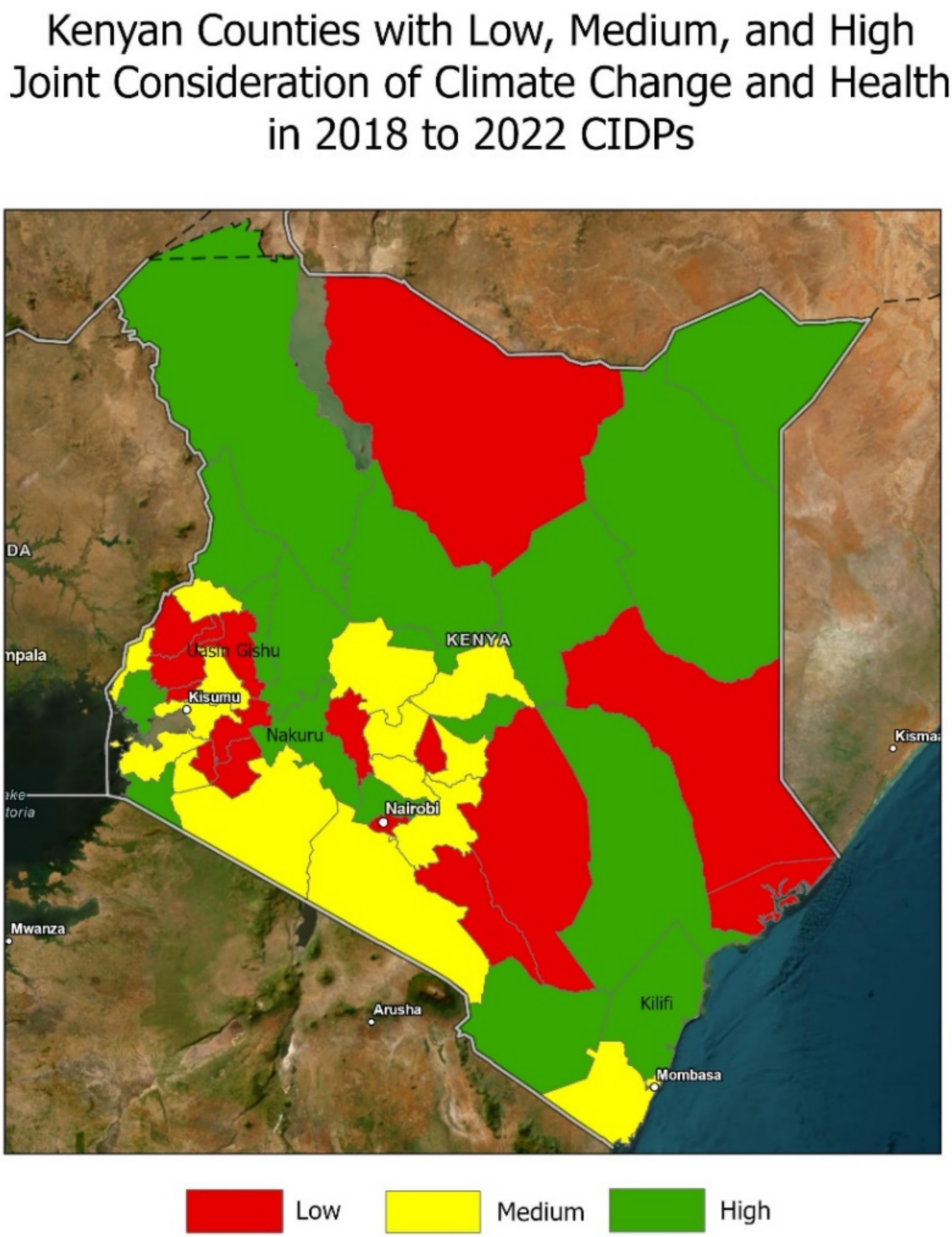

Figure 3. Map of Kenyan counties by degree of connection between climate change and health in 2018 - 2022 CIDP

Rather than requiring county administrators to take on new tracking requirements for evaluating the extent of climate and health adaptation at the county level, the assessment of existing planning documents may be useful while not increasing reporting requirements. Kenya's CIDP's provide some insight into the extent that subnational planning documents can be used to evaluate preparedness of the health sector for climate change. The use of existing planning processes to prepare for climate change is consistent with the 2015-2030 Kenyan National Adaptation Plan which promoted the mainstreaming climate change adaptation into CIDPs (Government of the Republic of Kenya 2016b). Additionally, strengthening integration of climate change adaptation into the health sector was specified, but this intervention has a miniscule budget compared to the other sector specific interventions, with a budget of 40 million USD compared to 20 billion USD in the infrastructure sector (Government of the Republic of Kenya 2016b).

If health planning and climate change adaptation planning are done in concert, the results would, potentially, be better than if they were considered separately. Climate change alters how and where population health is impacted by factors such as flooding, drought, temperature, and the distribution of vector borne and zoonotic diseases. Additionally, health care facilities may require additional resources to respond to a larger number of cases of diarrheal disease. By considering climate change in planning future needs of local health care systems and health care facilities, the result should be better preparedness, increase international funding, reduced future vulnerability, smaller gaps between climate change risk and preparedness (Ebi and Prats 2015, Public Health & Environment Department WHO 2010).

This evaluation framework of Kenyan CIDPs and our conclusions about the readiness of county planners for the health impacts of climate change have several limitations. First and foremost, this evaluation framework has not yet been validated against observed differences in the burden of climate sensitive disease at the county level. We analyzed county-level development plans to develop CHA scores; it is unknown whether CHA scores reflect metrics of health system adaptive capacity such as the number of hospital beds, resilience of health care facility structures and infrastructure, vector control programs, or climate hazard response capabilities in these counties. Second, it is likely that different data sources and the use of weighting factors to calculate composite scores may be more predictive of the extent to which county planning is preparing for local impacts of climate change on health systems. Third, it is not known to what extent this approach would be transferrable to other LMICs. To address this limitation, this evaluation framework would need to be applied to other subnational development plans in other LMICs. Fourth, this framework for evaluating plans for health adaptation at the subnational level is based on specific actions and interventions laid out in frameworks – NAP, HNAP, ACCAPAHS – that have been developed for use at the national level. Given this change in spatial scale, the evaluation metrics may not accurately capture the true joint consideration of climate change and health on a subnational scale. Specifically, county level governments may not have the resources to increase adaptive capacity for health even if they did address them in the CIDPs. Fifth, the measures used to evaluate the CIDPs were proxies for the actions mentioned in the NAP, HNAP and ACCAPAHS and were based on the information present in Kenyan CIDPs. Therefore, the results are not a precise evaluation of the extent that the specific actions were implemented and there is no data available to validate level of investment, duration, or quality of these actions. This study did not evaluate greenhouse gas emissions of the health sector or approaches to mitigating those contributions to climate change. Globally, the health care sector contributes 4.4% of the net emissions of greenhouse gases (Karliner et al, 2019). In the KNCCRS and other Kenyan policies or reports, the only mitigation measures mentioned by the health sector is adding green space and increasing the promotion of using low carbon methods of transportation among patients. Since this evaluation framework is based on adaptation plans that do not address how the health sector can contribute to mitigation, mitigating climate change is not represented in this analysis.

To address the limitations mentioned above, future research could address the extent to which these estimates are predictive of health sector adaptive capacity at the subnational scale. For that to occur, valid metrics of adaptive capacity that make use of readily available data are needed. This can be done by utilizing the composite climate and health adaptation (CHA) scores as a predictor of other metrics of adaptive capacity in counties in Kenya. For example, exploring the association between CHA scores and number of hospital beds, vector control programs, or climate hazard response capabilities in these counties. Secondly, further exploration of which county level factors could be driving the difference in CHA scores could be explored further, as could potential differences in climate hazards, sensitivity or other structural factors. Third, the extent to which this evaluation framework transfers from CIDP's in Kenya to subnational plans in another sub-Saharan African country needs to be evaluated. Specifically, reapplying this framework to the next round of CIDPs in Kenyan or county level development plans in another sub-Saharan African country. Despite limitations, it is apparent that there is a wide range of the extent to which county planners address adaptive capacity of counties in Kenya regarding the health impacts of climate change, with some counties lagging far behind others. Therefore, resources to support planning by county governments for increasing health sector adaptive are needed, as are resources to implement those plans. As an initial step, additional support for the counties with low CHA scores should be expedited. For example, financial support to increase adaptive capacity of the health sector, scale up existing public health programs, education on the health impacts of climate change and other capacity building measures.

E. Acknowledgements

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III. CLIMATE AND HEALTH RISK INDEX FOR LAKE VICTORIA REGION ECONOMIC BLOCK SUB-COUNTIES IN KENYA

A. Introduction

Climate change impacts human health by altering the system in which individuals live, specifically by changing exposure to various environmental hazards (Romanello et al. 2021). These changes in environmental hazards can cause cascading effects across entire systems, for example, health care system, social systems, and natural systems; therefore, it is important to take a systems-based approach to understanding the health impacts of climate change. In 2014, the IPCC addressed this need in the Fifth Assessment Report (AR5) by presenting a 'framework … for identifying key vulnerabilities, key risks, and emergent risks' due to climate change (Begum, Lempert, Ali, Benjaminsen, Bernauer, Cramer, Cui, Mach, Nagy, Stenseth, Sukumar, and Wester 2022). The process of identifying risks and vulnerabilities can position communities and governments to prioritize and implement adaptation strategies. The framework includes the concepts of hazard, exposure, and vulnerability – a function of sensitivity and "lack of capacity to cope and adapt" (referred to here as adaptive capacity). Exposure is defined as the people, institutions or systems impacted by the hazard allowing this framework to be applied to a variety of systems, such as the health care sector, population at risk of disease, etc. The inclusion of exposure may allow this framework to be better at identifying high risk communities compared to the prior frameworks of vulnerability, which include the concepts of hazard, sensitivity, and adaptive capacity.

The hazards posed by, and health impacts of climate change are not homogenous across regions, countries, or sub-national scales. It is especially important to account for this heterogeneity to identify at-risk communities that need to be prioritized for resource allocation for building adaptive capacity. Taking a systems-based approach to understand risk heterogeneity allows policy makers and researchers to explore the impact of societal and structural factors on the health impacts of climate change. A recent study applied the vulnerability and AR5 frameworks to weather, social, demographic, and other types of data from the Indian Bengal Delta, found that the rankings of subdistricts by risk generated using an earlier vulnerability framework and the AR5 frameworks differed substantially (Das et al. 2020). A study in Brazil evaluated associations between social determinants of health and the observed dengue incidence rate from 2014 to 2017 in municipalities (Do Carmo et al. 2020). High population density, low levels of education, poor housing, and social vulnerabilities were associated with increased incidence of dengue in the community. Similarly, vulnerability assessment conducted using a WHO framework in Dominica, identified children under 5 as a highly vulnerable population and found that incidence of gastroenteritis increased two weeks following dry conditions (Schnitter et al. 2018). The key vulnerability factors were poor health status, poor housing conditions, lack of access to improved drinking water and sanitation, poverty, food insecurity, low education level, and the compound effect of multiple health risks (Schnitter et al. 2018). In Botswana, a research team developed a social vulnerability index for being affected by natural hazards, found that predicted social vulnerability was driven by size of household, disability, level of education, age, people receiving social security, employment status, household status, and poverty level (Dintwa et al. 2019). Additionally, it was found that having a higher percentage of the population under 5 increased the likelihood that the population was highly vulnerable. It is clear from the above-mentioned vulnerability assessments that social factors play a role in vulnerability. To date only 4.3% of studies on the social vulnerability to the impacts of climate change have addressed locations in Africa, 10% focused on precipitation, and only 3% focused on gastrointestinal disease (Li, Toll, and Bentley 2023).

SSA is expected to bear the greatest burden of mortality attributable to climate change in 2030 (World Health Organization 2014a). One of the major climate hazards facing sub-Saharan Africa is the increased frequency and intensity of extreme rainfall (Trisos et al. 2022). It has been well documented that flooding is associated with increased incidence of cholera and that higher-than-average rainfall was associated with increases in incidence of diarrheal disease (Levy et al. 2016,). A study in Malindi, Kenya found a strong positive correlation between increased rainfall and cases of childhood diarrhea (Saidi et al. 1997). Additionally, a study in Malawi found that moderate rainfall is associated with an increased relative risk of invasive non-typhoidal salmonella (Thindwa, et al. 2019). Temperature also has an association with diarrheal disease, a recent study in Ethiopia found an 16.66% increased risk of diarrheal disease in children under 5 for every 1˚ C increase in temperature (Alemayehu et al. 2020). Many studies have shown seasonality of waterborne infections, such as cholera, with 71% of 34 SSA countries showing a statistically significant seasonal pattern (Perez-Saez et al. 2022). Prior research in Kenya, has demonstrated seasonal cholera peaks in December to January, the short wet and warm dry seasons respectively (Perez-Saez et al. 2022). Due to the association between precipitation, temperature, and season with diarrheal disease it is beneficial to policymakers and scientists to understand which parts of a system drive this risk. Evaluating risk on a sub national scale is important as there is substantial heterogeneity in demographics, environment, and adverse health outcomes, such as mortality and stunting on a subnational level in Kenya (Kenya National Bureau of Statistics 2019a).

Currently, no risk index following the IPCC AR5 framework has been developed to address the association between weather and diarrheal disease. Prior indices have not included the system that is exposed, in this case the population that is exposed, and therefore do not take a systems-based approach. Additionally, health data is hard to obtain in low resource countries, but demographic and social data are more readily available. As a result, the development of a disease specific risk index following the IPCC AR5 framework is a useful tool for these settings. The risk index may ultimately provide policy makers, public health officials, and other key stakeholders with a general sense as to where they should expect an increase in cases of diarrheal disease without the need for health data. This is important, as this index could provide an early warning identification of areas at risk and be useful in situations where health data are not readily available. While it is well understood that sub-Saharan Africa is disproportionately adversely affected by climate change, the risk that climate change hazards pose to systems on a local level is not well understood (Romanello et al. 2021). Therefore, the main aim of this research is to develop a risk index for the association between precipitation extremes and diarrheal disease. In doing so, we aim to identify meaningful sub-components of the IPCC AR5 risk components to assist in development of a framework of risk of diarrheal disease due to extreme precipitation.

B. Methods

1. Setting

Kenya is a lower middle-income nation in Eastern SSA with a population of 47.5 million (Kenya National Bureau of Statistics 2019a). As of 2019, approximately 30% of Kenyans live in peri-urban informal settlements (also referred to as slums), and 46% of the population was classified as poor (Macharia, Joseph, and Okiro 2020). Additionally, only 34% of households have access to piped water and 8.2% of households do not have access to a sanitation facility (Macharia, Joseph, and Okiro 2020). The current life expectancy at birth in Kenya is 66.7, a drastic improvement from 50 years in 2000 (World Bank Group 2020, Ministry of Health Kenya 2014). Kenya has made improvements in the health sector--increases in workforce and facilities--in recent years but is still facing a high burden of disease. As of 2019, the top 5 leading causes of death in Kenya were, HIV/AIDs, lower respiratory infections, diarrheal disease, and neonatal disorders, respectively (Ministry of Health Kenya 2014, GBD 2019 Diseases and Injuries Collaborators 2020). In 2010, the Kenyan Constitution developed six regional economic blocks, grouping counties based on similarities in history, politics, and economics (Kenya State Department for Devolution 2023). As seen in Figure 4 the Lake Victoria Region Economic Block (LVRB) of Kenya consists of 14 counties in Western Kenya: Migori, Nyamira, Siaya, Vihiga, Bomet, Bungoma, Busia, Homa Bay, Kakamega, Kisii, Kisumu, Nandi, Trans Nzoia, and Kericho (Kenya State Department for Devolution 2023). Within these 14 counties there is a total of 99 sub-counties. As of 2019 the LVRB had a population of 14.8 million, representing 31% of the total population of Kenya (Kenya National Bureau of Statistics 2019a). Approximately 85% of the LVRB population lives in rural settings, 37% of households have access to improved drinking water sources, sources that are protected from contamination, and 71% have access to improved sanitation facilities, where there is no contact with human waste(Kenya National Bureau of Statistics 2019a, World Health Organization and UNICEF a., World Health Organization and UNICEF b.). Despite this region being a relatively small area of the country, there is substantial heterogeneity in demographics, environment, and adverse health outcomes, such as mortality and diarrheal disease(Kenya National Bureau of Statistics 2019a).

2. Causal Pathway Model

The existing literature on social vulnerability, diarrheal disease, extreme precipitation, climate change, and health in Kenya were reviewed (Table XXIV, Appendix B). This was used to construct a causal pathway model (Figure 5). Indicators were then classified into the AR5 IPCC categories of hazard, sensitivity, adaptive capacity, and exposure. The IPCC defines exposure as the presence of people, institutions, infrastructure, or other systems that are exposed to the hazard. Given the focus on diarrheal disease, exposure in this system is defined as the presence of people.

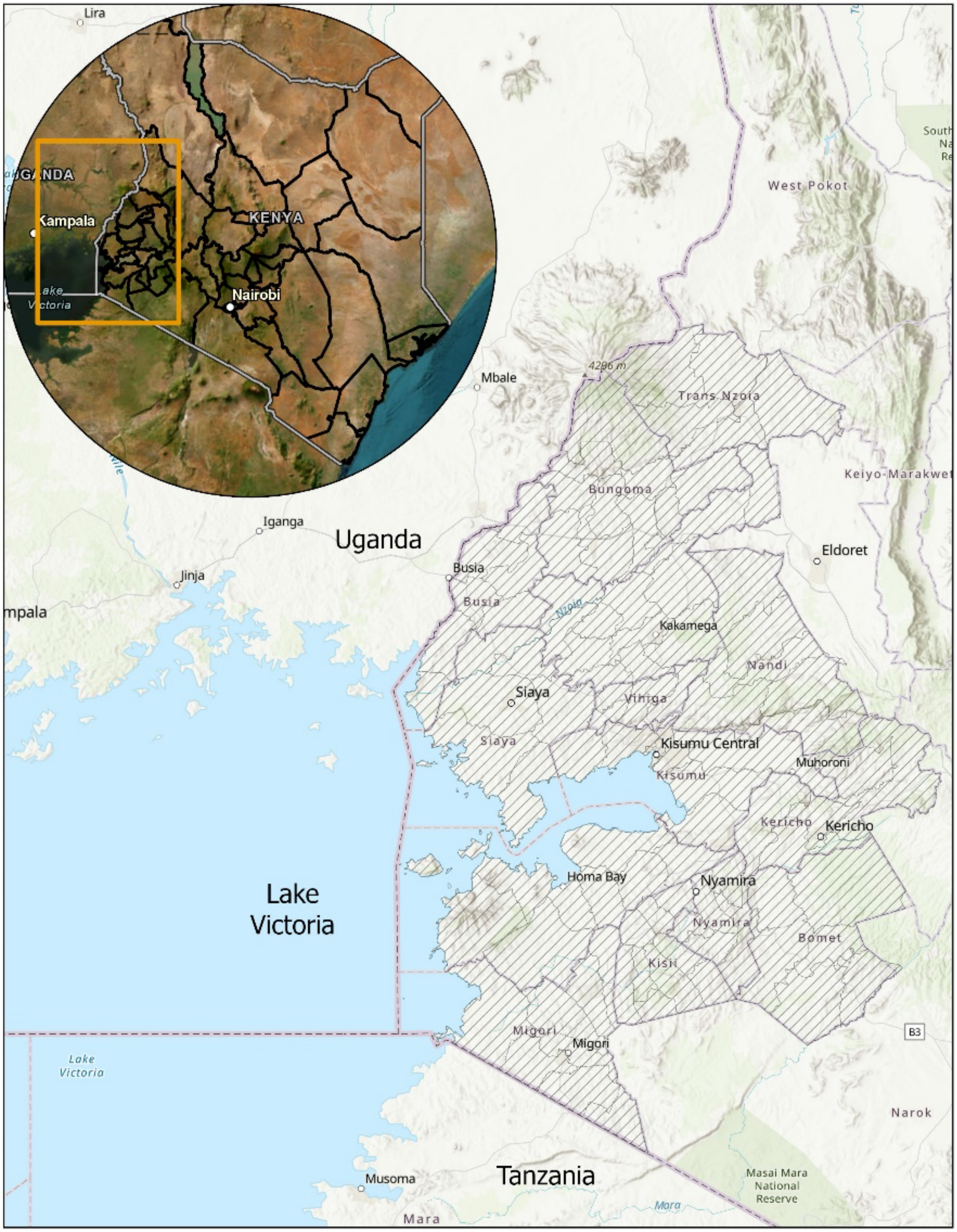

Figure 4. Map of LVRB sub-counties in Kenya (made using ArcGIS Pro 3.1.0 2023)

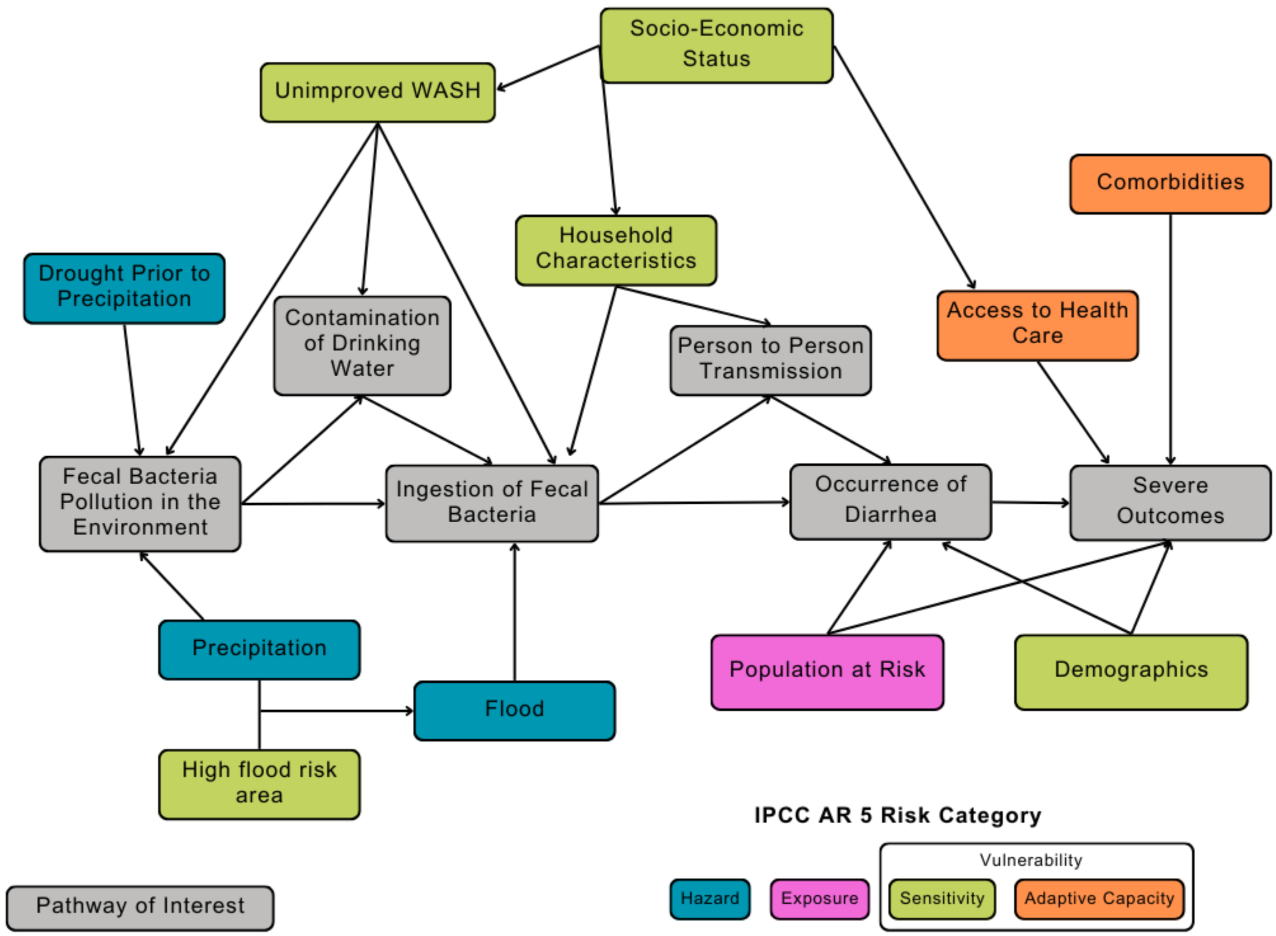

Figure 5. Causal model of risk of diarrheal disease following precipitation events

3. <u>Data Sources</u>

We sought to identify data compiled by the government in Kenya regarding the pathway of interest, seen in Figure 5. Following a search of publicly available data we were able to obtain 30 variables on the county and sub-county level. The variables were then grouped into categories defined by the components of risk (as seen in Table XI). The hazard component consists of measures of climate variability, average, and extreme events and was obtained from the Kenya Meteorological Department (KMD). Climate variability was measured by the average standard deviation of the monthly maximum temperature, minimum temperature, and total precipitation from 2010 to 2022, due to the change in sub-county structure in 2010. The average climate was measured as the average monthly maximum temperature, minimum temperature, and total precipitation from 2010 to 2022. Extreme events were measured as the frequency of days over the 95th percentile of precipitation, maximum temperature, and minimum temperature per month from 2014 to 2022, to match the time of other available data. Adaptive capacity, sensitivity and exposure variables were abstracted from data sources such as census data from the Kenya National Bureau of Statistics (KNBS), Kenya Ministry of Health, Food and Agriculture Organization, National Imagery and Mapping Agency of the US, and the peer reviewed literature (as seen in Table XII).

