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# Application of the Intergovernmental Panel on Climate Change risk framework to estimate risk of weather-related diarrheal disease in Western Kenya

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## Abstract

Identifying the underlying climate sensitive health risk factors is critical to establish actionable strategies to mitigate the health impacts of climate change. This is particularly true within low- and middle-income countries (LMICs) with limited resources, heterogenous climates, and varying degrees of social vulnerability. In Kenya, diarrheal disease is one of the leading causes of death and identifying climate sensitive risk factors is critical. This research aims to characterize factors associated with a high risk of diarrheal disease in western Kenya by developing a risk index based on the Intergovernmental Panel on Climate Change (IPCC) risk framework. We developed a conceptual model of risk factors based on prior research with risk factors grouped into the four components of the IPCC risk framework: hazard, exposure, and vulnerability (which is comprised of sensitivity and adaptive capacity). We obtained 30 data elements corresponding to the four components for 99 sub-counties in 14 western Kenya counties. We conducted principal component analysis (PCA) to develop a risk index for diarrheal disease. Our risk index aligns with epidemiological literature, including precipitation, temperature, water sanitation and hygiene (WASH), sensitive populations, education, poverty, and health facilities. Within counties, we found that the modeled risk varied substantially, and a geographic cluster of high-risk sub-counties was identified. Further research is needed to determine whether modeled risk proves to be consistent with observed risk of diarrheal disease in relation to weather variables. Further work is needed to determine whether this approach is useful to policymakers.

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# 1 Introduction

## 1.1 The Intergovernmental Panel on Climate Change (IPCC) framework for characterizing risks of climate change

Climate change impacts human health by altering systems in which individuals live by changing exposure to various environmental hazards [1]. These changes in environmental hazards can cause cascading effects across the health care, social, and natural systems. Therefore, it is important to take a systems-based approach to understanding and predicting the health impacts of climate change. In 2014 the IPCC addressed the need for such a systems-based approach in the Fifth Assessment Report (AR5) by presenting a 'framework … for identifying key vulnerabilities, key risks, and emergent risks' due to climate change; that risk framework has remained substantially the same in the IPCC's Fifth and Sixth Assessment Reports (AR6) [2,3]. The IPCC defines risk as the 'potential for adverse consequences for human… systems' and vulnerability as the 'propensity or predisposition to be adversely affected' [2,3]. The process of identifying risks and vulnerabilities can inform the prioritization of communities by governments for the development and implementation of adaptation strategies. The framework's broad categories of risk components are hazard, exposure and vulnerability. Hazard refers to climatic factors, such as temperature, precipitation, wind, and extreme events. Exposure is defined as the people, institutions or systems impacted by the hazard. Vulnerability is a function of "susceptibility to harm" and "lack of capacity to cope and adapt" (referred to here as sensitivity and adaptive capacity) [2,3]. The framework developed by the IPCC encompasses various aspects of health impacts under climate change. Many studies as discussed below, have used this framework to comprehensively evaluate climate sensitive health risks and found useful systems-based indicators in understanding health impacts due to climate change [4–7].

## 1.2 Implementation of the IPCC framework for characterizing risk

Several studies have applied the IPCC framework to estimate risk in various settings, at various scales, using a range of methodologies to estimate different types of risk (Table A in S1 Text). For example, in a study for the Indian Bengal Delta, the IPCC AR5 risk framework was applied to subdistricts of the Indian Bengal Delta, though not for the risk of a specific outcome. Using principal component (PCA) analysis, the authors found that the rankings of subdistricts by risk varied significantly [4]. Another study developed a risk index to address women's reproductive and children's health in India [5]. That study analyzed the association between a previously developed vulnerability index (a function of sensitivity, adaptive capacity, and exposure) and indicators of maternal and child health [5]. Another index was developed for risk of heat-related mortality in the Philippines, weighted several indicators for heat-related mortality to create an index based on expert opinions [6]. In Mexico, a research team developed an urban risk index for climate change using previous vulnerability indices, available data and equal weighting [7]. The IPCC risk framework has also been used for risk of climate hazards in Africa, West Bengal, Indian Sundarbans, Bangladesh, India, Korea, and the United States [4,8–11]. Yet each of these indices were developed using differing data identification methods – such as, expert opinion, literature, data availability, and indices in high income countries – and index development methods – such as, equal weighting, principal component analysis, and technique for order preference by similarity to ideal solution (Table A in S1 Text). Additionally, risk indices following the IPCC risk index have been developed for health impacts such as mortality, women's reproductive health, children's health, and health-related illness (Table A in S1 Text). Similarly to the previous indices, the data included in these indices were derived from the literature, data availability, and expert opinion and used a wide range of methods, including technique for order preference by similarity to ideal solution, average, and weighting based on expert opinion (Table A in S1 Text). While use of the IPCC risk framework is expanding, the lack of consistency in the ways researchers operationalize the risk framework limits our ability to compare risks across hazards, settings, and outcomes.