The validity, reliability, and quality of the various datasets included in this analysis were assessed. The census data from the Kenya National Bureau of Statistics was collected in accordance with the principles and recommendations for conducting censuses put forth by the United Nations (Kenya National Bureau of Statistics 2019b). Prior to the 2019 census questionnaires and manuals were developed by a committee of stakeholders, pilot census and two pretests were conducted, census committees at the county and sub-county level were developed, and comprehensive guidelines were developed and shared with personnel (Kenya National Bureau of Statistics 2019b). All data was collected using tablets, encrypted, backed-up, and edited based on guidelines from the United Nations, and monitored by independent observers (Kenya National Bureau of Statistics 2019b). Weather data from the Kenya Meteorological Department was obtained from automatic weather stations, added to an electronic database, merged with satellite estimates to obtain weather data on a 0.5x0.5 km grid, and aggregated to the sub-county level (Kenya Meteorological Department 2021). Geospatial data from the Food and Agriculture Organization of the United Nations and National Imagery and Mapping Agency of the United States regarding rivers and flood plains are from the early 2000's and have not been updated. Finally, the data obtained from peer reviewed literature is subject to issues in validity due to limitations of methods used.

4. Principal Component Analysis and Risk Calculation

Data for 26 variables for all 99 sub-counties in the LVRB were obtained. For the 4 variables that were only available at the county level, county-level values were applied to all sub-counties within the county. A total of 69 sub-counties had complete data; the most frequently missing data element was urban population; 9% were missing population density and female population; less than 3% were missing education level, hospital beds, electricity, child, and elderly population. Missing values for individual sub-counties were replaced with the average for the county in which the subcounty is located. Additionally, there were several changes in sub-county boundaries in recent years which may result in misclassification of sub-county risk if these boundaries do not represent the actual boundaries. Some sub-counties had changes to their names, others were divided into two or combined into a single sub-county.

TABLE XI. SELECTED VARIABLES FOR RISK INDEX AND JUSTIFICATION

IPCC CATEGORY	***VARIABLE***	***JUSTIFICATION***	***SCALE***	***YEARS***	***SOURCE***
Hazard	*Temperature* - *Standard Deviation* - *Average Monthly Maximum*	*follows IPCC definition of hazard, used as exposure in CC vulnerability indices in Kenya*	*Subcounty*	*2010-2022*	*KMD*
	Precipitation - *Standard Deviation* - *Average Monthly Total*	*follows IPCC definition of hazard, used as exposure in CC vulnerability indices in Kenya*	*Subcounty*	*2010-2022*	*KMD*
	Extreme Rain Days	*follows IPCC definition of hazard, used as exposure in CC vulnerability indices in Kenya*	*Subcounty*	*2014-2022*	*KMD*
	Extreme Heat and Cold Days	*follows IPCC definition of hazard, used as exposure in CC vulnerability indices in Kenya*	*Subcounty*	*2014-2022*	*KMD*
Adaptive Capacity	*CIDP connects Climate change and health*	*policies and development plans can increase adaptive capacity to the hazards posed by CC*	*County*	*2018-2022*	*Kowalcyk, et al* (Kowalcyk and Dorevitch 2024, 1-11)
	Electricity	*household characteristic that can increase adaptive capacity to the hazards*	*Subcounty*	*2019*	*KNBS*
	Distance to urban center	*used in COVID 19 SEVI*	*Subcounty*	*2015*	*Nelson et al.* (Nelson et al. 2019)
	Improved drinking water	*used in CC VI's for Kenya but in sensitivity category - move to AC due to the inverse relationship between access to improved drinking water and waterborne disease*	*Subcounty*	*2019*	*KNBS*

TABLE XI. SELECTED VARIABLES FOR RISK INDEX AND JUSTIFICATION (CONTINUED)

IPCC CATEGORY	***VARIABLE***	***JUSTIFICATION***	***SCALE***	***YEARS***	***SOURCE***
	Improved sanitation facility	*used in CC VI's for Kenya but in sensitivity category - move to AC due to the inverse relationship between access to improved sanitation and waterborne disease*	*Subcounty*	*2019*	*KNBS*
	Health workforce	*COVID SEVI*	*County*	*2021*	*Okoroafor et al.* (Okoroafor et al. 2022)
	Health facility access	*CC vulnerability indices*	*Subcounty*	*2017*	*Ouma et al.* (Ouma et al. 2018)
	Literacy rate	*CC vulnerability indices*	*Subcounty*	*2019*	*KNBS*
	Education level	*CDC SVI, COVID SEVI*	*Subcounty*	*2019*	*KNBS*
	Hospital beds	*COVID SEVI*	*Subcounty*	*2020*	*Kenya Ministry of Health*
SENSITIVITY	*Stunting rates*	*COVID SEVI*	*County*	*2019*	*KNBS*
	Poverty	*CDC SVI, COVID SEVI, and CC vulnerability indices*	*County*	*2019*	*KNBS*
	Housing type	*CC vulnerability, CDC SVI*	*Subcounty*	*2019*	*KNBS*
	Population living in informal settlements	*COVID SEVI*	*Subcounty*	*2020*	*Macharia et al* (Macharia, Joseph, and Okiro 2020)
	Flood plains	*based on nature of flooding and dd*	*Subcounty*	*2000*	*FAO* (Food and Agriculture Organization (FAO) of the United Nations 2000)
	Rivers	*based on nature of flooding and dd*	*Subcounty*	*2007*	*NIMA* (National Imagery and Mapping Agency of the United States, (NIMA) 1997)

TABLE XI. SELECTED VARIABLES FOR RISK INDEX AND JUSTIFICATION (CONTINUED)

IPCC CATEGORY	***VARIABLE***	***JUSTIFICATION***	***SCALE***	***YEARS***	***SOURCE***
	Child population	*CDC SVI*	*Subcounty*	*2019*	*KNBS*
	Female population	*population included in CC vulnerability*	*Subcounty*	*2019*	*KNBS*
	Average household size	*COVID SEVI, CDC SVI - includes crowded households but this could be a similar component*	*Subcounty*	*2019*	*KNBS*
	Elderly population	*COVID SEVI, CDC SVI*	*Subcounty*	*2019*	*KNBS*
	Mortality Rate	*COVID SEVI*	*County*	*2019*	*KNBS*
Exposure	*Population density*	*cc vulnerability*	*Subcounty*	*2019*	*KNBS*
	Rural population	*based on the specific hazard and health outcome*	*Subcounty*	*2019*	*KNBS*
	Urban population	*COVID SEVI*	*Subcounty*	*2019*	*KNBS*

TABLE XII. DEFINITION OF VARIABLES INCLUDED IN THE RISK INDEX

IPCC Category	***Variable***	***Definition***
Exposure	***Rural Population***	*Total population living in rural areas as defined by national statistical offices*
	Urban Population	*Total population living in urban areas as defined by national statistical offices*
	Population Density	*Population per 1 sq km*
Sensitivity	***Child Population***	*Total population under the age of 18*
	Elderly Population	*Total population that is 65 and older*
	Housing Type - Non-Permanent	*Number of households with non-permanent housing – houses which are built with either mud walls or grass thatched roof*
	Average Household Size	*Average number of people in a household*
	Female Population	*Total population that is female*
	Number of Distinct River Segments	*Number of distinct river segments in the sub county*
	Number of Flood Plains	*Number of flood plains in the sub county*
	Population living in Informal Settlements	*Total population living in informal settlements*
	Number of Households living in Poverty per 1,000	*Number of households living off less than 1 USD per day per 1,000*
	Stunting rate of children	*Percentage of children who are stunted*
	Infant Mortality Rate	*Probability of dying before age 1 per 1,000 live births*
	Under 5 Mortality Rate	*Probability of dying before age 5 per 1,000 live births*
	Adult Mortality Rate – Male	*Probability of dying between 15 and 60 per 1,000 people*
	Adult Mortality Rate – Female	*Probability of dying between 15 and 60 per 1,000 people*
	Elderly Mortality Rate – Male	*Probability of dying after age 60 per 1000 population for males*
	Elderly Mortality Rate – Female	*Probability of dying after age 60 per 1000 population for females*
Adaptive Capacity	***Literacy Rate***	*Percentage of the population over the age of 18 that can read and write*
	Improved Sanitation	*Number of households with access to improved sanitation facilities*
	Electricity	*Number of households with access to electricity*
	Improved Drinking Water	*Number of households with access to improved drinking water sources*
	Number of pharmaceutical Dispensary's	*Number of health facilities classified as a dispensary*

TABLE XII. DEFINITION OF VARIABLES INCLUDED IN THE RISK INDEX (CONTINUED)

IPCC Category	***Variable***	***Definition***
	Number of Health Centers	*Number of health facilities classified as a health centre*
	Number of Hospitals	*Number of health facilities classified as a hospital*
	Number of Medical Centers	*Number of health facilities classified as a medical centre*
	Number of Medical Clinics	*Number of health facilities classified as a medical clinic*
	Number of Nursing Homes	*Number of health facilities classified as a nursing home*
	Number of Stand-Alone facilities	*Number of health facilities classified as a stand alone*
	Number of Primary Health Centers	*Number of health facilities classified as primary health*
	Total Hospital Beds and Cots	*Number of cots and beds in each sub county at any type of health facility*
	Primary Education	*Proportion of the adult population with an elementary education*
	Secondary Education	*Proportion of the adult population with a secondary education*
	University Education	*Proportion of the adult population with university education*
	TVET Education	*Proportion of the adult population with Technical and Vocational Education and Training*
	Adult Basic Education	*Proportion of the adult population with an adult basic education – reading, writing, and math skills*
	Madrasa Duksi Education	*Proportion of the adult population with a madrasa duksi education*
	Distance to an Urban Center	*Average distance in minutes to an urban center in the sub-county*
	CIDP Total Score	*CHA score for the county*
	Density of Doctors	*Number of doctors per 10,000 people*
	Density of Nurses	*Number of nurses per 10,000 people*
	Density of Clinical Officers	*Number of clinical officers per 10,000 people*
Hazard	***Standard Deviation in Monthly Total Rainfall***	*Standard deviation of monthly total precipitation from 2010 to 2022 in mm*
	Standard Deviation in Monthly Average Maximum Temperature	*Standard deviation of average monthly maximum temperature from 2010 to 2022 in C*

TABLE XII. DEFINITION OF VARIABLES INCLUDED IN THE RISK INDEX (CONTINUED)

IPCC Category	***Variable***	***Definition***
	Average Monthly Difference in Temperature	*Difference in average monthly minimum and maximum temperature in C*
	Total Number of Extreme Heat Days from 2014 to 2022	*Total number of days from 2014 to 2022 where the maximum temperature was above the 95th percentile for the period*
	Total Number of Extreme Cold Days from 2014 to 2022	Total number of days from 2014 to 2022 where the minimum temperature was below the 5th percentile for the period
	Total Number of Extreme Rain Days from 2014 to 2022	Total number of days from 2014 to 2022 where the total precipitation was above the 95th percentile for the period

Sub-counties with name changes were renamed, those that were divided had the data applied to both sub-counties, and the average of the sub-counties that were merged was used.

Principal component analysis (PCA) was performed to identify sub-components of hazard, exposure, sensitivity, and adaptive capacity. First, the Kaiser – Meyer – Olkin (KMO) statistic was calculated to test the strength of correlation between component specific variables. The set of exposure variables had a KMO 0f 0.48, indicating that PCA should not be run. The sensitivity variables had a KMO below 0.5 resulting in the removal of variables with the lowest individual KMO's. The final KMO measures for the set of hazard, sensitivity and adaptive capacity variables were 0.604, 0.58, and 0.7 respectively. Finally, Bartlett's Test of Sphericity was significant for all three components, emphasizing the appropriateness of principal component analysis. Factors with an eigen value > 1.0 were retained and varimax rotation was performed. Variables were placed into a sub-component if their factor loading coefficient was greater than 0.3 and/or aligned with similar variables as defined by the epidemiologic literature and the conceptual model. Each subcomponent consisted of variables on the same scale, all sub-county, or all county level variables. An index for each of the risk components was calculated as the sum of the weighted subcomponents and the unweighted variables that did not fall into a subcomponent. Each component indices were scaled from 0 to 1, resulting in a possible risk index range of 0 to 1. The risk index was then calculated using the following equation:

$$R = H \; x \; E \; x \; S \; x \; (1 - AC) \quad (1)$$

Where Hazard x Exposure X Sensitivity (H x E x S) represents the potential impacts to the system and 1- Adaptive Capacity (AC) represents the system's ability to cope with those impacts (Das et al. 2020, Marigi 2017). After calculation of the risk index, the index was rescaled to be between 0 and 100 using the methodology used for the calculation of the Human Development Index (Das et al. 2020).

$$R_{ij} = \frac{(R_i - Min\ R_j)}{(Max\ R_j - Min\ R_j)}\ x\ 100 \quad (2)$$

Where R_{ij} is the normalized risk index, R_i is the raw risk index for the sub-county, and max and min R_j is the minimum and maximum values of risk for all sub-counties (Das et al. 2020). Based on the distribution of the normalized risk index, sub-counties were assigned to a risk quintile to compare with other LVRB sub-counties. These methods have been used in other applications of the AR5 framework as seen in Table XXIV, Appendix D.

C. Results

The Lake Victoria Region Block of Western Kenya consists of 99 sub-counties across 14 counties. As seen in Table XIII, there is a great deal of variability in measures of exposure, sensitivity, adaptive capacity, and hazard. The three variables with the highest coefficient of variation are, the percentage of the total population living in informal settlements, the number of flood plains, and the number of extreme cold days, below the 5th percentile, between 2014 and 2022. The variables with the smallest coefficient of variation are the adult literacy rate, mortality rate for the female population over the age of 65, and the average monthly maximum temperature in Celsius from 2010 to 2022.

1. Principal Component Analysis

Principal component analysis demonstrated significant sub-components within three of the four IPCC risk components. In the hazard component, three sub-components accounted for 87% of the communal variance, as seen in Table XIV, precipitation accounted for 36%, the frequency of extreme heat days and monthly average maximum temperature accounted for 28%, and the remaining 23% of the communal variance. Sensitivity was found to have four sub-components accounting for 78% of the communal variance, as seen in Table XV.

TABLE XIII. SUMMARY STATISTICS OF VARIABLES INCLUDED IN RISK INDEX

IPCC Category	Variable	Mean	STD	Median	Range	CV
Exposure	Rural Population	250,692	303,210	142,476	1,644,738	1.21
	Urban Population	49,231	81,966	141,916	438,795	1.67
	Population Density	718.3	588.6	567	4572	0.82
Sensitivity	Child Population	74,629	21,048	72,539	106,940	0.28
	Elderly Population	6,670	2,556	6,437	16,686	0.38
	Housing Type - Non-Permanent	47,328	58,736	25,986	325,158	1.24
	Average Household Size	4.35	0.362	4.3	2	0.08
	Female Population	82,476.53	25,505.87	79,540	128,703	0.31
	Number of Distinct River Segments	20.969	15.74	18	114	0.75
	Number of Flood Plains	0.1919	0.865	0	6	4.51
	Population living in Informal Settlements	1,031.387	9147	0	90,780	8.87
	Number of Households living in Poverty per 1,000	424.53	141.1304	396	468	0.33
	Stunting rate of children	15.77	3.422	15	13	0.22
	Infant Mortality Rate per 1,000	38.58	11.98	37	41	0.31
	Under 5 Mortality Rate per 1,000	61.74	19.062	60	65	0.31
	Adult Mortality Rate – Male per 1,000	0.36579	0.1	0.407	0.273	0.27
	Adult Mortality Rate – Female per 1,000	0.237	0.047	0.23	0.164	0.07
	Elderly Mortality Rate – Male per 1,000	0.693	0.0065	0.74	0.171	0.01
	Elderly Mortality Rate – Female per 1,000	0.59	0.04	0.594	0.152	0.07
Adaptive Capacity	Literacy Rate	89.4	2.548	89.5	17.5	0.03
	Improved Sanitation	25,959.72	18,442	24,774	161,570	0.71
	Electricity	10,876.5388	8,578.28	8,575.5	46,070	0.79
	Improved Drinking Water	13,692.0707	9,750.24	12,347	55,012	0.71
	Number of pharmaceutical Dispensary's	14.41	8.04	13	35	0.56
	Number of Health Centers	5.15	3.84	4	20	0.75
	Number of Hospitals	2.72	2.33	2	15	0.86
	Number of Medical Centers	1.3838	1.7262	1	9	1.25
	Number of Medical Clinics	7.04	6.44	6	44	0.91
	Number of Nursing Homes	0.33	0.603	0	3	1.83
	Number of Stand-Alone facilities	0.6	1.2	0	7	2

TABLE XIII. SUMMARY STATISTICS OF VARIABLES INCLUDED IN RISK INDEX (CONTINUED)

IPCC Category	***Variable***	***Mean***	***STD***	***Median***	***Range***	***CV***
	Number of Primary Health Centers	0	0	0	0	0
	Total Hospital Beds and Cots	276.15	254.22	200.5	1684	0.92
	Proportion of Adult Population with Primary Education	0.5813	0.086	0.598	0.467	0.15
	Proportion of Adult Population with Secondary Education	0.1867	0.027	0.188691	0.20833	0.15
	Proportion of Adult Population with University Education	0.018	0.0085	0.015852	0.05	0.47
	Proportion of Adult Population with TVET Education	0.0215	0.0056	0.02	0.0266	0.26
	Proportion of Adult Population with Adult Basic Education	0.0009	0.00047	0.0008	0.0023	0.52
	Proportion of Adult Population with Madrasa Duksi Education	0.00001744	0	0.000014	0.002	0
	Distance to an Urban Center	8.963	14.94	4.99	123.09	1.67
	CIDP Total Score	6.86	3.278	6	11	0.48
	Density of Doctors per 10,000	0.51	0.257	0.45	0.78	0.50
	Density of Nurses per 10,000	6.27	1.475	6.04	6.03	0.24
	Density of Clinical Officers per 10,000	1.55	0.45	1.46	1.6	0.29
Hazard	Standard Deviation in Monthly Total Rainfall*	81.705	15.53	80	103	0.19
	Standard Deviation in Monthly Average Maximum Temperature*	1.56	0.227	1.565	1.623	0.15
	Average Monthly Difference in Temperature*	12	1.14	12.27	5.89	0.28
	Total Number of Extreme Heat Days from 2014 to 2022	250	292	138	1275	1.17
	Total Number of Extreme Cold Days from 2014 to 2022	247	583	68	3453	2.36

TABLE XIII. SUMMARY STATISTICS OF VARIABLES INCLUDED IN RISK INDEX (CONTINUED)

IPCC Category	***Variable***	***Mean***	***STD***	***Median***	***Range***	***CV***
	Total Number of Extreme Rain Days from 2014 to 2022	245	99.52	233	609	0.41
				*2010 to 2022		

The four sub-components, sensitive populations, child mortality, environment, and living conditions accounting for 28%, 21%, 15%, and 14% of the communal variance respectively. Finally, eight sub-components accounted for 74% of the communal variance for the Adaptive Capacity component, as seen in Table XVI. Health sector adaptive capacity, education, health workforce, WASH, early education, health facilities, structural capacity, and dispensaries accounted for 26%, 11%, 9 %, 7%, 6%, 5%, 5% of the communal variance respectively.

2. Risk Index Based on the IPCC AR5 Framework

The calculated risk index scores among the 99 sub-counties ranged from 0 to 100, with a median of 0.635, mean of 4.29 and standard deviation of 14. Overall, the distribution was right skewed, 10^{th} percentile of 0.04, and 90^{th} percentile of 17. Given the non-normal distribution of the risk index, sub-counties were classified into quintiles for each component index and the overall risk index. As seen in Figure 6, hazard, exposure, sensitivity, and adaptive capacity vary on a subnational scale and do not follow a north-south or east-west gradient, but there does appear to be spatial clustering. For example, the northern region has higher levels of hazard, exposure, and sensitivity and low levels of adaptive capacity resulting in a spatial cluster of high risk. Figure 7 displays the estimated risk of diarrheal disease from extreme precipitation and temperature by subcounty quintiles. Additionally, weighting of sub-components with their factor loading scores results in only 14% of sub-counties having changes in risk rank compared to unweighted sub-components, with an average 0.11-unit decrease in risk (95% CI: -0.23, 0.02) (See Figure 18, Figure 19, and Table XXVI and Table XXVII in Appendix C).

D. Discussion

This application of the IPCC AR5 risk framework estimated risk for diarrheal disease due to weather variables at the sub-county level in the LVRB.