### 1.3 Estimating health risks due to climate change within Sub-Saharan Africa (SSA)

SSA is expected to bear the greatest burden of mortality attributable to climate change in 2030 [12]. One of the major climate hazards for SSA is the increased frequency and intensity of extreme rainfall [13]. Flooding has been associated with increased incidence of cholera and that higher-than-average rainfall was associated with increases in incidence of diarrheal disease [14]. A study in Malindi, Kenya and Malawi found strong positive correlations between increased rainfall and cases of childhood diarrhea and invasive non-typhoidal salmonella, respectively [15]. Additionally, as demonstrated in a systematic review, many studies have shown that flooding increases risk of diarrheal disease due to reduced access to improved sanitation and drinking water from standing water and damage or overflow of sanitation facilities [16]. Temperature has also been associated with diarrheal disease. A recent study in Ethiopia found an 16.7% increased risk of diarrheal disease in children under 5 years for every 1˚ C increase in monthly average temperature [17]. Many studies have shown seasonality of waterborne infections, such as cholera, with 71% of 34 SSA countries showing a statistically significant seasonal pattern [18]. Previous research in Kenya demonstrated seasonal cholera peaks in December to January, the short wet and warm dry seasons respectively [18]. Additionally, recent research in Ghana and Ethiopia have found that vulnerability factors such as education level of the mother, wealth index, living in a rural area, improved sanitation facilities and drinking water had a significant association with diarrheal disease in children under 5 [19,20]. Due to the association between precipitation, temperature, season, and vulnerability factors with diarrheal disease it should be beneficial to policymakers to understand which of these variables are key drivers of this risk. Yet, 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 [21].

### 1.4 Objectives of this research

In this research we aim to estimate a risk of diarrheal disease on a subnational scale in western Kenya. For this, we present a multistep approach for implementing the IPCC framework. While it is well understood that sub-Saharan Africa is disproportionately adversely affected by climate change, the variability of risk that climate change hazards pose to health on a local level is not well understood [1]. The hazards, exposures, and vulnerabilities that drive diarrheal disease, as well as the baseline incidence of diarrheal disease, vary on small spatial scales [22].

## 2 Methods

### 2.1 Study population

Kenya is a lower middle-income nation in Eastern SSA with a population of 47.5 million [22]. 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 [23]. Additionally, only 34% of households have access to piped water and 8.2% of households do not have access to a sanitation facility [23]. Kenya's 47 counties are grouped into six regional economic blocks based on similarities in history, politics, and economics [24]. As seen in Fig 1, 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,


**Fig 1. Map of LVRB sub-counties in Kenya (Made using ArcGIS Pro 3.1.0 2023) shapefile from humanitarian data exchange.** Available from https://data.humdata.org/dataset/cod-ab-ken. Base maps from Esri. Available from https://www.arcgis.com/home/item.html?id=10df-2279f9684e4a9f6a7f08febac2a9 and https://www.arcgis.com/home/item.html?id=7dc6cea0b1764a1f9af2e679f642f0f5.

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Nandi, Trans Nzoia, and Kericho [24]. Within these 14 counties are 99 sub-counties. As of 2019 the LVRB had a population of 14.8 million, representing 31% of the total population of Kenya [22]. 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 [22,25,26]. 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 [22].

### 2.2 A literature-informed conceptual model of risk of diarrheal disease in Kenya

To apply the IPCC risk framework to the context addressed here, we reviewed existing literature on social vulnerability, diarrheal disease, precipitation, climate change, and health in Kenya and constructed a conceptual model (Fig 2). The conceptual model is intended to encompass important determinants of diarrheal disease following extreme weather, to identify sub-counties at high risk, not to estimate occurrence of diarrheal disease. Using both available data and the conceptual model, key indicators were identified, such as housing type, temperature variability, doctors per population, and urban population (Table B in S1 Text), then classified into the four IPCC risk components 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 risk of diarrheal disease, exposure in this system is defined as the presence of people. Sensitivity refers to factors that increase a populations susceptibility to diarrheal disease, socio-economic status, household characteristics, demographics, environmental factors and water sanitation and hygiene have been found to increase susceptibility to diarrheal disease. In contrast, adaptive capacity focuses on a populations ability to prevent severe outcomes, hospitalization and death, such as access to health care and comorbidities.

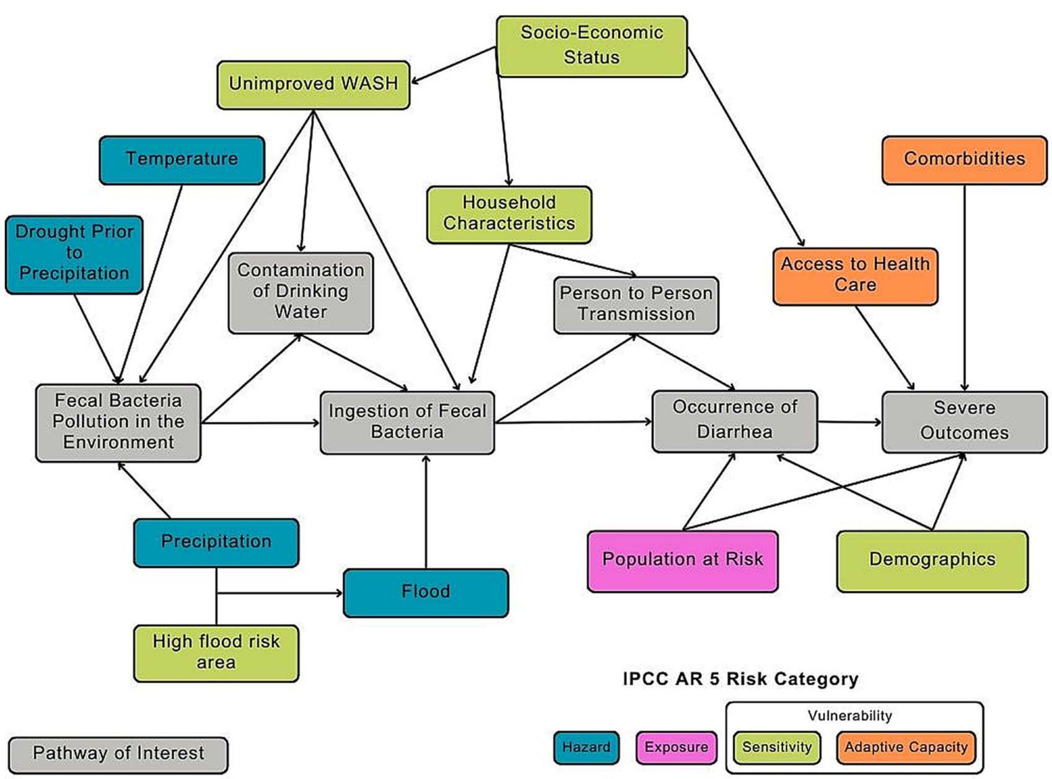


**Fig 2. Conceptual model of risk of diarrheal disease following precipitation events, by risk component.**

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The hazard component focuses on the hazards posed by climate change such as flooding, drought, precipitation, and temperature.

### 2.3 Data acquisition and quality assurance evaluation

We sought to identify Kenyan government data for each component of the causal pathway model (Fig 2). Following a search of publicly available data we were able to obtain 30 variables on the county or sub-county level. Weather data (the hazard component) such as average, and extreme precipitation and temperature, were obtained from the Kenya Meteorological Department (KMD). The average monthly maximum temperature, minimum temperature, and total precipitation were obtained for 2010–2022 on a daily scale and averaged by month. Data were not obtained for years before 2010 because changes in county boundaries that occurred between 2009 and 2010. Climate variability was measured as the average standard deviation of the monthly maximum temperature, minimum temperature, and total precipitation from 2010 to 2022. Extreme events were measured as the frequency of days over the 95$^{th}$ percentile of precipitation, maximum temperature, and minimum temperature per month from 2014 to 2022, to match the time of adaptive capacity and sensitivity data sources [14]. Adaptive capacity, sensitivity and exposure variables were abstracted from 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 (Table B in S1 Text).

Quality control procedures for the census data from the Kenya National Bureau of Statistics are those recommended by the United Nations [27]. Census data were collected using tablets, encrypted, backed-up, and edited based on guidelines from the United Nations, and monitored by independent observers [28]. The Kenya Meteorological Department aggregates weather data to the sub-county level using automated weather stations, an electronic database, and satellite estimates to obtain weather data on a 0.5x0.5 km grid [29]. 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.

Data for 22 adaptive capacity, sensitivity, and exposure variables were available at the subcounty level for all 99 sub-counties in the LVRB while four additional variables (mortality rate, stunting rate, poverty rate, and health workforce) were only available at the county level. Those county-level values were applied to all sub-counties within each 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 have been changes in sub-county boundaries since 2010, which may result in misclassification of sub-county risk if these boundaries do not represent the actual boundaries. Some sub-counties simply had changes to their names while 1 was subdivided into two and 13 were combined into a single sub-county. The sub-county (Kitutu Chache) that had been subdivided had the weather data applied to both sub-counties, and the average of the sub-counties that were merged was used.

### 2.4 Principal component analysis and risk calculation

Given the collinearity of many of factors, principal component analysis (PCA) was performed to identify a smaller number of independent sub-components of hazard, exposure, sensitivity, and adaptive capacity. First the Kaiser – Meyer – Olkin (KMO) statistic was calculated to test the strength of correlation among component-specific variables [30]. If the KMO was below 0.5, variables with the lowest individual KMO were removed, distance to urban center for adaptive capacity and stunting rates and average household size for sensitivity. Despite removal of variables with low KMO's the set of exposure variables had a KMO of 0.48, indicating that PCA would not be appropriate for exposure variables given the sample size. 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 conducted to test whether significant correlations are present among variables in each component, and was significant for all three components, confirming the appropriateness of principal component analysis [31]. Factors with an eigen value > 1.0 were retained and varimax rotation was performed. Variables were included in 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. Variables for each sub-component were all on the same scale (all sub-county, or all county level). Sub-components were named based on the variables within the sub-component as determined by PCA. An index for each of the risk components was calculated as the sum of the weighted sub-components and the unweighted variables that did not fall into a sub-component. Each component indices were scaled from 0 to 1, resulting in a possible risk index range of 0–1. Our risk index was then calculated using the following equation:

$$R = H \, x \, E \, x \, S \, x \, (1 - AC) \tag{1}$$

Where H = Hazard, E = Exposure and S = Sensitivity (H x E x S) and AC = Adaptive Capacity [4,32]. After calculation of the risk, a risk index was created to increase interpretability by scaling risk from 0 to 100 using the methodology for calculating the Human Development Index [4].