TABLE XIV. PCA RESULTS FOR THE HAZARD COMPONENT

Variable	**Factor1**	**Factor2**	**Factor3**	**Sub-Component**
Average Monthly Precipitation	**0.97428**	-0.08446	0.05785	*Precipitation*
Total Extreme Rain Days	**0.96873**	0.04077	-0.02397	*Precipitation*
Standard Deviation in Monthly Precipitation	**0.95946**	0.01703	0.06463	*Precipitation*
Average Mean Temperature	0.10756	0.25553	**0.76491**	*Temperature 1*
Total Extreme Cold Days	-0.15443	-0.66052	**0.62867**	*Temperature 1*
Standard Deviation in Monthly Maximum Temperature	0.03318	-0.07332	**0.9281**	*Temperature 1*
Average Monthly Maximum Temperature	-0.01206	**0.96307**	-0.05754	*Temperature 2*
Total Extreme Heat Days	-0.08459	**0.88263**	0.29634	*Temperature 2*

TABLE XV. PCA RESULTS FOR THE SENSITIVITY COMPONENT

Variable	**Factor1**	**Factor2**	**Factor3**	**Factor4**	***Sub- Component***
Child Population	**0.91006**	0.01385	0.14521	-0.0336	*Sensitive Population*
Female Population	**0.88648**	-0.0186	0.05073	0.1022	*Sensitive Population*
Elderly Population	**0.49298**	-0.1326	0.65337	-0.0402	*Sensitive Population*
Poverty	**0.44069**	-0.2092	-0.68	-0.0938	*Sensitive Pop*
Number of rivers	0.21545	-0.1116	**0.75716**	-0.0964	*Environment*
Non-permanent Housing	0.14698	-0.0341	0.09238	**0.77608**	*Living Conditions*
Population Living in Informal Settlements	-0.1074	0.0043	-0.1556	**0.80002**	*Living Conditions*
Under 5 Mortality Rate	-0.0255	**0.99395**	-0.0384	-0.0184	*Child Mortality*
Infant Mortality Rate	-0.0196	**0.99496**	-0.031	-0.0185	*Child Mortality*

TABLE XVI. PCA RESULTS FOR THE ADAPTIVE CAPACITY COMPONENT

Variable	*Factor 1*	*Factor 2*	*Factor 3*	*Factor 4*	*Factor 5*	*Factor 6*	*Factor 7*	*Factor 8*	*Sub-Component*
Medical Clinics	**0.85325**	0.0735	-0.0724	0.09897	-0.0866	0.07245	0.08402	-0.0299	*Health Sector*
Stand Alone Facilities	**0.81177**	0.14087	-0.0694	-0.0538	0.01034	-0.0141	-0.0346	0.16043	
Medical Centers	**0.79147**	0.06136	-0.1366	0.07528	0.26248	0.10589	-0.0333	-0.023	
Total Hospital Beds and Cots	**0.74985**	0.21455	0.13498	0.07044	0.01089	0.16176	0.04607	-0.0892	
Hospitals	**0.67447**	0.16769	0.31094	0.04064	-0.1893	0.1799	0.14369	-0.0772	
Electricity	**0.65955**	0.42507	0.32209	0.35757	-0.055	-0.0836	-0.007	-0.0816	
University Education	0.28845	**0.75533**	0.18605	0.22163	0.07707	0.02739	0.08334	-0.0258	*Education*
TVET Education	0.23497	**0.84046**	-0.0691	0.15443	0.02595	-0.0975	-0.0743	0.17662	
Literacy Rate	0.12351	**0.7907**	0.12175	0.00248	-0.2386	-0.0375	-0.1227	-0.0247	
Improved Sanitation Facility	0.13762	0.14433	-0.118	**0.85384**	0.09552	-0.009	-0.1204	0.06042	*WASH*
Improved Drinking Water Source	0.10659	0.10455	0.18891	**0.84443**	-0.1936	-0.0169	0.21082	-0.046	
Health Center	0.07648	0.02451	0.02769	-0.0289	-0.1196	**0.77255**	0.03683	0.00935	*Health Facilities*
Nursing Homes	0.0429	-0.003	-0.0628	-0.1357	0.20487	**0.53605**	0.48421	0.11176	
Clinical Officers per 10,000	0.07358	-0.0402	**0.29638**	-0.2901	0.65734	0.1365	0.22923	0.1044	*Health Work Force*
Doctors per 10,000	0.09253	0.11186	**0.86324**	0.13024	-0.0732	-0.0764	0.01481	-0.0942	
Nurses per 10,000	-0.0649	0.06625	**0.73299**	-0.1601	0.36243	0.19919	-0.1486	0.22133	
CIDP Total Score	0.13302	-0.2411	0.06707	0.06657	-0.1578	0.20387	**0.72353**	-0.0092	*Structural Capacity*
No Health Facilities	0.00355	0.16651	-0.1919	0.04938	0.36024	-0.2712	**0.65515**	-0.0687	
Adult Education	-0.1001	-0.4573	-0.0652	0.20343	**0.6298**	-0.1641	0.01003	-0.0595	

TABLE XVI. PCA RESULTS FOR THE ADAPTIVE CAPACITY COMPONENT (CONTINUED)

Variable	***Factor 1***	***Factor 2***	***Factor 3***	***Factor 4***	***Factor 5***	***Factor 6***	***Factor 7***	***Factor 8***	*Sub-Component*
Secondary Education	-0.5684	0.14973	-0.0788	-0.1513	**0.45294**	0.19658	-0.2443	-0.0918	*Early Education*
Dispensaries	0.00724	0.08398	0.03189	0.01923	0.0058	-0.0202	-0.009	**0.95738**	*Pharmacy*
Primary Education	-0.5819	-0.4219	-0.4562	-0.036	0.04795	0.12084	0.02792	-0.077	
Madrasa/Duksi Education	0.19256	-0.2991	0.02838	0.12928	0.3237	0.55591	-0.1124	-0.2099	

There is no clear north to south or east to west gradient but there is sub-national variability in both risk and the individual components. In addition to risk varying on a sub-national scale, the components of risk also vary -sub-nationally and appear to have some spatial clustering. There is considerable heterogeneity within counties, for example the risk index for the 10 sub-counties within Bungoma county range from 0.53 to 39.22. Additionally, the presented risk index is not sensitive to several changes in methodology. Specifically, weighting of sub-components resulted in minimal changes in risk rank, and standardization of the variables prior to PCA did not change the relative ranking of sub-counties but decreased factor loading scores.

The PCA results and a priori analysis identified meaningful sub-components of each of the risk components. These sub-components are important as they demonstrate the need to utilize both priori knowledge and statistical analysis in the development of risk indices. Additionally, these results provide a framework for future risk indices focused on the health impacts of climate change in other settings. These sub-components are consistent with confounders (environment, precipitation, and temperature) and effect modifiers (WASH, sensitive populations, education, poverty, and health facilities) identified by epidemiological studies of associations between diarrheal disease and extreme precipitation (Levy et al. 2016, Carvajal-Vélez et al. 2016, Sumampouw, Nelwan, and Rumayar 2019, Kombat et al. 2024). Yet, to date, risk indices have not explored or identified sub-components in their analysis. These sub-components are critical to developing risk indices for the health impacts of climate change as there are many different factors that affect sensitivity, adaptive capacity, hazard, and exposure in different ways. These results demonstrate the need to identify and utilize specific sub-components in the development of risk indices for the health impacts of climate change. For the hazard component of risk, precipitation accounted for 36% of the communal variance and the frequency of extreme heat days and monthly average maximum temperature accounted for 28%.

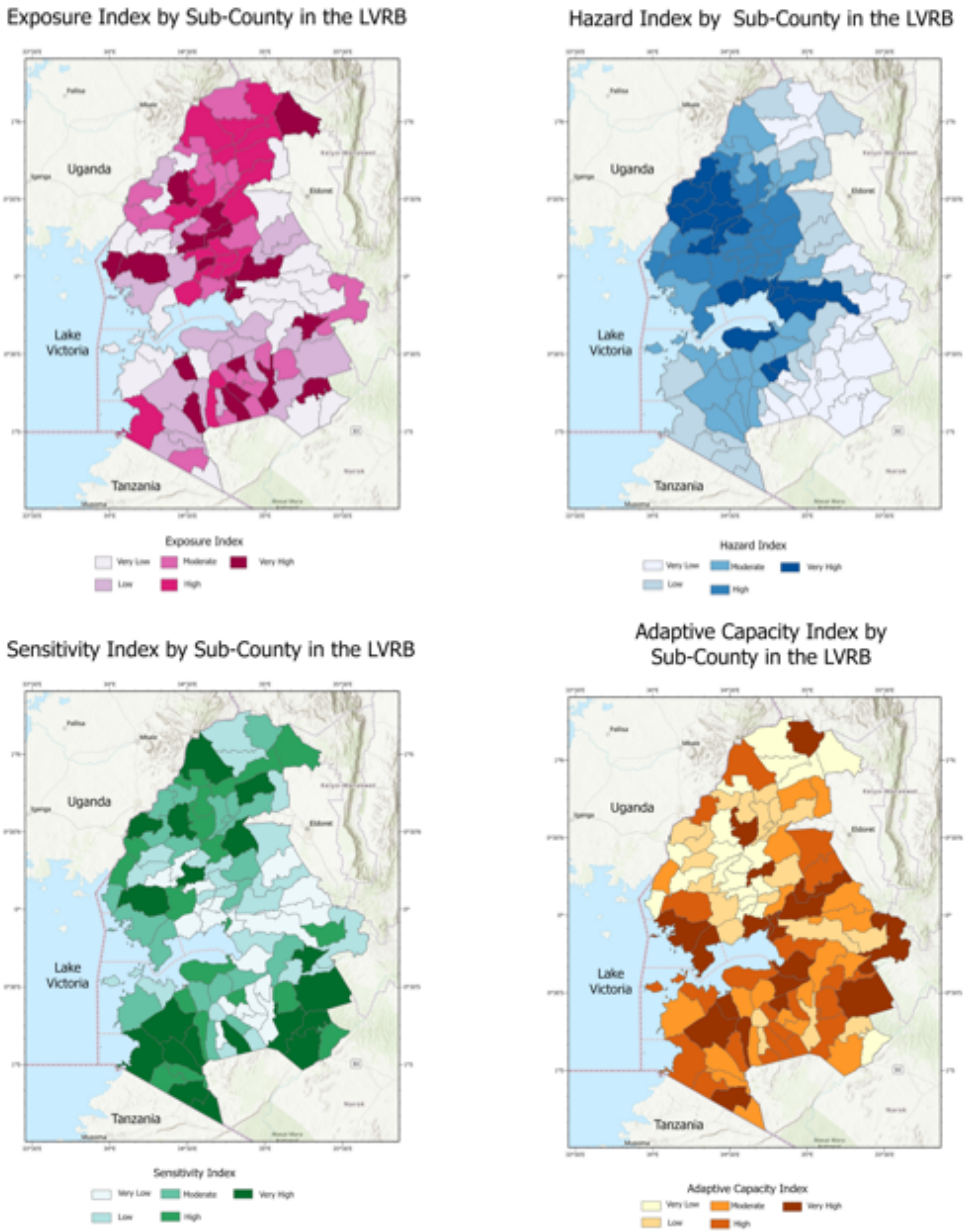

Figure 6. IPCC AR5 component indices in LVRB (made using ArcGIS Pro 3.1.0 2023)

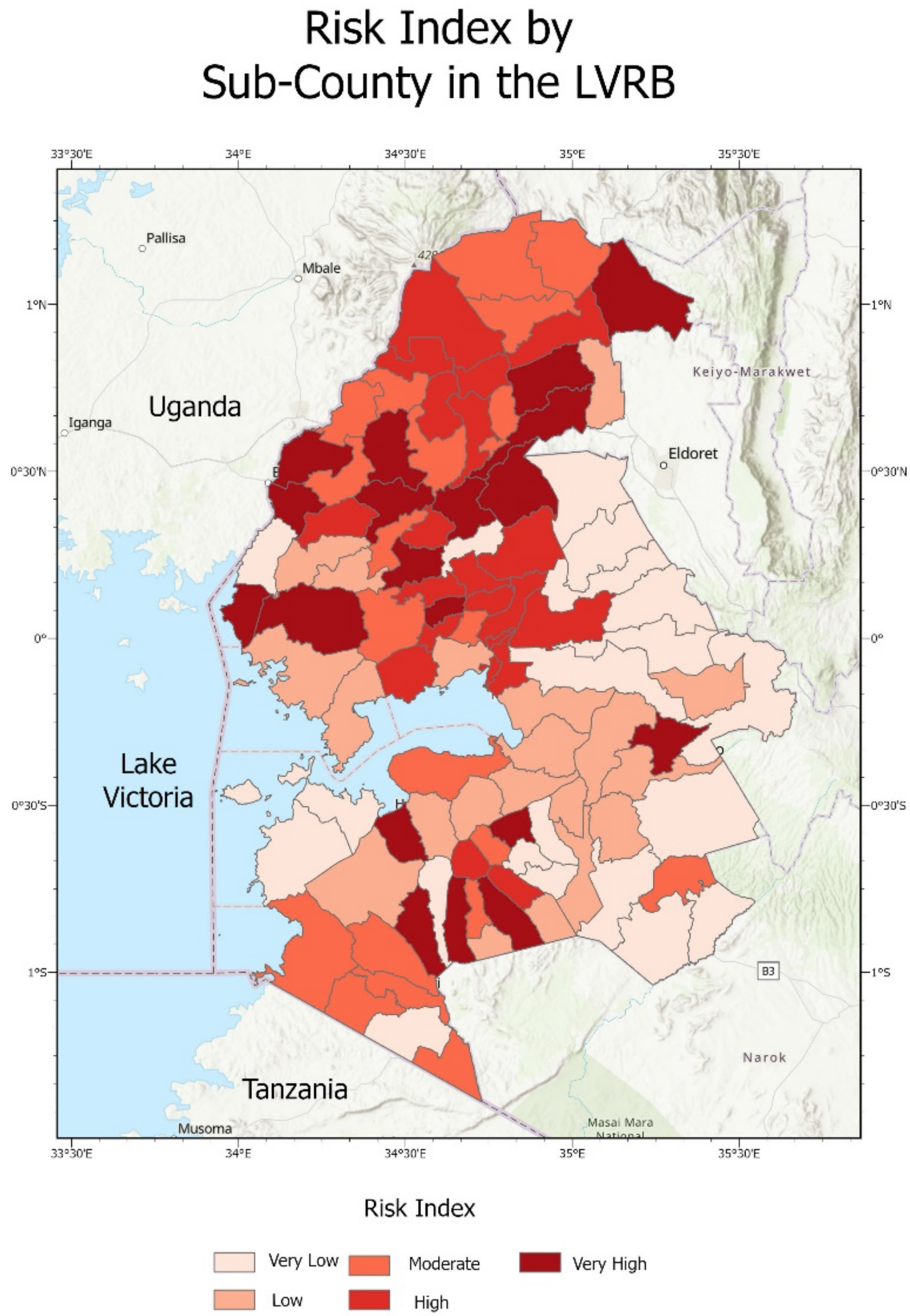

Figure 7. IPCC AR5 risk index for LVRB sub-counties (made using ArcGIS Pro 3.1.0 2023)

These findings are in line with prior research on the association between precipitation and temperature with diarrheal disease. Heavy rainfall has been found to have a strong positive association with diarrheal disease (Levy et al. 2016). For example, a recent study in Ethiopia found that for every one-millimeter increase in rainfall the cases of diarrheal disease under 5 increased by approximately 0.17%, although this association demonstrated spatial variability across districts (Alemayehu et al. 2020). Additionally, there is a positive association between diarrheal disease and flooding, with many studies showing increased detection of *Escherichia coli* and *Vibrio cholera* during or after floods (Levy et al. 2016). Temperature has also been shown to have a strong positive association with diarrheal disease (Levy et al. 2016). For example, on the district level in Ethiopia, the warm dry season was associated with increased cases of diarrheal disease under 5 and for every one degree Celsius increased, cases increased by approximately 16.6% (Alemayehu et al. 2020). Finally, studies have shown that droughts have a positive association with diarrheal disease in children under 5, with severe droughts increasing the risk of diarrhea by 8% (Wang et al. 2022). There is also a compounding effect of droughts on floods, in fact a drought prior to floods increases the risk of diarrheal disease in children under the age of 5 (Wang et al. 2023). Ultimately the variables that impact most of the variability in the hazard component are supported by epidemiological literature on the association between weather and diarrheal disease.

The meaningful sub-components of adaptive capacity and sensitivity identified by PCA are consistent with previous literature on the association between weather and diarrheal disease. For example, a recent study in Ghana found that education level of the mother, wealth index, living in a rural area, and having improve sanitation facilities had a significant association with diarrheal disease in children under 5 (Kombat et al. 2024). Another study, in Ethiopia, found that children living in households with more than 2 children and use of unimproved drinking water sources were significantly more likely to develop acute diarrhea (Natnael, Lingerew, and Adane 2021). Health care access and utilization is crucial to prevent cases of diarrheal disease from becoming severe or causing death. For example, a recent study explored cases and deaths of diarrheal disease in LMICs and found that more cases and deaths occur among poor populations when vaccines and treatment are unavailable (Chang et al. 2018). The alignment with the literature suggests that the sensitivity and adaptive capacity component indices may accurately reflect vulnerability to diarrheal disease.

Kenya is already facing the adverse impacts of climate change and they are only expected to increase, and the LVRB is especially susceptible to riverine flooding from precipitation (World Bank Group 2020). The developed risk index demonstrates the variability in risk of diarrheal disease from climate hazards on a sub-national scale. Additionally, with its focus on the system, this index has more of a systems-based approach compared to previous climate change vulnerability indices for the country, which followed the AR4 vulnerability framework and did not focus on health or a specific climate hazard (Marigi 2017, Mwangi et al. 2020). While the previous two climate change vulnerability indices for Kenya have shown a geographical gradient of vulnerability, the LVRB risk index does not (Marigi 2017, 52-74). This study is the first time the AR5 risk framework has been used to develop an index of weather-related risk in Kenya and the first-time an evaluation of policies has been included in a risk index for the country. The use of the AR5 framework allows for this index to be a starting point for other indices exploring the impacts of climate change. For example, given the AR5 framework definition of exposure, the risk of climate change to the health sector – how facilities, workforce, and the ability to provide care is impacted by climate change – could be explored. In this event, the exposure component would include information on the health sector infrastructure and facilities. The flexibility of the exposure component to be outcome specific is a major benefit of using the AR5 framework as opposed to previous frameworks.

This study has several limitations. First, as noted in the methods, some variables were only present on the county level, so they were applied to the sub-county level potentially missing within-county variability. However, this was the case for only 4 of the 30 variables, and for that reason, its impact was likely limited. Additionally, there were many changes in sub-county boundaries in recent years, from 2010 to 2019 affecting 10 of the 99 sub-counties, which may result in misclassification of sub-county risk if these boundaries do not represent the actual boundaries. There was also missing census data for 2 of the 99 sub-counties, Ainamoi and Nyaribari Chache, and these were dealt with by assigning the average for all the sub-counties within the county, potentially resulting in misclassifying the risk of these sub-counties. The variables included in this index came from a variety of sources, such as peer reviewed literature, geospatial data and others potentially causing issues with validity of the data. However, much of the data used came from the KNBS which utilizes rigorous quality control measures, so the impact is likely minimal. While the KNBS followed numerous control measures, the response rates for counties and sub-counties are unknown resulting in differences among sub-counties potentially being driven by variable and non-random data completeness. The variables included cover different time periods and as a result, some misclassification may occur. Additionally, variables with low factor loading scores below 0.3 were included in their respective sub-components based on a priori knowledge potentially resulting in misclassification. Finally, the risk index has not been evaluated on how well it predicts risk of diarrheal disease. Such an effort could include modeling diarrheal disease using components of the risk estimate and weather data to predict rates of diarrheal disease and comparing those estimates to observed rates by subcounty.

Overall, these results provide useful information to policy makers in Kenya identify sub counties that should be prioritized for climate change adaptation efforts have the most impact. For example, Bumula sub-county had the highest risk index and Emgwen had the lowest therefore it may be useful to prioritize Bumula sub-county over Emgwen to reduce the risk of weather-related diarrheal disease. This is the first climate change and health index following the IPCC AR5 framework for Kenya and the first sub-county level index that includes more than one county. Further research should be done to validate and expand this risk index to the entire country, and other climate-sensitive diseases in other LMICs. For example, this framework and meaningful sub-components could be applied to other diseases such as respiratory disease. Based on epidemiologic literature, relevant indicators of hazard, exposure sensitivity and adaptive capacity would be identified, for example, air pollution, type of cooking fuel, and female population may be important indicators. In this case, air pollution would be added to the hazard component, cooking fuel would be added to sensitivity but sensitive populations, temperature, health sector, living conditions, education and others would remain in the risk index. Ultimately, the sub-components identified here will likely remain the same from one climate-sensitive health outcome to another but the factors that make up these sub-components will be tailored to the specific health outcome. While comprehensive and accessible health data is the preferred way to estimate risk, the development of disease-specific risk indices following the IPCC AR5 framework is a good tool to use in low resource settings where comprehensive health data is not readily available. Additionally, this approach is a more comprehensive predictor of risk given the joint consideration of a variety of predictors of a climate-sensitive health outcome. A risk index provides policy makers, public health officials, and other key stakeholders with a general sense as to where they should expect an increase in cases of climate-sensitive health outcomes. This is important, as such an index could identify areas thought to be at greater risk of weather-related disease which will increase due to climate change.

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IV. EVALUATING THE IPCC RISK FRAMEWORK TO PREDICT DIARRHEAL DISEASE IN WESTERN KENYA

A. Introduction

Kenya is a lower middle-income nation in Eastern SSA with a population of 47.5 million people (Kenya National Bureau of Statistics 2019a). Approximately 60% of Kenyans living in urban areas live in informal settlements, such as slums, and as of 2021 38.6% of the population was classified as poor (United Nations Habitat 2023, Kenya National Bureau of Statistics 2023). Additionally, only 34% of households have access to piped water and 8.2% of households do not have access to a sanitation facility (Kenya National Bureau of Statistics 2019a). As of 2019, the life expectancy at birth in Kenya is 66.7, a drastic improvement from 50 years in 2000 (World Bank Group 2020, Ministry of Health Kenya 2014). As of 2019, the top 4 leading causes of death in Kenya were, HIV/AIDs, lower respiratory infections, diarrheal disease, and neonatal disorders respectively (Ministry of Health Kenya 2014, GBD 2019 Diseases and Injuries Collaborators 2020). Kenya is experiencing the effects of climate change nationwide, but the biggest threats are rising temperature, sea level rise, increased rainfall and floods in some areas, and droughts in others (Bauer and Mburu 2017, Harison, Boitt, and Imwati 2017, Public Health & Environment Department WHO 2010, Talisuna et al. 2020). Floods are projected to increase in frequency and intensity, posing a substantial risk to human life in Kenya (World Bank Group 2020, Romanello et al. 2021). In fact, every year since 2000, Kenya has experienced prolonged droughts and intense flooding (Thornton 2010). Additionally, riverine flooding in Kenya is projected to impact an additional 75,100 people by 2030, compared to impacting 29,600 people in 2010 (World Health Organization 2016). According to the World Bank, western Kenya has a high level of risk of riverine flooding (World Bank Group 2020).

The Kenya government considers waterborne diseases to be among the greatest health threats in the country in the near to long term future (World Bank Group 2020). It has been well documented that flooding is associated with increased incidence of cholera and higher than average rainfall was associated with increases in incidence of diarrheal disease (Olubulyera 2021, Levy et al. 2016). For example, flooding in Mombasa in 2006 led to a cholera outbreak resulting in 94 suspected cases, 13 confirmed cases, and 2 deaths (Awuor, Orindi, and Adwera 2008). A study in Malindi, Kenya found a strong positive correlation between increased rainfall and cases of childhood diarrhea (Saidi et al. 1997). Additionally, a study in Malawi found that moderate rainfall is associated with an increased risk of invasive, non-typhoidal salmonella compared to no rainfall (Thindwa, et al. 2019). The lag between peak rainfall and increased salmonella cases in Malawi has been estimated to be 15.46 weeks (Gauld, et al. 2022). Flooding and extreme rainfall can increase the already high burden of diarrheal disease in Kenya, but to date there has been limited research about this association in Kenya.

Vulnerability indices are useful tools to identify areas highly vulnerable to the impacts of climate change for resource allocation and prioritization. While there have been a variety of vulnerability indices created for climate change in LMICs, very few have been validated with epidemiological data. Assessing the predictive capabilities of vulnerability indices on the association between extreme rainfall and health impacts is relatively novel. The Centers for Disease Control and Prevention's Agency for Toxic Substance Disease Registry Social Vulnerability Index (SVI) (CDC/ATSDR SVI) was found to modify the effect of flood exposure on emergency department visits following Hurricane Harvey (Ramesh et al. 2022). As a result, they found that census tracks with high SVI had higher number of emergency department visits 2 months post flood compared to census tracks with low SVI demonstrating that the CDC/ATSDR SVI is a valid modifier of the association (Ramesh et al. 2022). This information could be very useful in low resource settings where comprehensive data on health outcomes may not be readily available. Specifically, policy makers can rely on a risk index to inform decision making and resource allocation in response to climatic hazards. Therefore, conducting analysis on the association between waterborne disease and extreme rainfall with a risk index included as both a predictor and an effect modifier may provide crucial information to policymakers in Kenya. Specifically, where to focus interventions to reduce the burden of waterborne disease following periods of extreme rainfall. The research presented in chapter III developed an index for risk of diarrheal disease following extreme precipitation in the Lake Victoria Region Economic Block (LVRB), a continuous group of 14 counties in western Kenya. The aim of this research is to model the association between rates of under 5 diarrheal disease and extreme precipitation as modified by risk of diarrheal disease. This research can inform climate and health researchers globally about predictive ability of the IPCC AR5 framework regarding climate-sensitive health outcomes.