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

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 [4]. Based on the distribution of the normalized risk index, sub-counties were assigned to a risk quintile.

The sensitivity of standardization and weighting methods used to develop the risk index was explored. In addition to the methods laid out above, the variables were standardized on a scale of 0–1 prior to conducting PCA analysis. Finally, an unweighted risk index was developed by not weighting variables within sub-components by their respective factor loading scores. This sensitivity analysis provides insight into whether our results change based on methodology and assumptions.

### 2.5 Hot spot analysis

To assess the presence of statistically significant clusters of high-risk sub-counties in the LVRB, hot spot analysis was run. Specifically, ArcGIS was used to calculate the Getis-Ord Gi* statistic for the risk index value of each sub-county. The Getis-Ord Gi* statistic identifies areas with significantly higher (hot spot) or lower (cold spot) values of the risk index compared to the overall distribution of the risk index [33]. This analysis determines whether clusters are unlikely to be due to chance and instead represent a true cluster.

All analyses were conducted using SAS version 9.4 (SAS Institute, Cary, NC) and ArcGIS Pro version 3.1.0 2023.

## 3 Results

Summary statistics of exposure, sensitivity, adaptive capacity, and hazard variables are summarized in Table C in S1 Text. Three variables with some of the greatest variability are the percentage of the total population living in informal settlements (10$^{th}$ percentile: 234, 50$^{th}$ percentile: 396, 90$^{th}$ percentile: 676), the number of extreme cold days, below the 5$^{th}$ percentile, between 2014 and 2022 (10$^{th}$ percentile: 33, 50$^{th}$ percentile: 68, 90$^{th}$ percentile: 560), and distance to urban center in minutes (10$^{th}$ percentile: 1.65, 50$^{th}$ percentile: 4.99, 90$^{th}$ percentile: 16.84) (Table C in S1 Text). Some variables with minimal variability among sub-counties were 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 (Table C in S1 Text).

### 3.1 Principal component analysis

PCA demonstrated three of the four IPCC risk components had distinct sub-components. Within the hazard component three sub-components accounted for 87% of the communal variance, as seen in Table 1. Precipitation accounted for 36%, temperature 2 sub-component accounted for 28%, and temperature 1 sub-component accounted for the remaining 23% of the communal variance. The sensitivity component of risk was found to have three sub-components accounting for 64% of the communal variance, as seen in Table 2. The three sub-components, sensitive populations, child mortality, and living conditions accounting for 28%, 21%, and 14% of the communal variance respectively. Finally, eight sub-components accounted for 69% of the communal variance for the adaptive capacity component, as seen in Table 3. Health sector adaptive capacity, education, health workforce, water sanitation and hygiene (WASH), early education, health facilities, and structural capacity accounted for 26%, 11%, 9%, 7%, 6%, 5% of the communal variance respectively.

### 3.2 Risk index

The scaled risk index of 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 strongly 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 Fig 3, hazard, exposure, sensitivity, and adaptive capacity vary on a subnational scale and do not follow a north-south or east-west gradient. Fig 4 displays the estimated risk of diarrheal disease from extreme precipitation and temperature by subcounty quintiles. Not only does the risk index vary across sub-counties, but there is substantial variability within counties. For example, the risk index for the 10 sub-counties within Bungoma county range from 0 to 100 (Table D in S1 Text).

**Table 1. Factor loading scores from PCA analysis of the hazard component of risk.**

| *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* |

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**Table 2. Factor loading scores from PCA analysis of the sensitivity component of risk.**

| *Variable* | *Factor1* | *Factor2* | *Factor3* | *Factor4* | *Sub-Component* |
|---|---|---|---|---|---|
| *Child Population* | **0.91006** | 0.01385 | 0.14521 | −0.0336 | *Sensitive Pop* |
| *Female Population* | **0.88648** | −0.0186 | 0.05073 | 0.1022 | *Sensitive Pop* |
| *Elderly Population* | **0.49298** | −0.1326 | 0.65337 | −0.0402 | *Sensitive Pop* |
| *Poverty* | **0.44069** | −0.2092 | -0.68 | −0.0938 | *Sensitive Pop* |
| *Number of rivers* | 0.21545 | −0.1116 | 0.75716 | −0.0964 | |
| *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* |

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**Table 3. Factor loading scores from PCA analysis of the adaptive capacity component of risk.**

| *Variable* | *Factor 1* | *Factor 2* | *Factor 3* | *Factor 4* | *Factor 5* | *Factor 6* | *Factor 7* | *Factor 8* | *Sub-Components* |
|---|---|---|---|---|---|---|---|---|---|
| *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 | *Early Education* |
| *Secondary Education* | −0.5684 | 0.14973 | −0.0788 | −0.1513 | **0.45294** | 0.19658 | −0.2443 | −0.0918 | |
| *Dispensaries* | 0.00724 | 0.08398 | 0.03189 | 0.01923 | 0.0058 | −0.0202 | −0.009 | 0.95738 | |
| *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 | |

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Based on the Getis-Ord Gi* test, spatial clustering in the northern area of the LVRB with greater than 90% confidence (Fig 5). Two sub-counties (Teso North and Matungu) were identified as hot spots with 99% confidence and four, Teso South, Sirisia, Ugunja, and Luanda are hot spots with 95% confidence. There were no significant cold spots and significant clustering was not apparent elsewhere.

Weighting of sub-components with their factor loading scores resulted in only 14% of sub-counties having changes in risk rank compared to unweighted sub-components, with an average 0.11-unit decrease in overall risk (95% CI: -0.23, 0.02). Additionally, standardization of variables from 0 to 1 prior to PCA analysis did not change the relative risk ranking as opposed to the raw covariance matrix but did reduce the factor loading scores.

## 4 Discussion

This application of the IPCC risk framework estimated risk for diarrheal disease due to weather variables at the sub-county level in the LVRB of Kenya. Components of risk and the overall risk index varied within the LVRB and within counties. Significant hot spots of risk were identified in the northern portion of the LVRB. There is considerable heterogeneity within counties, for example the risk index for the 10 sub-counties within Bungoma county ranged from 0 to 100. The literature-based conceptual model suggested specific elements of the hazard, exposure and vulnerability components of risk; the PCA results confirmed that many of those sub-components make statistically significant and distinct contributions to the modeled risk of diarrheal disease at the sub-county level. These sub-components identified are consistent with known predictors of diarrheal disease, such as precipitation, temperature, WASH, sensitive populations, education, poverty and health facilities [14,19,34,35]. Yet, to date, IPCC-based health risk indices have not explored or identified

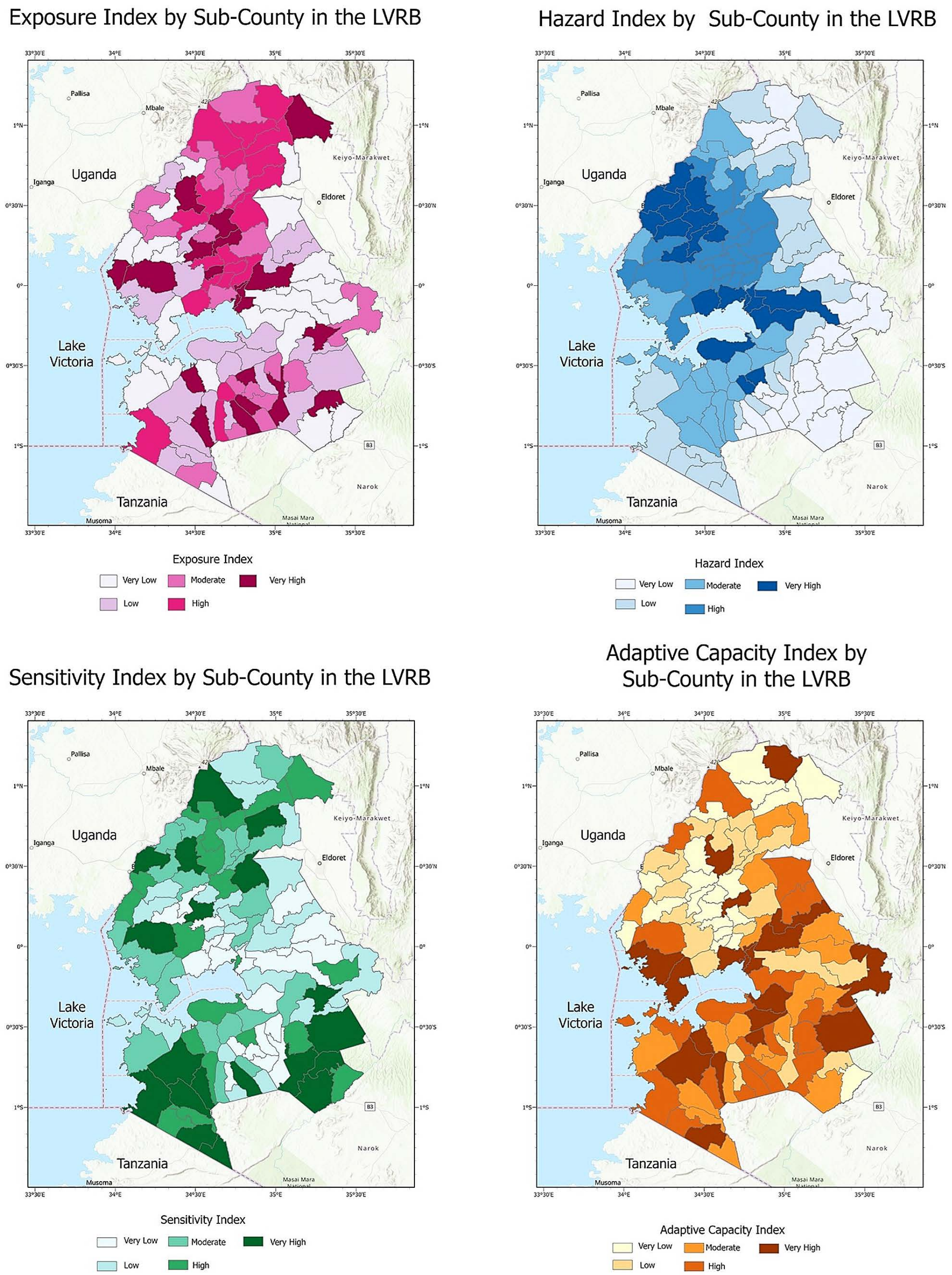


**Fig 3. Component indices in LVRB (made using ArcGIS Pro 3.1.0 2023) shapefile from humanitarian data exchange.** Available from https://data.humdata.org/dataset/cod-ab-ken. Base map from Esri. Available from https://www.arcgis.com/home/item.html?id=7dc6cea0b1764a1f9af2e679f642f0f5.

https://doi.org/10.1371/journal.pclm.0000549.g003

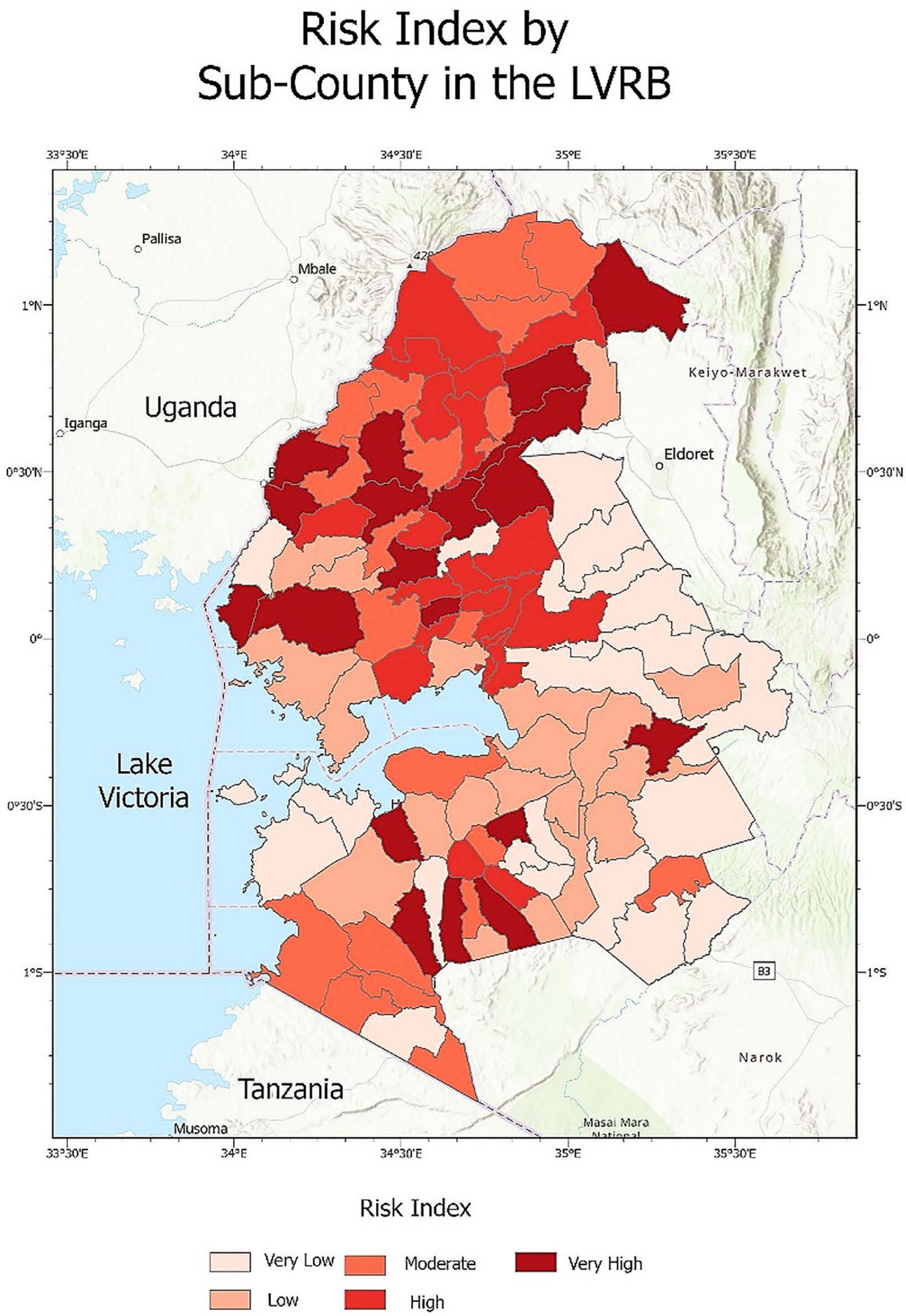


**Fig 4. Risk index for LVRB sub-counties (made using ArcGIS Pro 3.1.0 2023) shapefile from humanitarian data exchange.** Available from https://data.humdata.org/dataset/cod-ab-ken. Base map from Esri. Available from https://www.arcgis.com/home/item.html?id=7dc6cea0b1764a1f9af2e679f642f0f5.