B. Methods

1. Data Sources

In 2013, the Kenyan government devolved responsibilities of the Ministry of Health from a centralized to one that provides more responsibility to the 47 county governments (Masaba et al. 2020). Under this new system, county governments are responsible for community health, primary health, and county referral services and the national government is only responsible for national referral services (Masaba et al. 2020). Within the county level, the sub-county is responsible for community health and primary care services (Ministry of Health Kenya 2014). Community health services include promotion of healthy lifestyles, personal hygiene, treatment of minor ailments, and improving community awareness of services. Primary care services include basic outpatient diagnostic, ambulatory services, medical, surgical, and rehabilitative services. A large portion of diarrhea cases are treated at primary health care facilities. Primary health care facilities report outpatient cases to the Kenya Health Information System (KHIS) through the electronic community health information system (eCHIS) platform. The eCHIS is a mobile platform that assists in the management of health extension programs through the collection and use of demographic data, health services delivery information and service utilization. We have obtained monthly case counts of clinically defined diarrheal disease cases – cholera, typhoid, dysentery, and diarrhea – for those < 5 years and for those ≥ 5 years of age from 2014 to 2022. Those data were obtained from the Departments of Public Health of 13 of the 14 counties in the LVRB (Bomet county was missing), each county provided counts by sub-county. To estimate the number of children <5 years of age at the subcounty level, we applied the 2022 percentage of the county population < 5 to the total population of each subcounty. Daily weather data was obtained from the Kenya Meteorological Department from 2014 to 2022, which was then aggregated up to the monthly level. Risk level for each of the sub-counties in the LVRB was obtained from the research described in chapter III at the sub-county level. A risk index was developed based on the causal model seen in Figure 5, using demographic, environmental, and health care data sources. The variables were classified into the four components of risk as defined by the intergovernmental panel on climate change (IPCC) – hazard, exposure, sensitivity, and adaptive capacity – and combined based on results of principal component analysis. For this analysis those four component indices were used to create various time stable measures: one was comprised of all four components, one comprised of exposure, sensitivity, and adaptive capacity, and finally a vulnerability-index-only included sensitivity and adaptive capacity. The sub-counties were divided into low, moderate, and high-risk groups, based on the distribution of the risk index and previous literature (Ramesh et al. 2022).

2. <u>Modeling Approach</u>

The outcome of interest was the monthly rates and counts of diarrheal disease among children under 5 years of age for 94 sub-counties within 13 LVRB counties from 2014 to 202. A total of 108 records of diarrheal disease counts (nine years x 12 months/year) were present for each sub-county, other than the sub-counties in Migori county, which did not have data for 2016, but was used for other years. Outliers above the 99th percentile for rates of diarrheal disease were excluded from the analysis, due to these being extreme outliers, greater than 2 standard deviations above the mean, for a final dataset of 9,924 monthly subcounty-level observations. These values may be inaccurate or mistypes, for example one of these values reported that 75% of the total child population had diarrhea in a single month. The predictor variables included, season, number of extreme rain days, extreme heat and cold days, total precipitation, average minimum, and maximum temperature. Given the well-established lag period between weather variables and diarrheal disease incidence, with an average lag time of zero to four weeks, lag variables were created to reflect each of the weather variables noted above – for the prior month (Carlton et al. 2013, Wang et al. 2023). Although diarrhea cases data was only available by calendar month, weather data was available by date. Thus, weather variables lagged 1, 2 and 3 weeks prior to the start of the month were also included. Descriptive analyses were run for each variable. Bivariate analyses were conducted to evaluate associations between diarrheal disease and predictor variables. Friedman's non-parametric two-way ANOVA test was used to compare differences in rates of diarrheal disease by discrete predictors such as county, sub-county, season, risk rank, and vulnerability rank. Poisson regression was used to characterize associations between diarrheal disease and individual predictor variables incorporating the repeated measures at the sub-county level. Three groups of predictors with rates of diarrheal disease under 5 were explored: risk, seasonality, and extreme weather. Risk-focused analysis was done using non-parametric testing, stratification by risk tertile based on the distribution of the risk index, and inclusion of individual components of risk, such as exposure, hazard, and vulnerability. Season-focused analysis was also done using non-parametric testing and stratification. However, in seasonality analysis the risk index used for stratification did not include the hazard component of risk. Due to the high level of correlation among the weather variables, a model was run individually for each weather variable. These models were further stratified by season and the risk index without the hazard component to explore how associations change across season and risk. Interaction between weather variables was explored for uncorrelated temperature and precipitation variables. All models of rate of diarrheal disease included the log of the under 5 population as an offset.

All statistical analyses were done using SAS version 9.4 (SAS Institute, Cary, NC).

C. Results

1. Descriptive Statistics

On average from 2014 to 2022, LVRB sub-counties had 166 diarrhea cases per 10,000 children under the age of 5 per month. As seen in Table XVII, cholera and typhoid made up the smallest number of these cases, whereas dysentery and diarrhea made up the majority. Additionally, rates of diarrheal disease varied across the sub-counties, with a standard deviation of 163 cases per 10,000 children (Figure 8). In conjunction with disease variability, weather varied across sub-counties in this period. As seen in Table XVIII, the average monthly maximum temperature was 27.95˚C with a minimum of 15.81 ˚C, the average total monthly rainfall was 14.85 cm, with an average of 1.7 days with rainfall above the 95th percentile. The sub-county variability demonstrated by the standard deviation and range of the descriptive statistics is complemented by county level variability. Daily precipitation from 2000 to 2022 varies significantly across the 13 counties in the LVRB of Kenya, as seen in Figure 8.

2. Risk Index

Rates of diarrheal disease under 5 vary significantly across risk group, low, moderate, and high. Additionally, this association is seen across vulnerability groups, which exclude hazard and exposure variables and only include the components of sensitivity and adaptive capacity. Rates of diarrheal disease under 5 have been decreasing since 2014 across the LVRB of Kenya, with 0.2% decline (p=

0.0021). This trend is also seen across risk level (Figure 10). There were two peaks in diarrheal disease cases, in 2015 and 2019, with the highest peak in high-risk sub-counties. Figure 11 demonstrates the observed diarrheal disease rates over time by risk level. Rates of diarrheal disease under 5 decreased significantly in the low and moderate risk sub-counties but the decrease in the high-risk sub-counties was not statistically significant, IRR (95% CI) of 0.998 (0.996, 1), 0.997 (0.996, 0.998) and 1 (0.998, 1.001) respectively. The risk index is positively correlated with total cases of diarrheal disease under 5 (correlation coefficient of 0.50).

TABLE XVII. DESCRIPTIVE STATISTICS OF DIARRHEAL DISEASE DATA FROM 2014 TO 2022 IN LVRB SUB-COUNTIES

Diarrheal Disease Variables	***Mean***	***STD***	***Median***	***Range***
Diarrhea Counts Under 5	287.454	292.798	247	15640
Diarrhea Counts Over 5	322.402	452.875	265	35465
Typhoid Count Under 5	10.462	34.327	3	982
Typhoid Count Over 5	210.923	217.385	153	8133
Dysentery Count Under 5	4.162	6.985	2	311
Dysentery Count Over 5	14.605	84.287	7	8258
Cholera Count Under 5	0.027	0.926	0	63
Cholera Count Over 5	0.112	2.868	0	157
Total Diarrheal Disease Count Under 5	302.106	298.865	259	15642
Total Diarrheal Disease Count Over 5	548.043	531.161	466.5	35663
Rate of Diarrheal Disease Under 5 per 10,000	166.44	163.113	144.05	7701
Rate of Diarrheal Disease Over 5 per 10,000	42.121	29.311	36.24	793.135

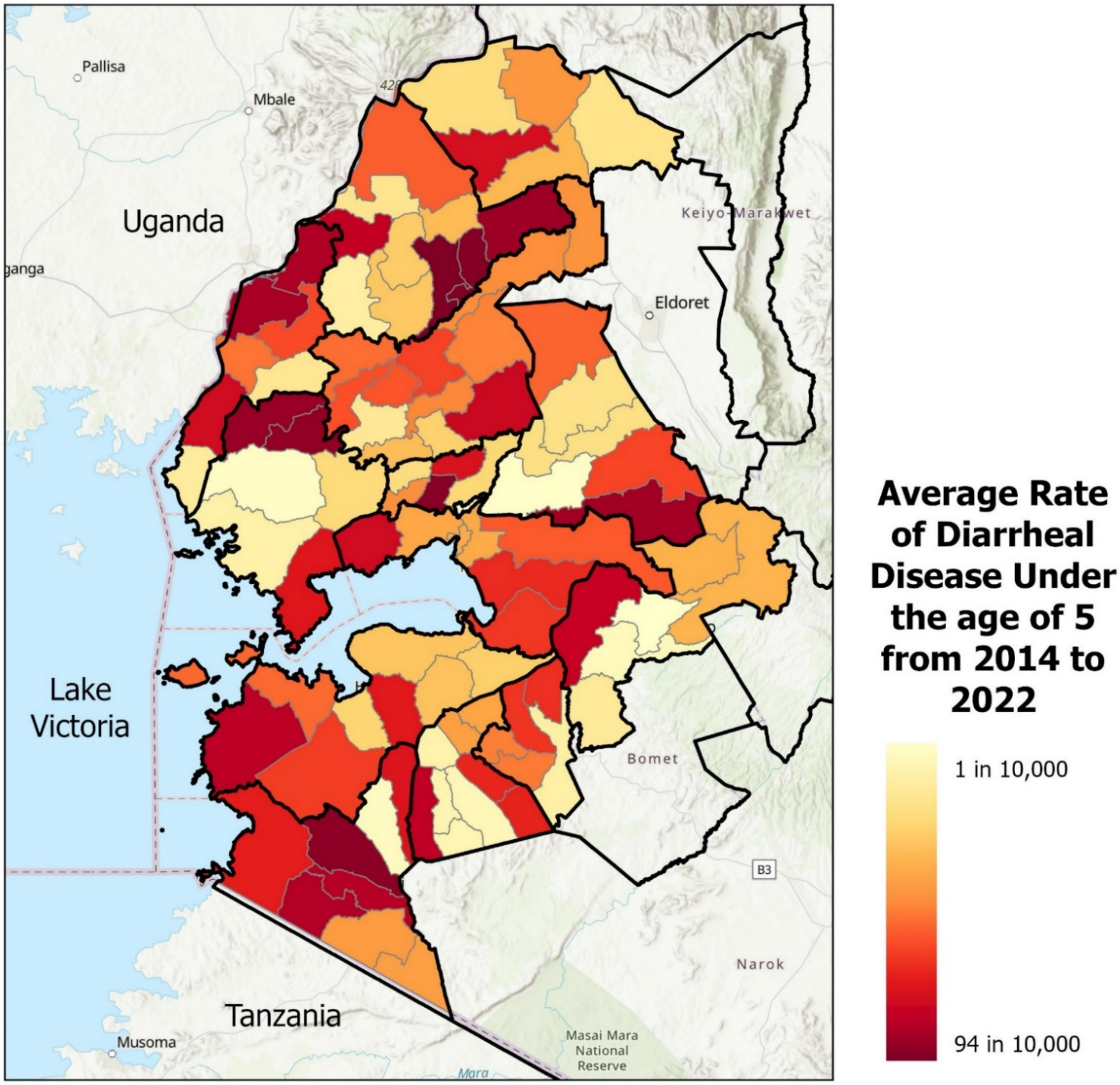

Figure 8. Average rate of diarrheal disease under 5 per 10,000 children by sub-county within 13 LVRB counties from 2014 to 2022 (made using ArcGIS Pro 3.1.0 2023)

TABLE XVIII. DESCRIPTIVE STATISTICS OF WEATHER VARIABLES

Variable	***Mean***	***Std Dev***	***Median***	***Range***
Average Monthly Maximum Temperature (C)	27.95	2.53	27.97	23.49
Average Monthly Minimum Temperature (C)	15.81	2.35	16.00	19.51
Total Monthly Precipitation in cm	14.85	9.11	13.30	79.99
Number of Extreme Rain Days	1.74	2.20	1.00	20.00
Number of Extreme Heat Days	1.96	5.13	0.00	37.00
Number of Extreme Cold Days	1.33	4.51	0.00	31.00
Number of Extreme Rain Days in the Month Prior	1.73	2.20	1.00	20.00
Number of Extreme Cold Days in the Month Prior	1.34	4.51	0.00	31.00
Number of Extreme Heat Days in the Month Prior	1.96	5.13	0.00	37.00
Total Precipitation in cm 1 week before the start of the month	1.97	2.32	1.16	18.50
Average Maximum Temperature 1 week before the start of the month	27.95	2.76	27.95	26.95
Average Minimum Temperature 1 week before the start of the month	15.82	2.56	16.04	23.11
Average Maximum Temperature 2 weeks before the start of the month	27.96	2.61	27.93	25.00
Total Precipitation in cm 2 weeks before the start of the month	3.62	2.93	2.87	23.77
Average Minimum Temperature 2 weeks before the start of the month	15.86	2.44	16.07	18.57
Total Precipitation in cm 3 weeks before the start of the month	3.02	2.54	2.43	16.53
Average Maximum Temperature 3 weeks before the start of the month	28.09	2.77	28.07	26.01
Average Minimum Temperature 3 weeks before the start of the month	15.79	2.48	16.01	21.26
Total Precipitation in the Month Prior in cm	14.83	9.13	13.27	79.99
Average Maximum Temperature in the Prior Month (C)	27.96	2.53	27.98	23.49
Average Minimum Temperature in the Prior Month (C)	15.80	2.34	16.00	19.51

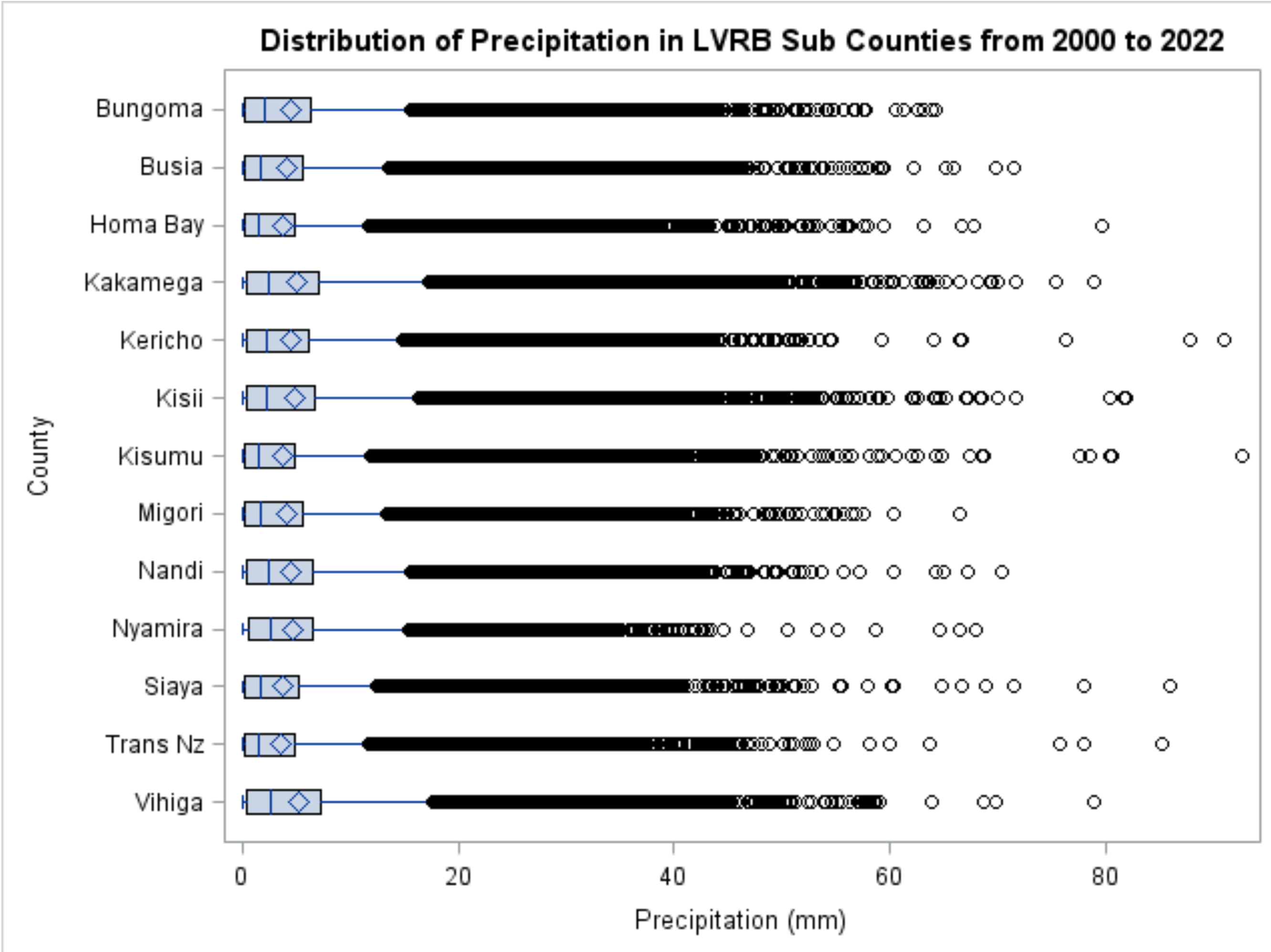

Figure 9. Daily precipitation by 13 LVRB counties from 2000 to 2022

The individual components of risk, exposure, hazard, and vulnerability have varying associations with rates of diarrheal disease under 5. Exposure is not associated with cases of diarrheal disease IRR (95%) of 0.512 (0.22, 1.20) (Table XXIX, Appendix D). While not associated, the hazard index is positively correlated with rates of diarrheal disease, Figure 12. Finally, vulnerability is positively associated with rates of diarrhea with an IRR of (95% CI) of 1.012 (1.00, 1.02) (Table XXIX, Appendix D). Predicted monthly case counts of diarrheal disease were estimated using time, season, and risk index. As seen in Figure 13, the predicted monthly case counts are similar to the observed, with a median of the 276 and 256 respectively and a mean Pearson residual of 0.003. When the rank of the observed total number of cases from 2014 to 2022 is compared to the predicted rank, there is a significant negative correlation with a p-value of <0.0001 and a moderately strong Spearman Rho of -0.40238. As seen in Table XIX, the average difference between observed and predicted ranking relatively large: 35 with a standard deviation of 24.

3. <u>Seasonality and Extreme Weather</u>

As seen in Figure 14, rates of diarrheal disease over and under the age of 5 vary significantly across the four historical seasons in Kenya, cool dry, warm dry, long wet, and short wet, with distinct peaks in the long wet and warm dry seasons. In comparison to the cool dry season, there is an increased risk of diarrheal disease in the warm dry and long wet seasons with an IRR of 1.291 and 1.171 respectively, seen in Table XXX, Appendix D The direction of this seasonality does not change across low, moderate, and high-risk sub-counties, but as seen in Table XXXI, Appendix D the magnitude of the association between long wet season and rates of diarrheal disease increases as risk increases, but this pattern does not hold for the other seasons.

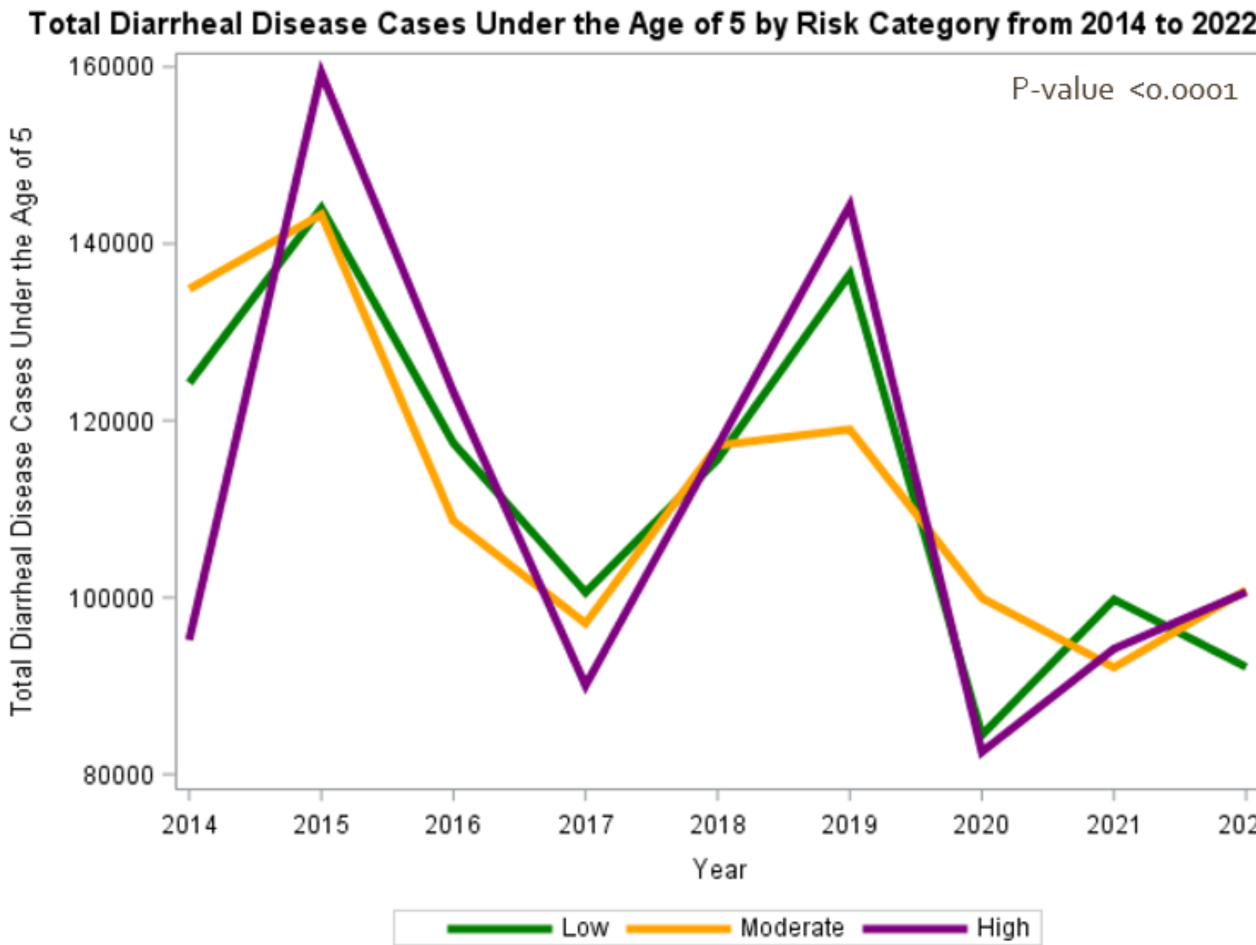

Figure 10. Total diarrheal disease cases under 5 in low, moderate and high - risk sub-counties from 2014 to 2022