https://doi.org/10.1371/journal.pclm.0000549.g004

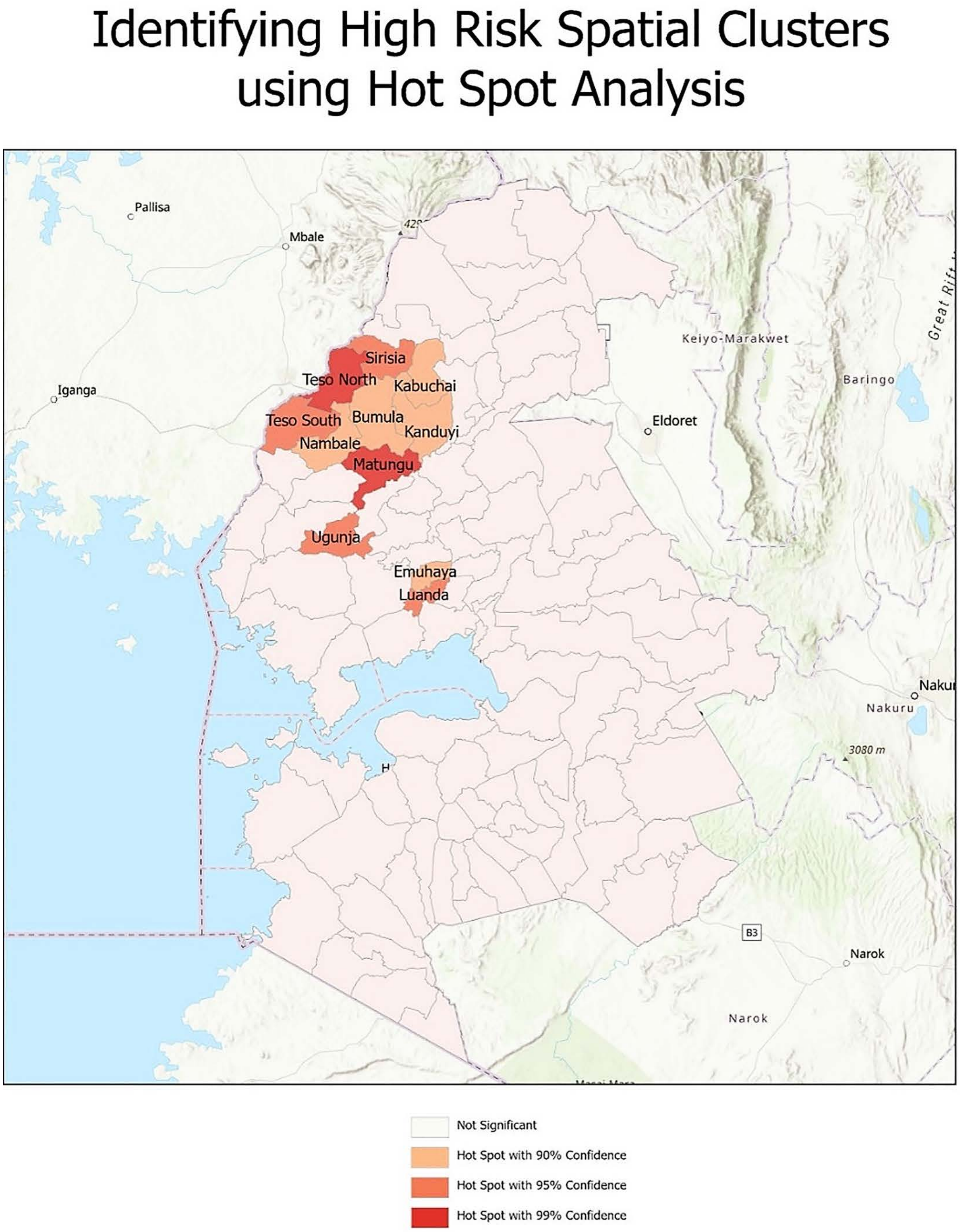


**Fig 5. Statistically significant hot spots of risk (made using ArcGIS Pro 3.1.0 2023) shapefile from humanitarian data exchange.** Available from https://data.humdata.org/dataset/cod-ab-ken. Base map from Esri. Available from https://www.arcgis.com/home/item.html?id=7dc6cea0b1764a1f9af2e679f642f0f5.

https://doi.org/10.1371/journal.pclm.0000549.g005

sub-components in their analysis. Identifying these sub-components is important so that climate adaptation efforts are directed towards modifiable and important factors.

The application of the IPCC risk framework in this study provides useful information on structure and standardization methods for future studies. First, while consulting previous literature is needed to identify key variables, the building of a conceptual model of the association between the climate change hazard and climate-sensitive health outcome is crucial. Not only is this important for identifying data to be used in the risk estimation, but also key to assigning variables to the appropriate risk component and identifying key sub-components that may be specific to the hazard or health outcome. Following the development of a conceptual model and subsequent data acquisition, PCA should be run on each of the components of risk. Not only is this important for reducing collinearity among many variables but it also can provide insights into relevant subcomponents. If the approach to developing risk indices for the health impacts of climate change hazards are standardized, transferability to other settings, populations, and health outcomes will be possible, as will comparisons of findings across studies that use similar methods.