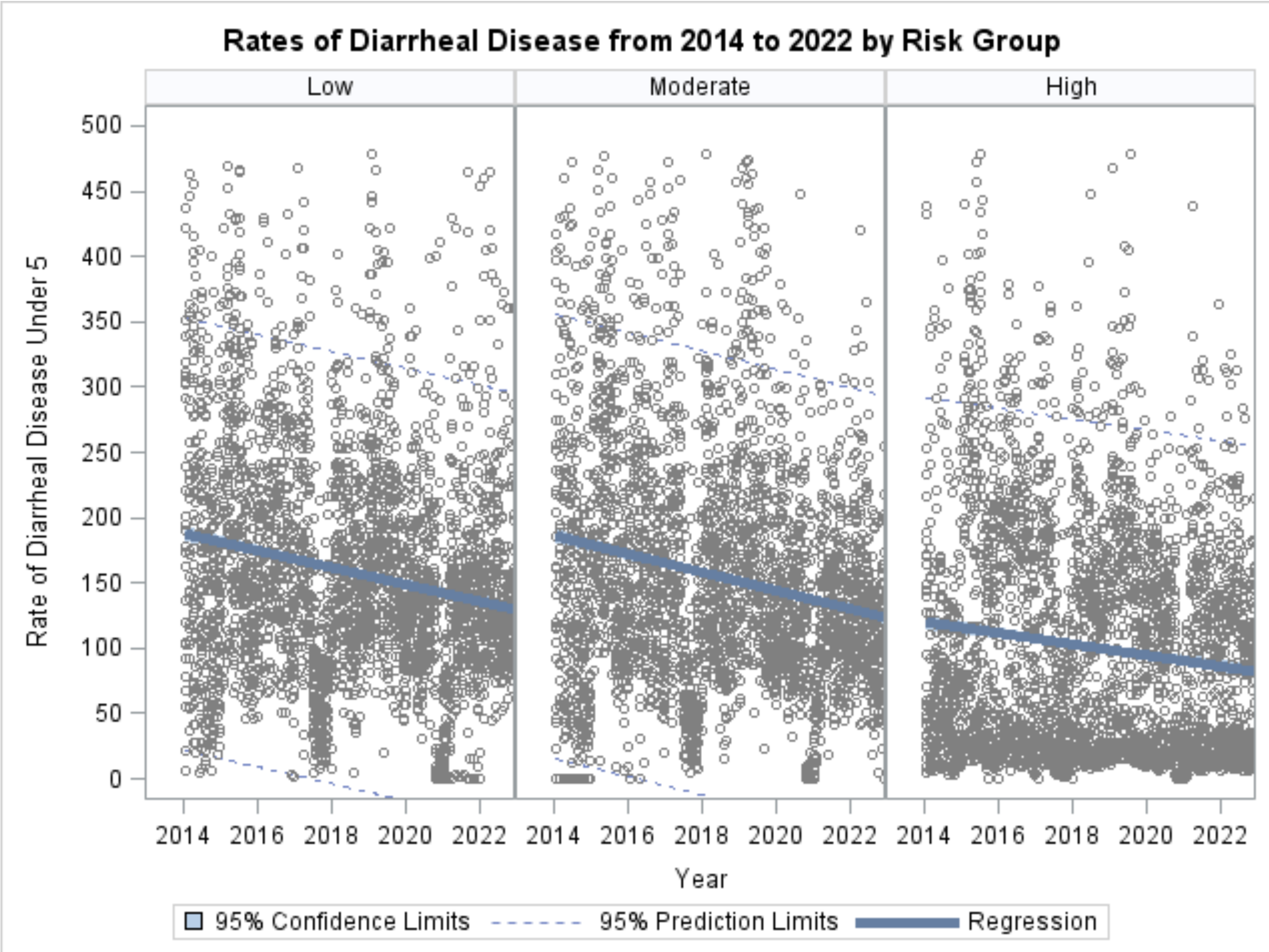

Figure 11. Rates of diarrheal disease from 2014 to 2022 by risk group

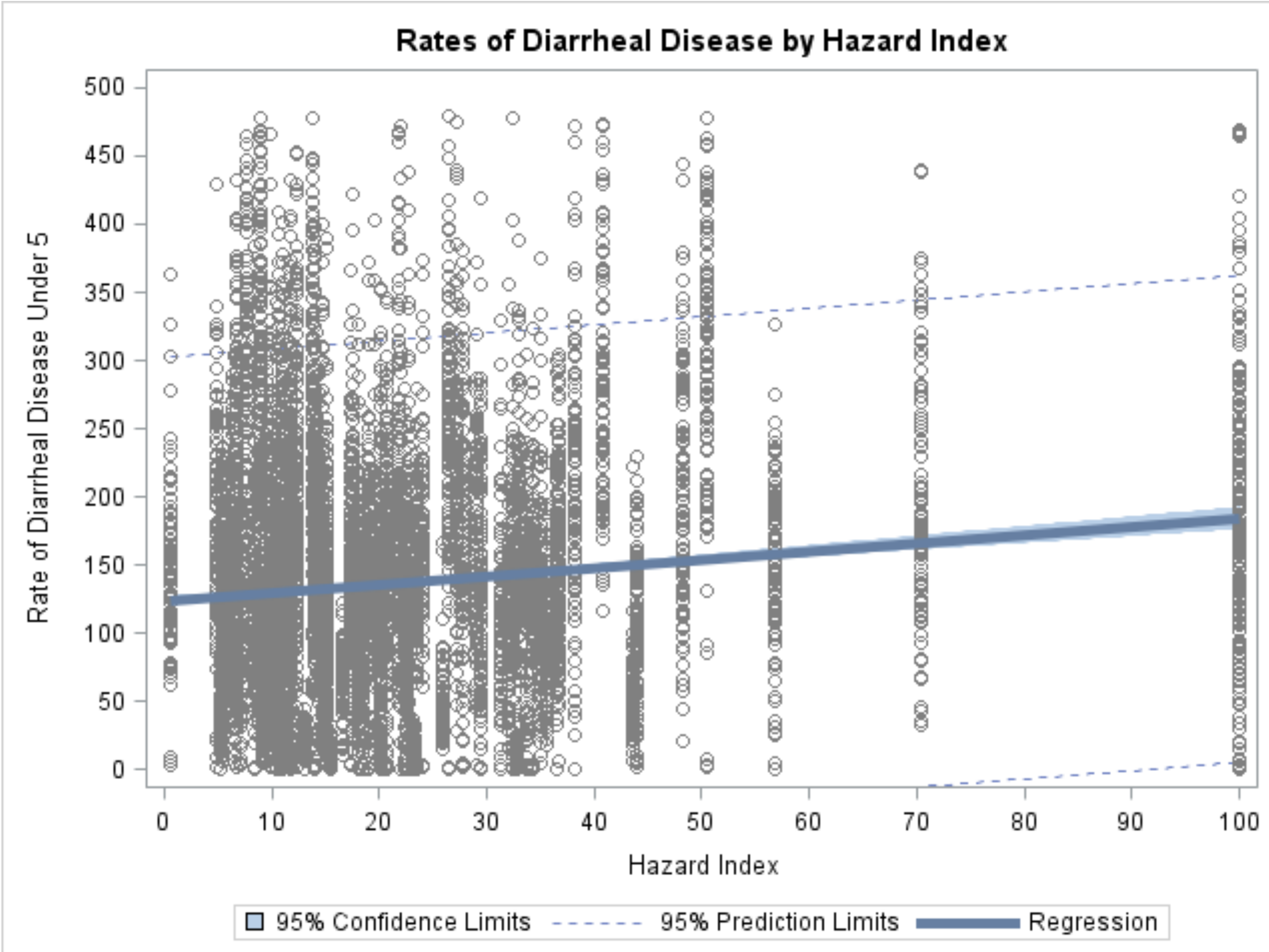

Figure 12. Association between rates of diarrheal disease under 5 and the hazard index

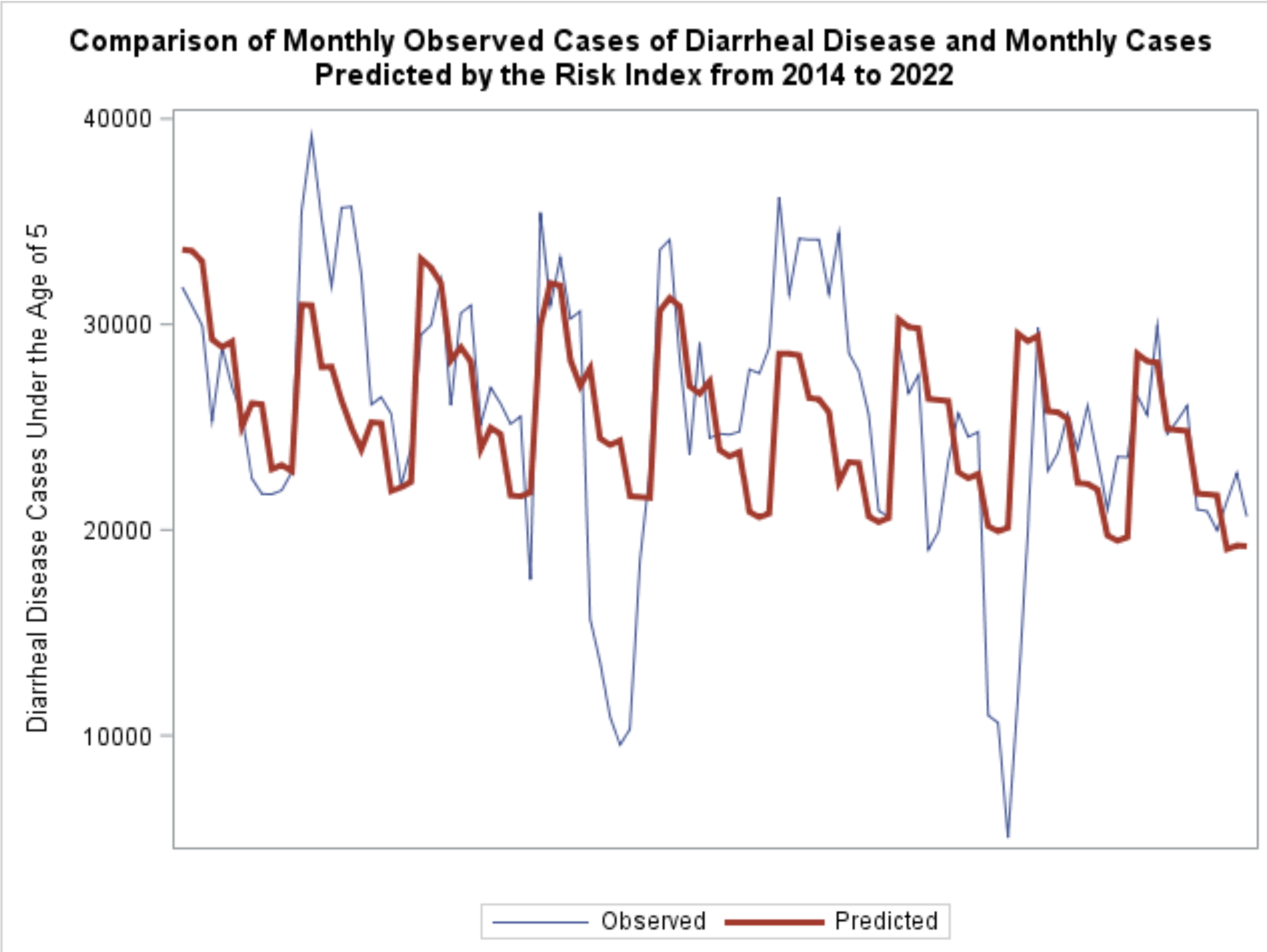

Figure 13. Predicted vs observed total monthly cases of diarrheal disease in the LVRB from 2014 to 2022

TABLE XIX. COMPARISON OF SUB-COUNTY RANK BASED ON OBSERVED AND PREDICTED TOTAL CASES OF DIARRHEAL DISEASE UNDER THE AGE OF 5 FROM 2014 TO 2022 (1 BEING THE HIGHEST, 99 BEING THE LOWEST)

County	Sub County	Observed Rank	Predicted Rank	County	Sub County	Observed Rank	Predicted Rank
Bungoma	Bumula	48	1	*Kisumu*	Kisumu Central	7	93
	Cheptais	50	82		Kisumu East	49	59
	Kabuchai	62	23		Kisumu West	58	18
	Kanduyi	3	87		Muhoroni	30	25
	Kimilili	53	32		Nyakach	52	28
	Mt. Elgon	59	53		Nyando	38	73
	Sirisia	63	38		Seme	61	55
	Tongaren	51	19	*Migori*	Awendo	79	4
	Webuye East	89	39		Kuria East	35	52
	Webuye West	81	20		Kuria West	11	27
Busia	Bunyala	65	5		Nyatike	31	71
	Butula	57	58		Rongo	67	70
	Matayos	1	90		Suna East	80	36
	Nambale	85	34		Suna West	77	41
	Samia	75	48		Uriri	70	54
	Teso North	33	63	*Nandi*	Aldai	40	76
	Teso South	25	10		Chesumei	15	79
Homa Bay	Homa Bay Town	41	6		Emgwen	29	61
	Kabondo Kasipul	60	57		Mosop	18	89
	Karachuonyo	34	14		Nandi East	10	84
	Kasipul	56	40		Tinderet	19	43
	Mbita	26	64	*Nyamira*	Borabu	71	16
	Ndhiwa	21	78		Manga	90	51
	Rangwe	44	37		Masaba North	82	42
	Suba	39	49		Nyamira	32	85
Kakamega	Butere	42	2		Nyamira North	74	29
	Ikolomani	73	24	*Siaya*	Alego Usonga	4	86

TABLE XIX. COMPARISON OF SUB-COUNTY RANK BASED ON OBSERVED AND PREDICTED TOTAL CASES OF DIARRHEAL DISEASE UNDER THE AGE OF 5 FROM 2014 TO 2022 (1 BEING THE HIGHEST, 99 BEING THE LOWEST) (CONTINUED)

County	Sub County	Observed Rank	Predicted Rank	County	Sub County	Observed Rank	Predicted Rank
	Khwisero	64	30		Bondo	23	77
	Likuyani	36	65		Gem	43	60
	Lugari	8	88		Rarieda	66	22
	Lurambi	2	91		Ugenya	83	31
	Malava	6	81		Ugunja	72	46
	Matungu	54	11		Cherangany	28	8
	Mumias East	78	62		Endebess	45	13
	Mumias West	84	35	*Trans Nzoia*	Kiminini	27	80
	Navakholo	46	72		Kwanza	20	21
	Shinyalu	47	74		Saboti	13	92
	Ainamoi	9	7		Emuhaya	93	12
	Belgut	24	83		Hamisi	68	17
	Bureti	17	94	*Vihiga*	Luanda	92	47
Kericho	Kipkelion East	12	15		Sabatia	94	33
	Kipkelion West	14	45		Vihiga	88	50
	Sigowet/Soin	5	75				
	Bobasi	16	3				
	Bomachoge Borabu	86	66				
	Bomachoge Chache	87	67				
	Bonchari	55	69				
Kisii	Kitutu Chache North	91	9				
	Kitutu Chache South	22	68				
	Nyaribari Chache	69	56				
	Nyaribari Masaba	76	44				
	South Mugirango	37	26				

The association between the number of same-month extreme rain days and rates of diarrheal disease is negative, IRR 0.975 (Table XXXIV, Appendix D). This association does not change when stratified by the risk index without the hazard component nor does it change substantially from one precipitation variable to another (Table XX). In contrast, the association between rates of diarrheal disease and temperature demonstrated a positive association (Table XX). While the association with extreme heat days does not change across risk tertile, the association with average maximum temperature and prior month average maximum temperature does change (Table XX). The positive association between previous month average maximum temperature and rates of diarrheal disease under 5 is only present for sub-counties designated as high risk by the risk index, IRR 1.034 (Table XLV, Appendix D).

Given the seasonality of rain in the LVRB of Kenya and the positive association between rates of diarrheal disease and extreme temperature, models of extreme heat were stratified by season.

shows the association between extreme heat days in the prior month and rates of diarrheal disease is highest in the long wet and short wet season, IRR (95% CI) of 1.008 (1.00, 1.01) and 1.009 (1.00, 1.02), respectively. Additionally, the strongest positive association between average maximum temperature and rates of diarrheal disease in the long wet and short wet seasons as well: IRR (95% CI) of 1.034 (1.02, 1.05) and 1.051 (1.02, 1.08), respectively (Table XLVIII, Appendix D). Because the designation of seasons (warm dry, etc) is based on temperature and precipitation, the seasonality of the association with extreme heat suggests an interaction effect between precipitation and temperature. Individually, the number of extreme precipitation days has a negative association with rates of diarrheal disease, IRR (95% CI) 0.977 (0.970, 0.984), and average maximum temperature in the prior month has a positive association, IRR (95% CI) 1.018 (1.004, 1.031) (Table XXI). Table XXII shows the association between rates of diarrheal disease and the interaction between extreme rain days and average maximum temperature in the prior month, IRR 1.006 (95% CI: 1.003, 1.008). When stratified by the risk index, Table LVI, Appendix D, there is no substantial difference in the association between rates of diarrheal disease and the interaction of extreme rain and previous month maximum temperature.

4. Specific Types of Diarrheal Disease

From 2014 to 2022 cases of cholera and dysentery remained relatively low and cases of typhoid decreased over time (Figure 15). The specific diseases varied significantly across sub-counties and seasons, with typhoid and dysentery varying significantly across low, moderate, and high-risk sub-counties. As seen in Figure 16, cases of typhoid increase as the risk index increases, with a p-value of <0.0001. In comparison to the overall associations between diarrheal disease and season, extreme precipitation and temperature, and average temperature and precipitation, disease specific analysis was not significantly different. Additionally, diarrheal disease cases over the age of 5 were explored but did not show any meaningful difference from the analysis presented above.

D. Discussion

The IPCC AR5 risk framework as implemented in this study was associated with the observed cases and rates of diarrheal disease at the sub-county level in the LVRB. Sub-counties in the top tertile of risk had the highest number of diarrheal disease cases from 2014 to 2022 with the lowest decline in cases over that time. This trend is also observed for the total cases of typhoid and among the > 5 years age category, suggesting that it is not very sensitive to changes in age group and disease type. The hazard component is one of the most crucial components of the index, with rates of diarrheal disease under 5 increasing as hazard index increases.

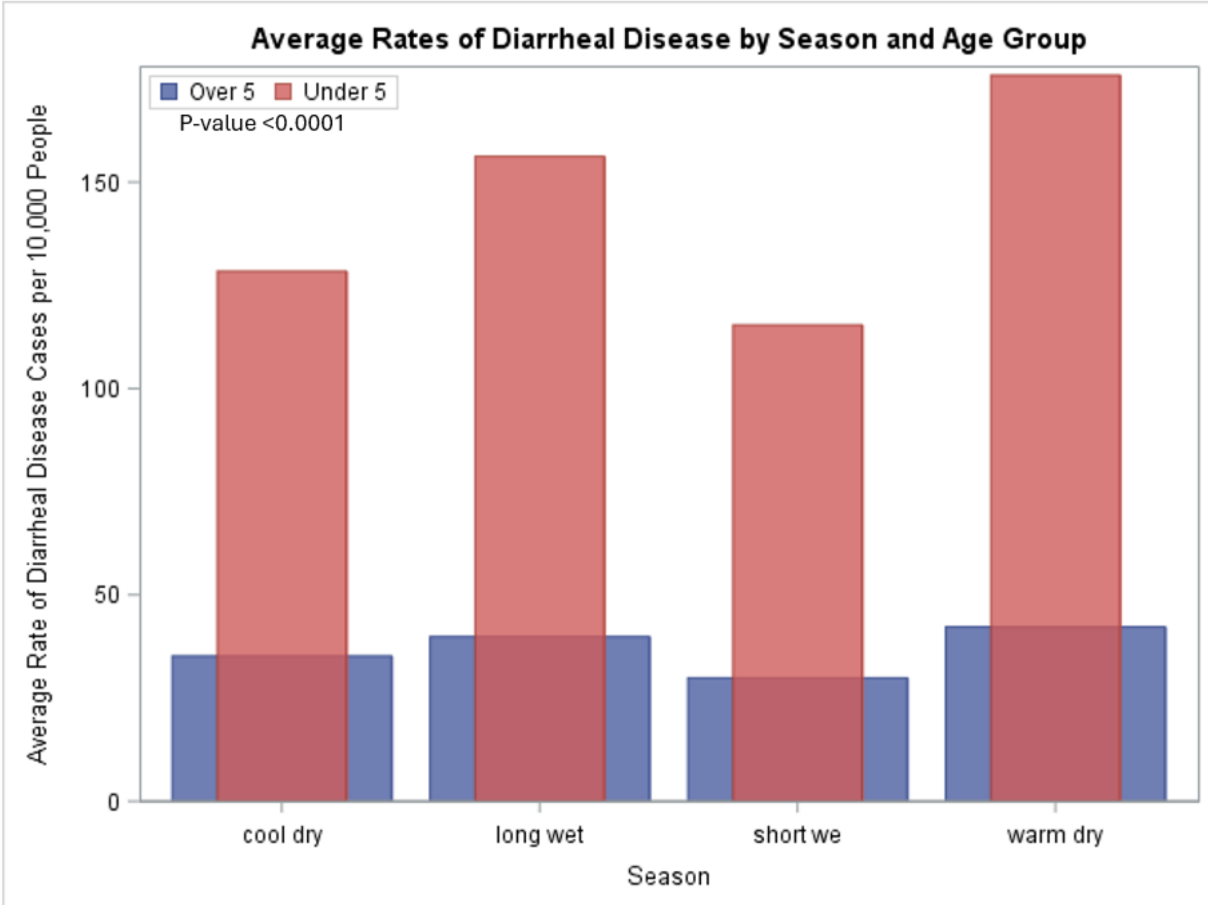

Figure 14. Rates of diarrheal disease by season and age group

TABLE XX. SUMMARY OF MODELING RESULTS

Variable	***Association without stratification (Table)***	***Stratified by***	***Stratified Association (Table)***
Season	↑ Long wet, warm Dry ↓ Short wet (Table XXVIII, Appendix D)	Risk tertile	No major difference (Table XXIX, Appendix D)
Monthly Total Precipitation	↓ (Table XXX, Appendix D)	Risk tertile	No major difference (Table XXXI, Appendix D)
Monthly Extreme rain days	↓ (Table XXXII, Appendix D)	Risk tertile	No major difference (Table XXXIII, Appendix D)
Prior month total precipitation	↓ (Table XXXVI, Appendix D)	Risk tertile	No major difference (Table XXXVII, Appendix D)
Prior month extreme rain days	↓ (Table XXXIV, Appendix D)	Risk tertile	No major difference (Table XXXV, Appendix D)
Total rainfall in the one week prior to the start of the month	↓ (Table XXXVIII, Appendix D)	Risk tertile	No major difference (Table XXXVIX, Appendix D)
Total rainfall two weeks before the start of the month	↓ (Table XL, Appendix D)	Risk tertile	No major difference (Table XLI, Appendix D)
Total rainfall three weeks before the start of the month	↓ (Table XLII, Appendix D)	Risk tertile	No major difference (Table XLIII, Appendix D)
Extreme Heat Days	↑ (Table XLVIII, Appendix D)	Risk tertile	No major difference (Table L, Appendix D)
Prior Month Extreme Heat Days	↑ (Table LI, Appendix D)	Risk tertile	No major difference (Table LIII, Appendix D)
Prior Month Extreme Heat Days	↑ (Table LI, Appendix D)	Season	Highest risk ratio in short wet and long wet seasons (Table LII, Appendix D)

TABLE XX. SUMMARY OF MODELING RESULTS (CONTINUED)

Variable	***Association without stratification (Table)***	***Stratified by***	***Stratified Association (Table)***
Average Maximum Temperature	↑ (Table XLIV, Appendix D)	Risk tertile	↑ only in highest risk tertile (Table XLV, Appendix D)
Average Maximum Temperature	↑ (Table XLIV, Appendix D)	Season	Highest risk ratio in short wet and long wet seasons (Table XLVI, Appendix D)
Prior Month Average Maximum Temperature	↑ (Table XLVII, Appendix D)	Risk tertile	↑ only in highest risk tertile (Table XLIX, Appendix D)
Number of Extreme Rain Days and Average Maximum Temperature in the Prior Month	↑ (Table XXII)	Risk tertile	No major difference (Table LIV, Appendix D)

TABLE XXI. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME PRECIPITATION AND HEAT IN THE PRIOR MONTH

Parameter	***Incidence Rate Ratio***	***95% Confidence Interval***		***P -value***
Intercept	1.008	0.664	1.529	0.9703
time	0.999	0.998	1.000	0.0064
Long Wet Season	1.143	1.093	1.195	<0.0001
Short Wet Season	0.902	0.866	0.940	<0.0001
Warm Dry Season	1.361	1.303	1.421	<0.0001
Number of Extreme Rain Days	0.977	0.970	0.984	<0.0001
Average Maximum Temperature in the Prior Month	1.018	1.004	1.031	0.0097

TABLE XXII. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND THE INTERACTION OF EXTREME PRECIPITATION AND HEAT IN THE PRIOR MONTH

Parameter	***Incidence Rate Ratio***	***95% Confidence Interval***		***P -value***
Intercept	1.419	0.871	2.313	0.1602
time	0.999	0.998	1.000	0.0088
Long Wet Season	1.140	1.090	1.193	<.0001
Short Wet Season	0.893	0.856	0.931	<.0001
Warm Dry Season	1.359	1.302	1.419	<.0001
Number of Extreme Rain Days	0.834	0.777	0.895	<.0001
Average Maximum Temperature in the Prior Month	1.005	0.989	1.022	0.5174
*Number of Extreme Rain Days * Average Maximum Temperature in the Prior Month*	1.006	1.003	1.008	<.0001

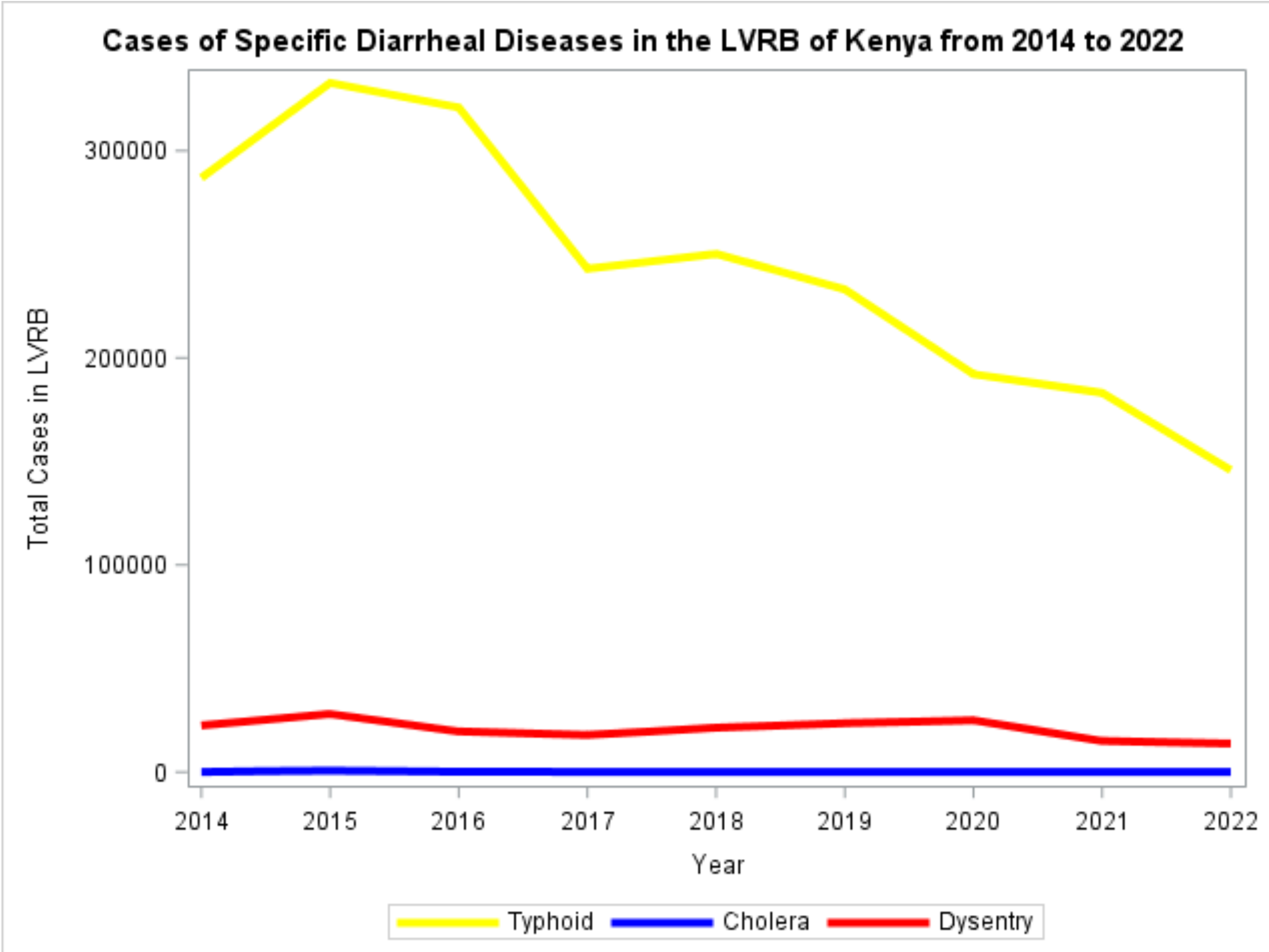

Figure 15. Total cases of specific diarrheal diseases from 2014 to 2022

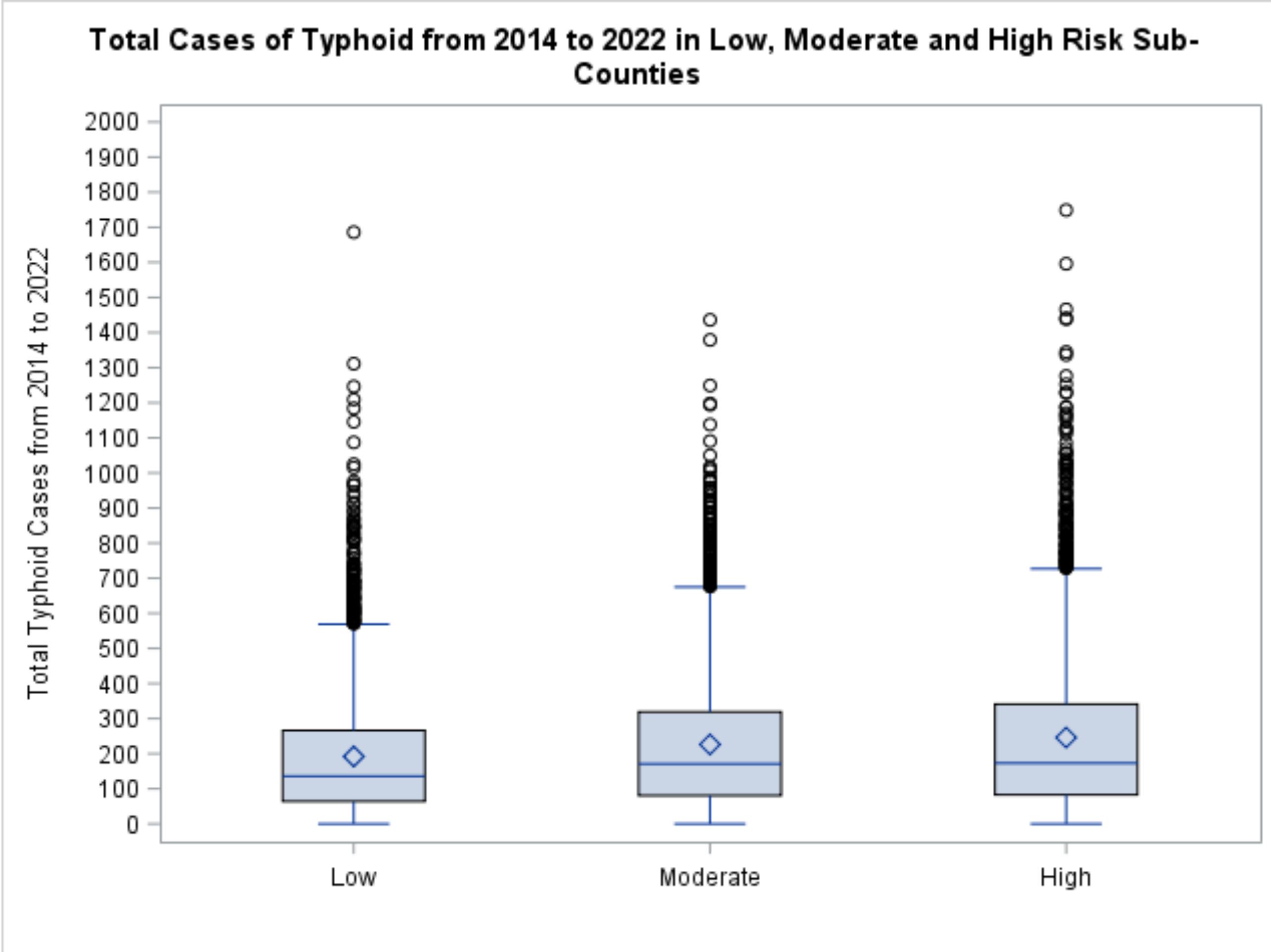

Figure 16. Distribution of cases of typhoid among low, moderate and high-risk sub-counties

Overall, when using the risk index, time, and season to model cases of diarrheal disease the predicted cases are similar to the observed, with a mean Pearson residual of 0.003 and standard deviation of 9. The observed ranking of sub-counties by total cases of diarrheal disease under the age of 5 was correlated with the predicted ranking. However, the average change in rank is 35 further demonstrates that the risk index as implemented here is an imperfect predictor of diarrheal disease cases at the subcounty level. Ranking of sub-counties is important for resource allocation and prioritization, given limited resources, funds, and capacity this helps guide health officials on where the aid is needed the most right now. The predictive nature of the risk index is also of use to the Ministry of Health and other stakeholders. For example, this is particularly useful to project future needs, develop early warning systems, explore how various climate scenarios will impact diarrheal disease and other prevention needs. Both the ranking and prediction value of the risk index is important for public health officials and other stakeholders. However, the predictive value of the risk index may be more important given its focus on prevention and prediction of future hotspots of diarrheal disease. This allows health officials to develop early warning systems and build adaptive capacity to the health impacts of climate hazards in the long run. The predictive ability of the risk index is not sensitive to several aspects of the research methodology. Specifically, modeling the association with risk rank, the risk index without the hazard component, and the vulnerability index have very similar results.

While risk indices for the association between diarrheal disease and extreme weather have not been evaluated before, our results align with epidemiological literature. For example, a recent study in Ghana found that education level of the mother, wealth index, living in a rural area, and having improved sanitation facilities had a significant association on individual cases of diarrheal disease in children under 5 (Kombat et al. 2024). Another study in Ethiopia, found that children living in households with more than 2 children and used unimproved drinking water sources were significantly more likely to develop acute diarrhea (Natnael, Lingerew, and Adane 2021). Health care access and utilization is crucial to prevent cases of diarrheal disease from becoming severe or causing death. For example, a recent study explored cases and deaths of diarrheal disease in LMICs and found that more cases and deaths occur among poor populations when vaccines and treatment are unavailable (Chang et al. 2018). The alignment with the literature suggests that our implementation of the AR5 risk index can estimate with some accuracy the risk of diarrheal disease at the sub-county level and includes key factors that fall on the causal pathway between extreme weather and diarrheal disease.

Kenya has four distinct seasons, cool dry, long wet, short wet, and warm dry. Our results demonstrate that in comparison to the cool dry season, rates of diarrheal disease under the age of 5 increase in the long wet and warm dry season. Additionally, the association between long wet season and rates of diarrheal disease increases in magnitude as the risk index increases, further suggesting that expected high risk sub-counties are at greater risk of diarrheal disease. In addition to season, there is an association between extreme weather and rates of diarrheal disease under the age of 5. The number of same-month extreme precipitation days has a negative association with rates of diarrheal disease, IRR of 0.977, across all risk groups. The average maximum temperature in the previous month has a positive association with rates of diarrheal disease, IRR 1.034, for the high-risk sub-counties. A recent study in Ethiopia found that for every one-millimeter increase in rainfall the cases of diarrheal disease under 5 increased by approximately 0.17%, and the warm dry season was associated with increased cases of diarrheal disease under 5 and for every one degree Celsius increased, cases increased by approximately 16.6% (Alemayehu et al. 2020). Additionally, there is a positive association between diarrheal disease and flooding, with many studies showing increased detection of *Escherichia coli* and *Vibrio cholera* during or after floods (Levy et al. 2016). Temperature has also been shown to have a strong positive association with diarrheal disease (Levy et al. 2016). Given the inverse association with precipitation and temperature in two of the risk groups, but the positive association with the warm dry season there may be a synergistic effect of temperature and precipitation on rates of diarrheal disease. The monthly average maximum temperature has the strongest association with rates of diarrheal disease in the short wet and long wet seasons. This synergistic effect of precipitation and temperature is further supported by the positive association between the interaction of extreme rain days and average maximum temperature in the prior month, IRR of 1.006. While the extreme precipitation association differs from the literature, the interaction of temperature and precipitation is in line with previous literature. Previous literature in LMICs has found a positive association between rainfall and diarrheal disease following a drought period and in the dry to wet transition seasons (Wang et al. 2022, Dimitrova et al. 2023, Levy et al. 2016).

This study has several limitations. First, as noted in the methods, the percentage of the county population that was under the age of 5 in 2022 was used to calculate rates of diarrheal disease on the sub-county level, potentially resulting in incorrect rates of diarrheal disease. However, we are aware of no reason to think that there are systematic differences in the percentage of the population below age 5 years among sub-counties within a given county. The temporal and spatial scale of the health and weather data may have influenced the results of this study. Previous studies have shown an average lag time of 0 to 4 weeks between precipitation and diarrheal disease, this lag time is not accurately accounted for in this study due to the use of monthly case counts (Carlton et al. 2013) . Sub-counties are relatively large areas, and therefore only population level conclusions can be drawn, given the ecological design of the study. Additionally, there was missing data present, Bomet county was missing entirely, and data was missing for Migori county for 2016. The diarrheal disease data used is likely incomplete, only individuals that went to a primary health care center are captured in this dataset. Finally, there are limitations to the risk index that was evaluated. The risk index was developed using data at both the county and sub-county level, potentially not capturing true inter county variability. As a result, the predicted cases of diarrheal disease may not capture true variability and cannot speak to individual level causation. Over the last decade, there have been a variety of changes to the sub-county boundaries potentially resulting in misclassification of risk if these boundaries do not represent the actual boundaries.

To our knowledge this is the first evaluation of a risk index developed following the IPCC AR5 risk framework by comparing predicted with observed health data. Our results are in line with previous literature in the United States, where census tracts with higher SVI had higher rates of emergency department visits in the 2 to 3 months following flooding, however, these results did not hold when exploring the period during flood, 1 month post flood, or for specific flood sensitive health outcomes (Ramesh et al. 2022). Similar to our findings, Ramesh et al. found that overall numbers of emergency department visits decreased the least in moderate and high vulnerability census tracts during the flood and 1 month post flood periods (Ramesh et al. 2022). Our results demonstrate positive associations between risk, temperature, temperature prior to precipitation, long wet and warm dry season, vulnerability, and hazard and negative associations with precipitation, short wet and cold dry season, as well as exposure with rates of diarrheal disease under 5 (Figure 17). The varying associations with weather and season tell us a lot about the predictors of diarrheal disease in this region of SSA. Like the literature, diarrheal disease follows a seasonal trend and is associated with increases in temperature. Unlike previous literature, precipitation is negatively associated with rates of diarrheal disease. However, the information on the association with precipitation following increases in temperature is important in understanding how climate change will impact diarrheal disease in this region. The positive associations between the risk index and component indices with rates of diarrheal disease is an important finding.

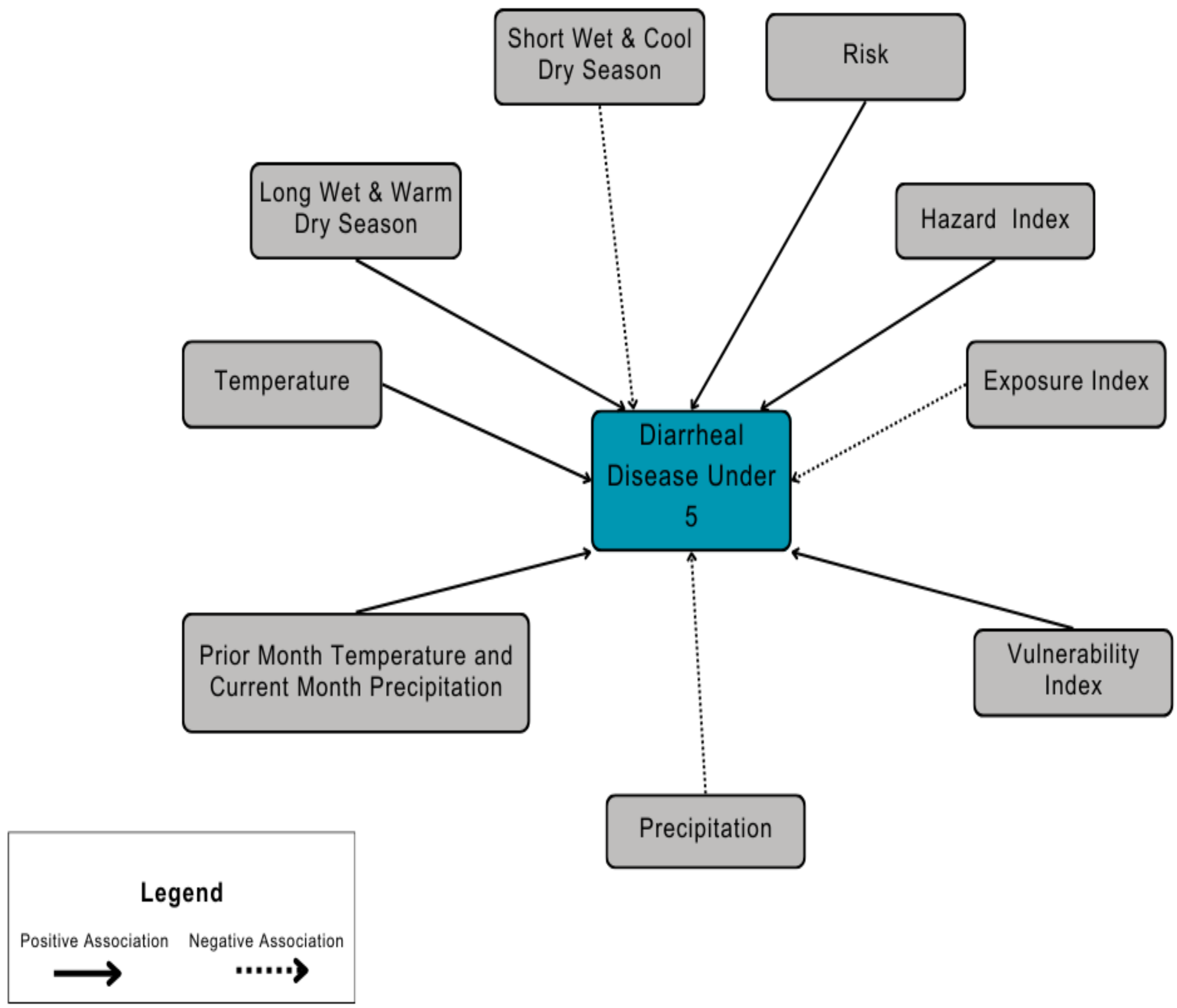

Figure 17. Conceptual model of the association between risk, weather and season with diarrheal disease under the age of 5 in the LVRB of Kenya from 2014 to 2022

The positive association between the hazard index, a function of temperature and precipitation, further supports the positive association with the interaction of temperature and precipitation seen in our results. Since the health outcome was rates of diarrheal disease, it is expected that there would be a negative association with exposure in the population that is exposed, since rates per population decrease as population increases. Finally, in line with the literature, vulnerability is positively associated with rates of diarrheal disease, which validates the use of vulnerability as an indicator when health data is not readily available.

Given this, risk indices developed following the IPCC AR5 framework may accurately represent health risk due to climate change when developed for a specific climate-sensitive health outcome. In low-resource settings, health data is hard to obtain, but demographic and social data are easier to obtain. As a result, the development of disease specific risk indices following the IPCC AR5 framework is a good tool to use in these settings. The risk index ultimately provides policy makers, public health officials, and other key stakeholders with a general sense as to where they should expect an increase in cases of diarrheal disease without the need for health data. This is important, as this index could provide an early warning identification of areas at risk and be useful in situations where health data is not readily available.

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V. DISCUSSION

Climate change is one of the greatest global health threats of our time and it is expected to disproportionately impact LMICS such as Kenya (Wright et al. 2021). Due to the impact of climate change on the upstream drivers of disease, the health risk of, and preparedness for, climate change varies on a subnational level. At the international level, HNAPS have been evaluated. Additionally, research in Botswana, Madagascar, Dominica, Brazil, and Kenya has been conducted to estimate vulnerability to climate change on a subnational level. While there is a framework for evaluating HNAPs, only five nations currently have such a framework, thus calling for a need to develop a framework of evaluation for existing subnational plans in Kenya. To date, most research on the vulnerability to the health impacts of climate change in LMICs has been based on the IPCC Assessment Report 4 (AR4) framework of vulnerability. The most up -to date framework by the IPCC, AR 5, is a framework of risk to a system and takes a more systems-based approach to understanding climate change and health risk on a subnational scale. For example, a research team in the Indian Bengal Delta compared the AR4 and AR5 framework on a subnational level and found that the AR5 framework was a better estimate of risk regarding climate change (Das et al. 2020). Additionally, the two climate change vulnerability assessments in Kenya do not assess vulnerability to the health impacts of climate change nor do they focus on a specific health outcome. The goal of this research is to develop a risk index of the impact of climate change on diarrheal disease on a subnational level in Kenya.

The specific aims of this research are intended to evaluate vulnerability to the health impacts of climate change, with a focus on diarrheal disease, on a subnational level in Kenya. First, we assessed the extent to which climate change and health are addressed in county-level integrated development plans. This was done by manually evaluating CIDPS for all 47 counties in Kenya based on the presence or absence of the joint consideration of climate change and health in all four sections of the CIDPs.

Next, we developed and evaluated a risk index based on the IPCC AR5 risk framework for risk of diarrheal disease following extreme weather. This risk index contains four components: exposure, hazard, sensitivity, and adaptive capacity. Component indices were developed from secondary data obtained from the Kenya National Bureau of Statistics, Demographic Health Survey, literature, and international data sources. Principal component analysis was used to identify meaningful subcomponents and to aggregate the data. Finally, we aimed to validate the risk index with historical diarrheal disease data. Using Poisson regression on the sub-county level we explored how well the risk index predicted observed cases of diarrhea, the association between rates of diarrheal disease and season, precipitation, and temperature and how these associations were modified by risk.

Kenya's CIDP's provide some insight into the extent that subnational planning documents can be used to evaluate preparedness of the health sector for climate change. While nearly all Kenyan CIDPs note climate change in the context of development, only half mention health in the context of climate change in the CIDP "County Description" section. When discussing health impacts of climate change, only 16 (34%) counties noted one or more specific climate-sensitive health outcomes. In the Development Priorities section, 12 (25.3%) counties had a sub-program for both adaptive capacity to climate change and environmental health. Further, 24 (51%) counties prioritized an environmental health subprogram and/or adaptation strategies in the health sector. While all 24 of these counties specified capacity building and scaling up public health interventions in the health sector, none specified conducting baseline risk and capacity assessments, less than 30% specified increasing research on climate change, integrating health into disaster risk reduction, and raise awareness. CHA scores show no clear spatial pattern and were not correlated with county level poverty rates. The use of existing planning processes, such as CIDPs, to prepare for climate change is consistent with the 2015-2030 Kenyan National Adaptation Plan which promoted the mainstreaming climate change adaptation into CIDPs. (Government of the Republic of Kenya 2016b) Additionally, strengthening integration of climate change adaptation into the health sector was specified, but this intervention has a miniscule budget compared to the other sector specific interventions, with a budget of $40 million USD compared to $20 billion USD in the infrastructure sector (Government of the Republic of Kenya 2016b).