Within 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%. These findings are in line with prior research on the association between precipitation and temperature with diarrheal disease in SSA [14,17]. Heavy rainfall has been found to have a strong positive association with diarrheal disease [14]. 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 [17]. 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 [14]. Temperature has also been shown to have a strong positive association with diarrheal disease [14]. 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% [17]. 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% [36]. There is also a modifying 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 [37]. Ultimately the variables that account for 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 studies of associations 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 [19]. 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 [20]. Health care access and utilization are important for reducing morbidity and mortality due to diarrheal disease. For example, a recent study of the occurrence of diarrheal disease in LMICs and found that more cases and deaths occur among poor populations where vaccines, for rotavirus are unavailable [38]. The alignment with the literature suggests that the sensitivity and adaptive capacity index components should be addressed through adaptation efforts.

Kenya is already facing the adverse impacts of climate change which are only expected to increase, and the LVRB is especially susceptible to riverine flooding from precipitation [39]. The approach developing a risk index described in this study demonstrates the variability in risk of diarrheal disease from climate hazards on a sub-national scale. While the previous two climate change vulnerability indices for Kenya have shown a geographical gradient of vulnerability, the LVRB risk index does not [32]. This study is the first time the risk framework described by the IPCC has been used to develop an index of weather-related risk in Kenya and the first-time an evaluation of policies has been included as an element of adaptive capacity. The use of the current IPCC risk framework allows for this index to be a starting point for other indices developed for climate-sensitive health outcomes.

There are several strengths to this study. First, the use of the IPCC risk framework as opposed to other vulnerability, risk or epidemiologic frameworks to estimate risk. Not only is the IPCC framework more systems based than frameworks in the European Union and the United States, but the framework provides a mechanistic pathway to estimate risk compared to other frameworks [40,41]. Additionally, the IPCC framework was developed by an extensive group of experts on risk of climate change from around the world, allowing this framework to easily transfer from one location to another. Secondly, the risk index was robust to changes in two aspects of the methodology. 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 the factor loading scores. Finally, 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 where rigorous quality control measures were put in place, so the impact is likely minimal.

Despite these strengths, there are several limitations to this study. 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 four of the 30 variables, and for that reason, its impact was likely limited. Additionally, there have been many changes in sub-county boundaries in recent years which may result in misclassification of risk within 8 of the 99 sub-counties. There was also missing census data for two of the 99 sub-counties, and these were dealt with by assigning the average for all the sub-counties within the county, potentially resulting in misclassifying the modeled risk of diarrheal disease within those sub-counties. The variables included cover different time periods, for example census data is from 2019 but data from other sources range from 2000 to 2020, and as a result, some misclassification may occur. This research used data from a relatively rural areas of Kenya, though one city (Kisumu) has a population of nearly 400,000 and several municipalities with more than 40,000 people. Whether the key drivers of risk would have been different had a more urbanized or more rural region of the country been studied is not known. Additionally, the stakeholders targeted with this risk index were not part of the study design to determine the usefulness of this risk index. Finally, the risk index was not intended to estimate past rates of diarrheal disease but to characterize potential risks sensitive to climate change in the future, providing a foundation for establishing actionable strategies. Future research 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.

## 5 Conclusion

Overall, these results may provide a useful framework for policy makers in Kenya to develop useful tools such as dashboards to inform resource allocation. For example, Bumula sub-county had the highest risk index and Bomachoge chache had one off the lowest therefore it may be useful to prioritize Bumula sub-county over Bomachoge chache to reduce the risk of diarrheal disease. This is the first climate change and health index following the IPCC risk framework for Kenya. Further research should be done to validate and expand this risk index to the entire country, and other climate-sensitive diseases in other LMICs. While comprehensive and accessible health data is the preferred way to estimate health risk, the development of disease-specific risk indices following the IPCC risk framework is a good initial tool to use in low resource settings where comprehensive health data is not readily available. A risk index provides policy makers, public health officials, and other key stakeholders with a general sense as to whether they should expect an increase in cases of climate-sensitive health outcomes. This is important, as such an index could provide an early warning identification of areas at greater risk as the effects of climate change increase in frequency and intensity. Close collaboration among researchers, public health practitioners and policy-makers in Kenya will be needed to translate our findings about drivers of risk into adaptation programs. Likewise, the value added to adaptation plans by this work will only be known after implementation and subsequent evaluation.

## Supporting information

**S1 Text. S1 Text Table A. Previous health oriented indices for risk due to climate change in LMICs using IPCC frameworks. S1 Text Table B. Selected variables for risk index. S1 Text Table C. Summary statistics of variables included in the risk index. S1 Text Table D. Risk of diarrheal disease for each sub-county by county in the Lake Victoria region block of Kenya [42–50].**
(DOCX)

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