Kenya is already facing the adverse impacts of climate change and these impacts are only expected to increase; the LVRB is especially susceptible to riverine flooding from precipitation (World Bank Group 2020). The developed risk index demonstrates the variability in risk of diarrheal disease from climate hazards on a sub-national scale. There is no clear north to south or east to west gradient but there is sub-national variability in both risk and the individual components. There is considerable heterogeneity within counties, for example the risk index for the 10 sub-counties within Bungoma county range from 0.53 to 39.22. Additionally, the PCA results and a priori analysis identified meaningful sub-components of each of the risk components. These sub-components are important as they demonstrate the need to utilize both priori knowledge and statistical analysis in the development of risk indices. Additionally, these results provide a framework for future risk indices focused on the health impacts of climate change in other settings. These sub-components are consistent with confounders – environment, precipitation, temperature – and effect modifiers – WASH, sensitive populations, education, poverty, health facilities – identified by epidemiological studies on the association between diarrheal disease and extreme precipitation (Levy et al. 2016, Carvajal-Vélez et al. 2016, Sumampouw, Nelwan, and Rumayar 2019, Kombat et al. 2024). These sub-components are critical to developing risk indices for the health impacts of climate change as there are many different factors that affect sensitivity, adaptive capacity, hazard, and exposure in different ways. These results demonstrate the need to identify and utilize specific sub-components in the development of risk indices for the health impacts of climate change. Additionally, the methods and results presented provide guidance to the general scientific community regarding the implementation of the IPCC AR5 risk framework on a subnational scale for specific climate-sensitive health outcomes.

The risk index developed based on the IPCC AR5 risk framework predicted diarrheal disease at the sub-county level in the LVRB. Overall, when using the risk index, time, and season to model cases of diarrheal disease the predicted cases are similar to the observed, with a mean Pearson residual of 0.003 and standard deviation of 9, the ranking of sub-counties by predicted risk differs from the ranking of sub-counties by observed cases of diarrheal disease in children. These results show that the risk index is a good predictor of observed cases of diarrheal disease under 5 though the variability of predicted cases is less than the variability in observed cases. Kenya has four distinct seasons, cool dry, long wet, short wet, and warm dry and our analysis demonstrated that rates of diarrheal disease under the age of 5 increase in the long wet and warm dry season in comparison to the cool dry season. Additionally, the association between warm dry season and rates of diarrheal disease increases in magnitude as the risk index increases, further suggesting that high risk sub-counties are at greater risk of diarrheal disease. Regarding the association between weather and rates of diarrheal disease under 5, a strong positive association with temperature and a negative association with precipitation was seen. To our knowledge this is the first evaluation of the IPCC AR5 risk framework with historical health data. However, our results are in line with previous literature in the United States, where census tracts with higher SVI had more all cause emergency department visits in the 2 to 3 months after the flooding, but this did not hold for flood-sensitive emergency department visits (insect bites, dehydration, intestinal infectious diseases, and pregnancy complications) (Ramesh et al. 2022). The IPCC AR5 framework may accurately represent health risk due to climate change when developed for a specific climate-sensitive health outcome. In low-resource settings, health data is hard to obtain, but demographic and social data is easier to obtain. As a result, the development of disease specific risk indices following the IPCC AR5 framework is a good tool to use in these settings.

Future research is needed to evaluate the extent to which this research extends beyond Kenya and to other climate-sensitive health outcomes. First, valid metrics of adaptive capacity that make use of readily available data are needed, this can be done by utilizing composite climate and health adaptation (CHA) scores as a predictor of other metrics of adaptive capacity in counties in Kenya. Secondly, to what extent the evaluation framework in chapter II. A FRAMEWORK FOR EVALUATING LOCAL ADAPTIVE CAPACITY TO HEALTH IMPACTS OF CLIMATE CHANGE: USE OF KENYA'S COUNTY-LEVEL INTEGRATED DEVELOPMENT PLANStransfers from CIDP's in Kenya to other subnational plans in SSA. This can be done by reapplying this framework to the next round of CIDP's or to other county level development plans in another SSA country. Additionally, the risk index developed in chapter III. CLIMATE AND HEALTH RISK INDEX FOR LAKE VICTORIA REGION ECONOMIC BLOCK SUB-COUNTIES IN KENYA should be expanded to the entire country and other climate-sensitive health outcomes in Kenya as well as other LMICs. Once developed, the risk index should be evaluated with historical health data to better understand the predictive abilities of the index. Ideally, risk and health data at a smaller spatial and temporal scale should be used to address the limitations of the research presented.

The results of the three aims of this study provide useful information to stakeholders in Kenya, LMICs and to the general scientific community. The framework of evaluation provides useful information on how the joint consideration of climate change and health is addressed in existing policies and plans in LMICs. The risk index ultimately provides policy makers, public health officials, and other key stakeholders with a general sense as to where they should expect an increase in cases of diarrheal disease. Additionally, the sub-components identified are useful for the creation of risk indices for other climate-sensitive health outcomes and other settings. The ability of the risk index to accurately predict cases of diarrheal disease is important as it supports the idea that risk indices accurately reflect risk. Additionally, this index could provide an early warning identification of areas at risk and in situations where health data is not readily available as the impacts of climate change increase in frequency, intensity, and duration.

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APPENDICES

Appendix A

Data Extraction Protocol from County IDP's

Binary Data Extraction:

Code: 1 = yes 0 = No

- Background Section:
  - Climate change is mentioned.
- Linkages to Other Plans:
  - Linked CIDP to sustainable development goal 13 (combating climate change and its effects)
  - Linked to Vision 2030 Medium Term Plans (MTP) III climate change goal.
- Last CIDP (2013-2017) Achievements:
  - Climate change is mentioned in health sector achievements.
  - Health mentioned in environment/climate change sector achievements.

Categorical Data Extraction:

- Background Section:
  - Environment/Climate Change section
    - Does not mention health = 0
    - Mentions the word health = 1
    - Mentions one specific health impact of climate change = 2
    - Mentions two or more specific health impacts of climate change = 3
- Current CIDP Sector Goals:
  - Health Sector goals:
    - Does not mention the environment/climate change = 0
    - Mentions the environment or climate change =1
    - Has a sub program on environmental health = 2
    - Has a full program on environmental health = 3
  - Health sector goals:
    - Count number of key outputs that would build AC in the health sector
      - Examples, connect to piped water, electricity, water storage tank, generator
  - Goal of building adaptive capacity to climate change
    - Does not have this goal = 0
    - The goal is mentioned =1
    - This goal is a sub program = 2
    - This goal is a full program = 3
  - Climate sensitive health impacts and health sector adaptive capacity goals
    - 0: did not mention adaptation strategies in the "key outcomes" or climate change-sensitive conditions or adaptation in the background
    - 1: did not mention adaptation strategies in key outcomes but mentioned (1 or more) climate-sensitive health conditions in background
    - 2: mentioned adaptation strategies in key outcomes but not climate-sensitive health conditions in background

Appendix A (Continued)

- 3: mentioned adaptation strategies in key outcomes and one or more climate-sensitive health conditions in background.

TABLE XXIII. CODEBOOK FOR CIDP EVALUATION

Variable Name	Description	Variable Type	Codes
CC_back	Mentions climate change in background	Binary	0 = no 1 = yes
CC_health	Mentions health within the cc/environmental section of the background	Binary	0 = no 1 = yes
SDG13	CIDP is linked to SDG 13	Binary	0 = no 1 = yes
MTPIII	CIDP is linked to MTP III climate change goal	Binary	0 = no 1 = yes
CC_h_achieve	Climate changed mentioned in health sector achievements.	Binary	0 = no 1 = yes
H_e_achieve	oHealth mentioned in environment/climate change sector achievements.	Binary	0 = no 1 = yes
Envr_health_goal	Health sector goal mentions the envir/cc	categorical	0 = Does not have this goal 1 = The goal is mentioned 2 = This goal is a sub program 3 = This goal is a full program
CC_AC_goal	Goal of building adaptive capacity to or mitigating climate change	categorical	4 = Does not have this goal 5 = The goal is mentioned

Appendix A (Continued)

TABLE XXIII. CODEBOOK FOR CIDP EVALUATION (CONTINUED)

Variable Name	Description	Variable Type	Codes
			6 = This goal is a sub program 7 = This goal is a full program
CS_healthimpacts	Number of specific climate sensitive health impacts listed in the cc/envr section of the background	Continuous	count
HS_keyoutputs_AC	Count number of key outputs that would build AC in the health sector	Continuous	Count
CS_HS	Climate sensitive health impacts and health sector adaptive capacity goals	categorical	0 = did not mention adaptation strategies in the "key outcomes" or climate change-sensitive conditions or adaptation in the background 1= did not mention adaptation strategies in key outcomes but mentioned (1 or more) climate-sensitive health conditions in background 2 = mentioned adaptation strategies in key outcomes but not climate-sensitive health conditions in background 3 = mentioned adaptation strategies in key outcomes and one or more climate-

Appendix A (Continued)

TABLE XXIII. CODEBOOK FOR CIDP EVALUATION (CONTINUED)

Variable Name	Description	Variable Type	Codes
			sensitive health conditions in background.

Appendix B

TABLE XXIV. CDC VULNERABILITY INDEX

SVI Component	**Indicator**	**Description**
Socioeconomic status	Below Poverty	Percent of persons below federally defined poverty line
	Unemployed	Percentage of civilians unemployed
	Income	The mean income computed for every person in the census tract
	No High School Diploma	Percent of persons 25 years or older with less than a 12th grade education
Household composition & disability	Aged 65 or older	Percent of people 65 or older
	Aged 17 or younger	Percent of people 17 or younger
	Civilian with a disability	Percent of the population over 5 years old with a disability
	Single-parent household	Percent of householders with no spouse and a child under 18
Minority status & language	Minority	Percent of the population that is a minority
	Aged 5 or Older who speaks English "less than well"	The total of all people who speak English not well or not at all
Housing Type & Transportation	Multi-unit structure	Percent housing units with 10 or more units in the structure
	Mobile home	Percent housing units that are mobile homes
	Crowding	Percent of the total occupied housing units with more than one person per room in the house
	No vehicle	Percentage of households with no vehicle available
	Group quarters	Percent of people who live in both institutionalized and non-institutionalized group quarters

Appendix B (Continued)

TABLE XXV. COVID-19 SEVI FOR KENYA

SEVI Component	Indicator	Description	Data Source	Spatial Resolution
Socioeconomic deprivation	Informal employment	Percent of adults (aged 15-49) who work in a manual labor profession such as construction worker and motor vehicle driver	Fraym	1X1 km
	Detergent Availability	Percent of households where no soap/detergent was observed	Fraym	1X1 km
	Car ownership	Percent living in a household that does not own a private car	Fraym	1X1 km
	Place for handwashing	Percent of households with no place for handwashing	Fraym	1X1 km
	Education attainment	Mean years of school/education attainment	Graetz et al.	5x5 km
	Unimproved water source	Proportion of households without access to improved water sources	Spatial DHS data from 2014	5x5 km
	Malnutrition	Prevalence of stunting among children	Osgood-Zimmerman, et al.,	5x5 km
	Poor households	Proportion of households within the poorest and poorer wealth quintile	DHS 2014	Subcounty
	Shared sanitation facilities	Percentage of households sharing a toilet facility	DHs 2014	Subcounty

Appendix B (Continued)

TABLE XXV. COVID-19 SEVI FOR KENYA (CONTINUED)

SEVI Component	Indicator	Description	Data Source	Spatial Resolution
Population Characteristics	Informal settlements	Percentage of people living in informal settlements and IDP camps	UNHCR SDI	
	Elderly population	Percentage of the population aged 65+ years	Pezzulo et al.	1x1 km
	Single-parent families	Percentage of the population headed by a single parent	DHS 2014	Subcounty
	Crowded households	Percentage in the population with 3+ persons per bedroom	DHS 2014	Subcounty
	Log population density	Log of the total population per unit area	KNBS 2019 Census	
	Urban Population	Proportion of population living in urban areas	KNBS 2019 Census	
Access to Services	Access to hospitals	Proportion of population outside 2 hours travel of a hospital	Ouma et al.	1x1 km
	Health workforce	Number of clinicians and medical officers per population	KNBS 2019 Census	
	Hospital beds	Number of hospital beds per population	KNBS 2019 Census	
	Access to urban areas	Travel time to the nearest urban centre with >= 5000 people	Nelson et al.	1x1 km
Epidemiological factors	HIV	HIV prevalence among adults	Dwyer-Lindgren et al.	5x5 km

Appendix B (Continued)

TABLE XXV. COVID-19 SEVI FOR KENYA (CONTINUED)

SEVI Component	Indicator	Description	Data Source	Spatial Resolution
	Smoking	Percentage of households with a daily or weekly smoker	Fraym	1x1 km
	Obesity	Percentage of adults categorized as obese	NCD survey 2015	County
	Diabetes	Percentage of adults diagnosed with diabetes	NCD survey 2015	County
	Hypertension	Percentage of adults diagnosed with high blood pressure	NCD survey 2015	County

Appendix B (Continued)

TABLE XXIV. STUDIES THAT HAVE DEVELOPED A RISK INDEX BASED ON THE IPCC AR5 FRAMEWORK

Authors	**Location and Scale**	**Climate Change Hazard**	**Health Outcome**	**Data Reduction Method Specifics**
Malakar et al	India coastal districts	Extreme events – cyclones, storm surges and high tides	None	Did not use PCA – used TOPSIS
Roy et al	Bangladesh Arial Khan River	Flood risk	None	Done on exposure and vulnerability, had very small loading scores, did do weighting with the factor loading score, used a different approach for hazard
Shah Et al	Indian Himalayan Districts	Variety of Extreme Events	Loss of human life is mentioned for justification of the hazards included	Used TOPSIS
Mahapatra et al	India	NA – they only looked at sensitivity and adaptive capacity	Womens reproductive health and childrens health	Did not use PCA or weighting
Estoque et al	Philippine cities	heat	Heat related adverse health outcomes	Did not use PCA or any statistical based weights
Ahmadalipour et al	Africa – focused on countries	Drought	None	Did not use PCA – instead did a variety of different weighting methods
Singha et al	West Bengal – district blocks	Drought	None	Did not use PCA or other weighting

Appendix B (Continued)

TABLE XXIV. STUDIES THAT HAVE DEVELOPED A RISK INDEX BASED ON THE IPCC AR5 FRAMEWORK (CONTINUED)

Authors	**Location and Scale**	**Climate Change Hazard**	**Health Outcome**	**Data Reduction Method Specifics**
Das et al	Indian Bengal Delta – sub districts	Climate variability and natural hazards	None	Run on the correlation matrix of all variables and categorized the variables into four factors – some of the variables were placed into categories that did not make sense, very high loading scores
Mondal et al	Indian Sundarban villages	Hydro-meteorological extreme events	None	Correlation matrix as input to PCA, large loading scores
Alam et al	Indian Himalayan Region – on the district level	Not specific	Not specific	Did pca and equal weights, ended up going with equal weights , pca weights were small
Gregor-Gaona et al	Mexico – municipalities in Mexico City	All	Not specific	Did not use pca, unsure how the index was created
Singha et al	West Bengal – district level	Drought	Not specific	PCA or other weighting was not used

Appendix C

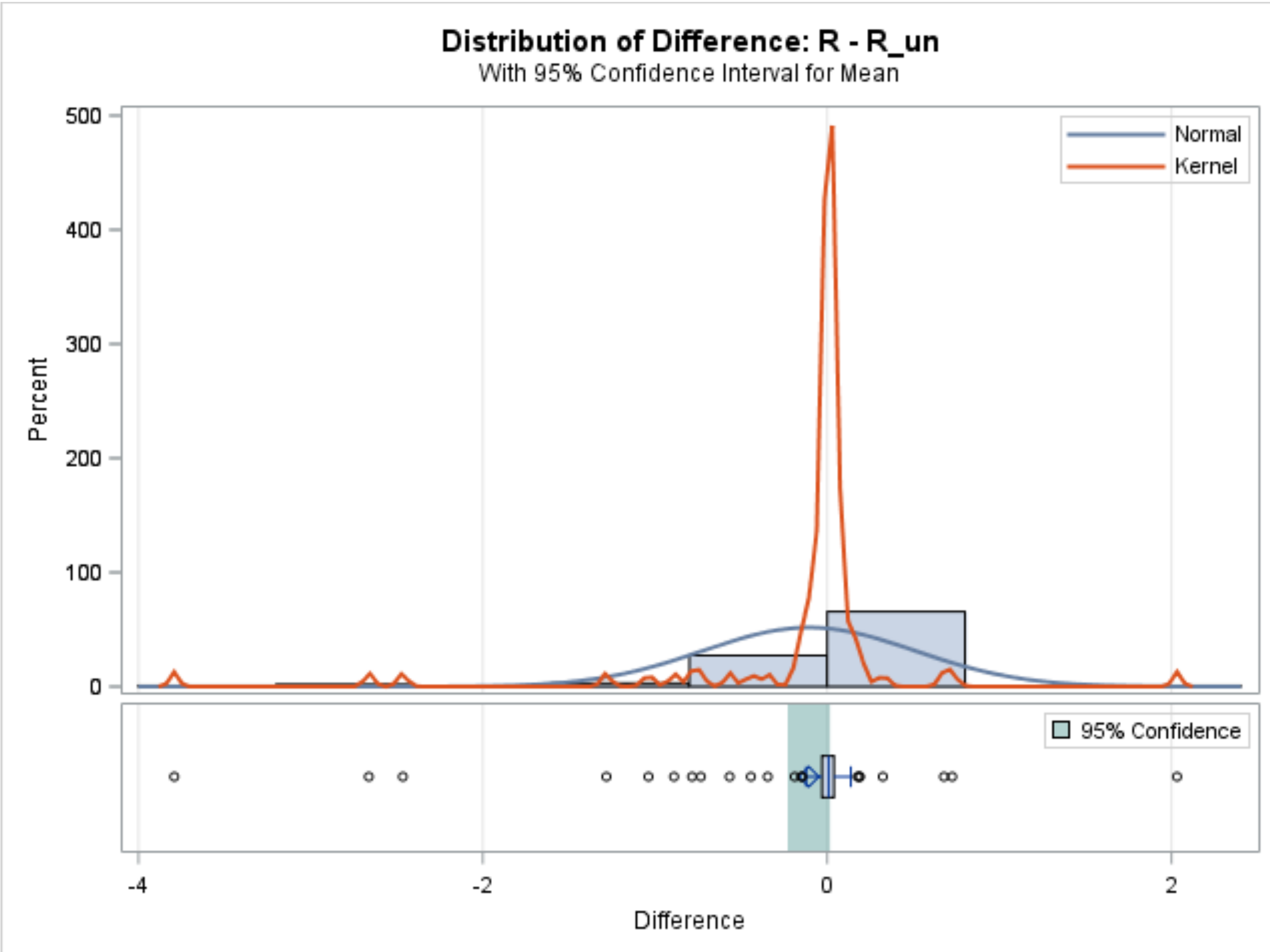

Figure 18. Difference between weighted and unweighted risk index

Appendix C (Continued)

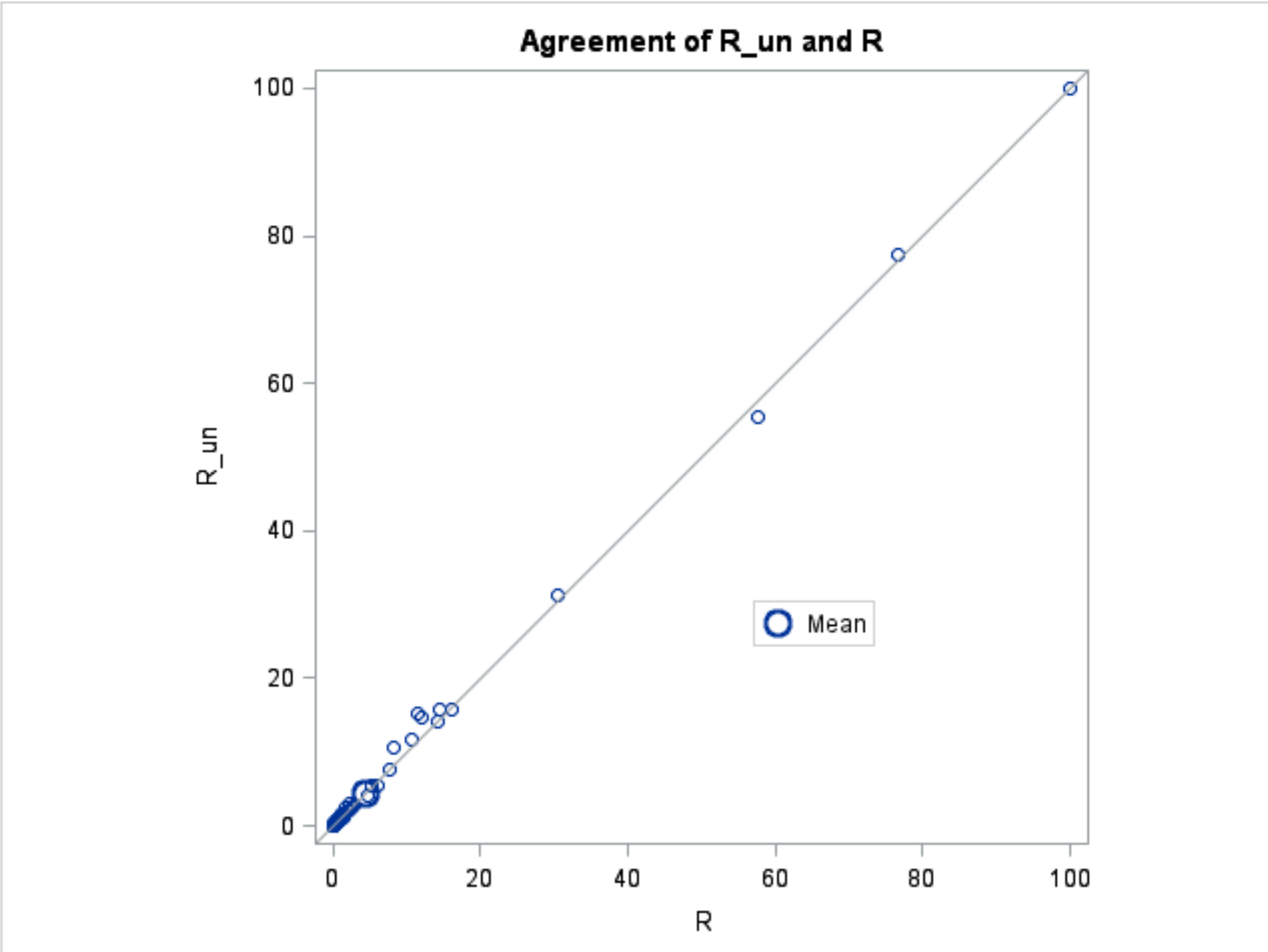

Figure 19. Agreement of weighted and unweighted risk index

Appendix C (Continued)

TABLE XXV. COMPARISON OF RISK RANK BASED ON WEIGHTED AND UNWEIGHTED RISK INDEX

Weighted Risk Rank	**Unweighted Risk Rank**			
	Low	Moderate	High	***Total***
Low	32	1	0	33
Moderate	1	31	1	33
High	0	1	32	33
Total	33	33	33	99

TABLE XXVI. COMPARISON OF WEIGHTED AND UNWEIGHTED VULNERABILITY INDEX RANK

Weighted Vulnerability Index Rank	**Unweighted Vulnerability Index Rank**			
	Low	Moderate	High	***Total***
Low	32	1	0	33
Moderate	1	31	1	33
High	0	1	32	33
Total	33	33	33	99

Appendix D

TABLE XXVII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 BY COMPONENT RISK INDICES

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	241.507	198.88	293.27	<0.0001
Time	0.998	1.00	1.00	<0.0001
Long Wet Season	1.189	1.15	1.23	<0.0001
Short Wet Season	0.890	0.87	0.91	<0.0001
Warm Dry Season	1.296	1.26	1.34	<0.0001
Exposure Index	0.512	0.22	1.20	0.1244
Hazard Index	1.132	0.77	1.67	0.5292
Vulnerability	1.012	1.00	1.02	0.0142

TABLE XXVIII. SEASONALITY OF RATES OF DIARRHEAL DISEASE UNDER 5

Parameters	*Incidence Rate Ratio*	*95% Confidence Interval*		*p-value*
Intercept	1.637	1.36	1.96	<0.0001
time	0.998	0.99	1.00	0.0005
Long Wet Season	1.171	1.13	1.22	<0.0001
Short Wet Season	0.886	0.85	0.92	<0.0001
Warm Dry Season	1.291	1.25	1.33	<0.0001

Appendix D (Continued)

TABLE XXIX. SEASONALITY OF RATES OF DIARRHEAL DISEASE UNDER 5 BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR**	**p-value**	**IRR**	**p-value**	**IRR**	**p-value**
Intercept	2.647 (2.23, 3.15)	<0.0001	2.097 (1.82, 2.42)	<0.0001	0.862 (0.57, 1.30)	0.4753
Time	0.998 (0.99, 1.00)	0.0031	0.998 (0.99, 1.00)	0.007	0.997 (0.99, 1.00)	0.0006
Long Wet Season	1.168 (1.11, 1.24)	<0.0001	1.174 (1.11, 1.24)	<0.0001	1.182 (1.08, 1.29)	0.0001
Short Wet Season	0.918 (0.87, 0.97)	0.001	0.858 (0.82, 0.89)	<0.0001	0.906 (0.81, 1.01)	0.0718
Warm Dry Season	1.298 (1.24, 1.36)	<0.0001	1.359 (1.29, 1.43)	<0.0001	1.203 (1.12, 1.29)	<.0001

TABLE XXX. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.773	1.47	2.14	<0.0001
Time	0.999	1.00	1.00	0.0094
Long Wet Season	1.148	1.10	1.20	<0.0001
Short Wet Season	0.898	0.86	0.93	<0.0001
Warm Dry Season	1.317	1.27	1.37	<0.0001
Total Precipitation (cm)	0.992	0.99	0.99	<0.0001

Appendix D (Continued)

TABLE XXXI. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION STRATIFIED BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.794 (2.32, 3.37)	<0.0001	2.305 (1.96, 2.70)	<0.0001	0.900 (0.6, 1.35)	0.6126
Time	0.998 (0.99, 1.00)	0.0118	0.999 (0.99, 1.00)	0.0701	0.998 (0.99, 1.00)	0.0038
Long Wet Season	1.211 (1.15, 1.28)	<0.0001	1.212 (1.15, 1.28)	<0.0001	1.120 (1.03, 1.22)	0.0105
Short Wet Season	0.931 (0.89, 0.98)	0.0039	0.853 (0.82, 0.88)	<0.0001	0.943 (0.86, 1.04)	0.233
Warm Dry Season	1.300 (1.24, 1.36)	<0.0001	1.321 (1.26, 1.39)	<0.0001	1.281 (1.14, 1.44)	<0.0001
Total Precipitation (cm)	0.994 (0.99, 1.00)	0.0002	0.991 (0.99, 0.99)	<0.0001	0.995 (0.99, 1.00)	0.001

Appendix D (Continued)

TABLE XXXII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND NUMBER OF EXTREME RAIN DAYS

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.645	1.37	1.98	<0.0001
Time	0.999	1.00	1.00	0.0077
Long Wet Season	1.147	1.10	1.20	<0.0001
Short Wet Season	0.901	0.87	0.94	<0.0001
Warm Dry Season	1.353	1.30	1.41	<0.0001
Number of Extreme Rain Days	0.976	0.97	0.98	<0.0001

Appendix D (Continued)

TABLE XXXIII. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME RAIN DAYS IN THE SAME MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.651 (2.22, 3.16)	<0.0001	2.113 (1.82, 2.45)	<0.0001	0.855 (0.57, 1.29)	0.4561
Time	0.998 (0.99, 1.00)	0.0144	0.999 (0.99, 1.00)	0.0479	0.998 (0.99, 1.00)	0.0032
Long Wet Season	1.206 (1.14, 1.27)	<0.0001	1.198 (1.13, 1.27)	<0.0001	1.124 (1.03, 1.23)	0.0112
Short Wet Season	0.932 (0.89, 0.98)	0.0049	0.856 (0.83, 0.89)	<0.0001	0.942 (0.85, 1.04)	0.2427
Warm Dry Season	1.326 (1.26, 1.39)	<0.0001	1.372 (1.30, 1.45)	<0.0001	1.304 (1.16, 1.46)	<0.0001
Number of Extreme Rain Days	0.978 (0.97, 0.99)	0.0001	0.972 (0.96, 0.98)	<0.0001	0.981 (0.97, 0.99)	<0.0001

Appendix D (Continued)

TABLE XXXIV. MODEL OF RATES OF DIARRHEAL DISEASE AND NUMBER OF EXTREME RAINFALL DAYS IN THE PRIOR MONTH

Parameter	**IRR**	***95% CI***		**P-value**
Intercept	1.639	1.36	1.97	<0.0001
Time	0.999	1.00	1.00	0.0044
Long Wet Season	1.169	1.12	1.22	<0.0001
Short Wet Season	0.910	0.88	0.95	<0.0001
Warm Dry Season	1.326	1.27	1.38	<0.0001
Number of Extreme Rainfall Days in the Prior Month	0.979	0.97	0.99	<0.0001

Appendix D (Continued)

TABLE XXXV. MODEL OF RATES OF DIARRHEAL DISEASE AND NUMBER OF EXTREME RAINFALL DAYS IN THE PRIOR MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.639 (2.21, 3.15)	<0.0001	2.104 (1.81, 2.44)	<0.0001	0.860 (0.57, 1.30)	0.4707
Time	0.998 (0.99, 1.00)	0.0112	0.999 (0.99, 1.00)	0.0245	0.998 (0.99, 1.00)	0.0029
Long Wet Season	1.218 (1.15, 1.29)	<0.0001	1.205 (1.14, 1.28)	<0.0001	1.144 (1.05, 1.24)	0.0012
Short Wet Season	0.939 (0.89, 0.99)	0.0124	0.865 (0.83, 0.90)	<0.0001	0.948 (0.86, 1.04)	0.257
Warm Dry Season	1.318 (1.26, 1.38)	<0.0001	1.362 (1.29, 1.44)	<0.0001	1.256 (1.13, 1.39)	<0.0001
Number of Extreme Rainfall Days in the Prior Month	0.980 (0.97, 0.99)	0.0002	0.980 (0.97, 0.99)	0.0013	0.980 (0.97, 0.99)	0.0018

Appendix D (Continued)

TABLE XXXVI. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE PRIOR MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.805	1.49	2.19	<0.0001
Time	0.999	1.00	1.00	0.0142
Long Wet Season	1.194	1.15	1.24	<0.0001
Short Wet Season	0.932	0.89	0.97	0.0007
Warm Dry Season	1.296	1.24	1.36	<0.0001
Total Precipitation in the Prior Month (cm)	0.990	0.99	0.99	<0.0001

Appendix D (Continued)

TABLE XXXVII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE PRIOR MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.850 (2.37, 3.43)	<0.0001	2.323 (1.98, 2.73)	<0.0001	0.938 (0.62, 1.42)	0.7638
Time	0.998 (0.99, 1.00)	0.0171	0.999 (0.99, 1.00)	0.5655	0.998 (0.99, 1.00)	0.0049
Long Wet Season	1.254 (1.19, 1.32)	<0.0001	1.244 (1.18, 1.31)	<0.0001	1.169 (1.07, 1.27)	0.0003
Short Wet Season	0.959 (0.91, 1.01)	0.0919	0.878 (0.85, 0.91)	<0.0001	0.969 (0.88, 1.06)	0.5016
Warm Dry Season	1.286 (1.22, 1.35)	<0.0001	1.309 (1.24, 1.38)	<0.0001	1.257 (1.12, 1.41)	<0.0001
Total Precipitation in the Prior Month (cm)	0.992 (0.99, 1.00)	<0.0001	0.990 (0.99, 1.00)	<0.0001	0.991 (0.99, 1.00)	<0.0001

Appendix D (Continued)

TABLE XXXVIII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE ONE WEEK PRIOR TO THE START OF THE MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.661	1.38	2.01	<0.0001
Time	0.999	1.00	1.00	0.0055
Long Wet Season	1.137	1.09	1.19	<0.0001
Short Wet Season	0.898	0.87	0.93	0.0007
Warm Dry Season	1.318	1.27	1.37	<0.0001
Total Precipitation in the One Week Prior to the Start of the Month (cm)	0.982	0.98	0.99	<0.0001

TABLE XXXIX. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE ONE WEEK PRIOR TO THE START OF THE MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.656 (2.21, 3.19)	<0.0001	2.141 (1.84, 2.49)	<0.0001	0.876 (0.58, 1.33)	0.5365
Time	0.998 (0.99, 1.00)	0.0166	0.999 (0.99, 1.00)	0.0185	0.998 (0.99, 1.00)	0.0054
Long Wet Season	1.189 (1.12, 1.26)	<0.0001	1.182 (1.12, 1.25)	<0.0001	1.110 (1.02, 1.21)	0.0164
Short Wet Season	0.922 (0.88, 0.97)	0.001	0.858 (0.83, 0.89)	<0.0001	0.952 (0.86, 1.05)	0.3189
Warm Dry Season	1.312 (1.25, 1.38)	<0.0001	1.354 (1.28, 1.43)	<0.0001	1.245 (1.11, 1.40)	0.0002
Total Precipitation in the One Week Prior to the Start of the Month (cm)	0.983 (0.98, 0.99)	<0.0001	0.981 (0.97, 0.99)	<0.0001	0.979 (0.97, 0.99)	<0.0001

Appendix D (Continued)

TABLE XL. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE SECOND WEEK PRIOR TO THE START OF THE MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.641	1.36	1.98	<0.0001
Time	0.998	1.00	1.00	0.0013
Long Wet Season	1.144	1.10	1.19	<0.0001
Short Wet Season	0.909	0.88	0.94	<0.0001
Warm Dry Season	1.337	1.28	1.39	<0.0001
Total Precipitation in the Second Week Prior to the Start of the Month (cm)	0.995	0.99	1.00	0.0071

Appendix D (Continued)

TABLE XLI. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE SECOND WEEK PRIOR TO THE START OF THE MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.651 (2.20, 3.19)	<0.0001	2.125 (1.83, 2.47)	<0.0001	0.860 (0.57, 1.31)	0.4816
Time	0.998 (0.99, 1.00)	0.01	0.998 (0.99, 1.00)	0.008	0.998 (0.99, 1.00)	0.0016
Long Wet Season	1.195 (1.13, 1.26)	<0.0001	1.176 (1.11, 1.25)	<0.0001	1.127 (1.04, 1.22)	0.0038
Short Wet Season	0.929 (0.88, 0.98)	0.0037	0.863 (0.83, 0.90)	<0.0001	0.970 (0.88, 1.07)	0.5444
Warm Dry Season	1.316 (1.25, 1.39)	<0.0001	1.362 (1.29, 1.44)	<0.0001	1.285 (1.16, 1.43)	<0.0001
Total Precipitation in the Second Week Prior to the Start of the Month (cm)	0.992 (0.99, 1.00)	0.0036	0.995 (0.99, 1.00)	0.1738	0.994 (0.99, 1.00)	0.0812

Appendix D (Continued)

TABLE XLII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE THIRD WEEK PRIOR TO THE START OF THE MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.705	1.41	2.06	<0.0001
Time	0.999	1.00	1.00	0.008
Long Wet Season	1.138	1.09	1.19	<0.0001
Short Wet Season	0.891	0.86	0.93	<0.0001
Warm Dry Season	1.315	1.26	1.37	<0.0001
Total Precipitation in the Third Week Prior to the Start of the Month (cm)	0.979	0.97	0.99	<0.0001

Appendix D (Continued)

TABLE XLIII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND TOTAL PRECIPITATION IN THE THIRD WEEK PRIOR TO THE START OF THE MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.687 (2.23, 3.24)	<0.0001	2.185 (1.87, 2.55)	<0.0001	0.887 (0.58, 1.34)	0.5704
Time	0.998 (0.99, 1.00)	0.0178	0.999 (1.00, 1.00)	0.029	0.998 (0.99, 1.00)	0.004
Long Wet Season	1.191 (1.13, 1.26)	<0.0001	1.191 (1.12, 1.26)	<0.0001	1.119 (1.02, 1.22)	0.0131
Short Wet Season	0.931 (0.88, 0.98)	0.0067	0.867 (0.83, 0.90)	<0.0001	0.929 (0.84, 1.03)	0.1643
Warm Dry Season	1.307 (1.24, 1.37)	<0.0001	1.338 (1.27, 1.41)	<0.0001	1.273 (1.15, 1.41)	<0.0001
Total Precipitation in the Third Week Prior to the Start of the Month (cm)	0.984 (0.98, 0.99)	0.0007	0.979 (0.97, 0.99)	<0.0001	0.984 (0.97, 1.00)	0.0075

Appendix D (Continued)

TABLE XLIV. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND MONTHLY AVERAGE MAXIMUM TEMPERATURE

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	0.760	0.49	1.17	0.2152
Time	0.998	1.00	1.00	0.0009
Long Wet Season	1.151	1.10	1.20	<0.0001
Short Wet Season	0.909	0.87	0.95	<0.0001
Warm Dry Season	1.307	1.25	1.37	<0.0001
Monthly Average Maximum Temperature	1.027	1.01	1.04	0.0002

Appendix D (Continued)

TABLE XLV. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND MONTHLY AVERAGE MAXIMUM TEMPERATURE BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.902 (1.36, 6.18)	0.0057	2.517 (1.39, 4.57)	0.0024	0.284 (0.15, 0.55)	0.0002
Time	0.998 (0.99, 1.00)	0.0027	0.998 (0.99, 1.00)	0.0058	0.998 (0.99, 1.00)	0.0016
Long Wet Season	1.169 (1.10, 1.24)	<.0001	1.159 (1.09, 1.23)	<.0001	1.144 (1.04, 1.25)	0.0043
Short Wet Season	0.926 (0.88, 0.97)	0.0025	0.861 (0.83, 0.89)	<.0001	0.954 (0.87, 1.05)	0.3212
Warm Dry Season	1.330 (1.23, 1.44)	<.0001	1.385 (1.30, 1.47)	<.0001	1.243 (1.10, 1.40)	0.0004
Monthly Average Maximum Temperature	0.996 (0.97, 1.02)	0.7915	0.994 (0.97, 1.01)	0.526	1.039 (1.02, 1.06)	<0.0001

Appendix D (Continued)

TABLE XLVI. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND AVERAGE MAXIMUM TEMPERATURE BY SEASON

	Cool Dry		***Long Wet***		***Short Wet***		***Warm Dry***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	6.63 (3.30, 13.31)	<0.0001	0.758 (0.50, 1.14)	0.1849	0.349 (0.15, 0.79)	0.012	1.156 (0.77, 1.73)	0.478
Time	0.999 (0.99, 1)	0.01	0.998 (0.99, 1)	<0.0001	0.999 (0.99, 1)	0.046	0.997 (0.99, 1)	<0.0001
Average Maximum Temperature	0.949 (0.93, 0.97)	<0.0001	1.034 (1.02, 1.05)	<0.0001	1.051 (1.02, 1.08)	0.001	1.024 (1.01 ,1.04)	0.0002

Appendix D (Continued)

TABLE XLVII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME HEAT DAYS

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	0.929	0.62	1.40	0.7261
Time	0.998	1.00	1.00	0.0004
Long Wet Season	1.134	1.08	1.19	<0.0001
Short Wet Season	0.909	0.87	0.95	<0.0001
Warm Dry Season	1.355	1.30	1.41	<0.0001
Monthly Average Maximum Temperature in the Previous Month	1.020	1.01	1.03	0.0033

TABLE XLVIII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND MONTHLY AVERAGE MAXIMUM TEMPERATURE IN THE PREVIOUS MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.600	1.33	1.93	<0.0001
Time	0.998	1.00	1.00	0.0005
Long Wet Season	1.143	1.09	1.20	<0.0001
Short Wet Season	0.905	0.87	0.94	<0.0001
Warm Dry Season	1.303	1.25	1.36	<0.0001
Number of Extreme Heat Days	1.009	1.01	1.01	<0.0001

Appendix D (Continued)

TABLE XLIX. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND PREVIOUS MONTH AVERAGE MAXIMUM TEMPERATURE BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	3.199 (1.59, 6.45)	0.0012	2.918 (1.62, 5.24)	0.0003	0.324 (0.17, 0.61)	0.0004
Time	0.998 (0.99, 1.00)	0.002	0.998 (0.99, 1.00)	0.0024	0.998 (0.99, 1.00)	0.0008
Long Wet Season	1.176 (1.11, 1.25)	<0.0001	1.172 (1.10, 1.25)	<0.0001	1.135 (1.04, 1.24)	0.0067
Short Wet Season	0.927 (0.88, 0.98)	0.004	0.865 (0.83, 0.90)	<0.0001	0.965 (0.88, 1.06)	0.4632
Warm Dry Season	1.340 (1.25, 1.44)	<0.0001	1.405 (1.33, 1.49)	<0.0001	1.326 (1.18, 1.49)	<0.0001
Previous Month Average Maximum Temperature	0.993 (0.97, 1.02)	0.5729	0.988 (0.97, 1.01)	0.2433	1.034 (1.02, 1.05)	0.0001

Appendix D (Continued)

TABLE L. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME HEAT DAYS BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.598 (2.18, 3.10)	<0.0001	2.073 (1.78, 2.42)	<0.0001	0.830 (0.55, 1.25)	0.3762
Time	0.998 (0.99, 1.00)	0.0039	0.998 (0.99, 1.00)	0.0148	0.997 (0.99, 1.00)	0.0008
Long Wet Season	1.174 (1.11, 1.25)	<0.0001	1.166 (1.10, 1.24)	<0.0001	1.132 (1.04, 1.24)	0.0066
Short Wet Season	0.926 (0.88, 0.97)	0.003	0.858 (0.83, 0.89)	<0.0001	0.956 (0.87, 1.06)	0.3724
Warm Dry Season	1.278 (1.21, 1.35)	<0.0001	1.347 (1.27, 1.43)	<0.0001	1.278 (1.15, 1.42)	<0.0001
Number of Extreme Heat Days	1.007 (1.00, 1.01)	0.0013	1.005 (1.00, 1.01)	0.08	1.006 (1.00, 1.01)	0.0144

Appendix D (Continued)

TABLE LI. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME HEAT DAYS IN THE PRIOR MONTH

Parameter	***IRR***	***95% CI***		***P-value***
Intercept	1.606	1.33	1.93	<0.0001
Time	0.998	1.00	1.00	0.0005
Long Wet Season	1.125	1.08	1.17	<0.0001
Short Wet Season	0.907	0.87	0.94	<0.0001
Warm Dry Season	1.341	1.29	1.39	<0.0001
Number of Extreme Heat Days in the Prior Month	1.006	1.00	1.01	<0.0001

Appendix D (Continued)

TABLE LII. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME HEAT DAYS IN THE PRIOR MONTH BY SEASON

	Cool Dry		***Long Wet***		***Short Wet***		***Warm Dry***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	1.556 (1.29, 1.88)	<0.0001	1.909 (1.60, 2.28)	<0.0001	1.383 (1.14, 1.68)	0.001	2.188 (1.82, 2.63)	<0.0001
Time	0.999 (0.998, 1)	0.071	0.998 (0.99, 1)	<0.0001	0.999 (0.99, 1)	0.032	0.997 (0.99, 1)	<0.0001
Extreme Heat Days in the Prior Month	1.002 (0.99, 1.01)	0.70	1.008 (1.00, 1.01)	<0.0001	1.009 (1.00, 1.02)	0.019	1.004 (1.00 ,1.01)	0.0014

Appendix D (Continued)

TABLE LIII. MODEL OF RATES OF DIARRHEAL DISEASE UNDER 5 AND EXTREME HEAT DAYS IN THE PRIOR MONTH BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	2.614 (2.19, 3.12)	<0.0001	2.097 (1.80, 2.44)	<0.0001	0.830 (0.55, 1.26)	0.3782
Time	0.998 (0.99, 1.00)	0.0037	0.998 (0.99, 1.00)	0.0087	0.997 (0.99, 1.00)	0.0007
Long Wet Season	1.159 (1.10, 1.23)	<0.0001	1.160 (1.09, 1.23)	<0.0001	1.120 (1.03, 1.22)	0.0099
Short Wet Season	0.925 (0.88, 0.97)	0.002	0.859 (0.83, 0.89)	<0.0001	0.960 (0.87, 1.06)	0.3966
Warm Dry Season	1.308 (1.24, 1.38)	<0.0001	1.368 (1.30, 1.44)	<0.0001	1.308 (1.18, 1.46)	<0.0001
Number of Extreme Heat Days in the Prior Month	1.004 (1.00, 1.01)	0.0526	1.001 (1.00, 1.01)	0.787	1.005 (1.00, 1.01)	0.0447

Appendix D (Continued)

TABLE LIV. ASSOCIATION BETWEEN RATES OF DIARRHEAL DISEASE UNDER 5 AND THE INTERACTION OF EXTREME PRECIPITATION AND PRIOR MONTH MAXIMUM TEMPERATURE BY RISK TERTILE

	Low Risk		***Moderate Risk***		***High Risk***	
Parameter	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**	**IRR (95% CI)**	**p-value**
Intercept	4.388 (2.03, 9.47)	0.0002	3.645 (1.81, 7.36)	0.0003	0.432 (0.27, 0.90)	0.0259
Time	0.998 (0.99, 1.00)	0.0119	0.999 (0.99, 1.00)	0.0314	0.998 (0.99, 1.00)	0.00208
Long Wet Season	1.209 (1.14, 1.28)	<0.0001	1.203 (1.13, 1.28)	<0.0001	1.131 (1.03, 1.24)	0.0107
Short Wet Season	0.936 (0.89, 0.98)	0.0097	0.858 (0.83, 0.89)	<0.0001	0.945 (0.85, 1.05)	0.2773
Warm Dry Season	1.352 (1.26, 1.45)	<0.0001	1.403 (1.33, 1.48)	<0.0001	1.328 (1.18, 1.5)	<0.0001
Number of Extreme Rain Days	0.842 (0.77, 0.92)	0.0003	0.831 (0.75, 0.92)	0.0002	0.905 (0.81, 1.02)	0.0914
Average Maximum Temperature in the Prior Month	0.982 (0.96, 1.01)	0.1877	0.981 (0.96, 1.00)	0.1078	1.024 (1.00, 1.05)	0.0373
*Extreme Rain Days * Average Maximum Temperature in the Prior Month*	1.005 (1.00, 1.01)	0.0009	1.006 (1.00, 1.01)	0.0015	1.003 (0.99, 1.01)	0.139

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	Megan Kowalcyk. 2023. CUGH. Washington D.C., USA.
	Megan Kowalcyk, Honghyok Kim, Lee Friedman, Samuel Dorevitch. 2024 ISEE Annual Meeting supplemental Environmental Health Perspectives Journal.
PUBLICATIONS	Nikita Gautam, David Shumway, Megan Kowalcyk, Sarthak Khanal, Doina Caragea, Corneila Caragea, Hande McGinty, Samuel Dorevitch. (2023) Leveraging Existing Literature on the Web and Deep Neural Models to Build a Knowledge Graph Focused on Water Quality and Health Risks. In Proceedings of the ACM Web Conference 2023. Association for Computing Machinery, New York, NY, USA

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