Analysis of environmental factors influencing endemic cholera risks in sub-Saharan Africa

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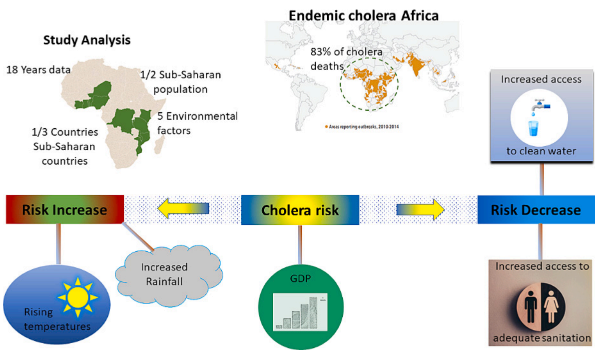
HIGHLIGHTS

- Sub-Saharan Africa still suffers recurrent cholera outbreaks.
- Comprehensive dataset assesses Africa's endemic cholera factors.
- Extensive analysis links factors to cholera risk.
- Water, sanitation, rainfall, and temperature impact risks significantly.
- Improving water and sanitation access is crucial for cholera control in Africa.

GRAPHICAL ABSTRACT



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ABSTRACT

The recurring cholera outbreaks in sub-Saharan Africa are of growing concern, especially considering the potential acceleration in the global trend of larger and more lethal cholera outbreaks due to the impacts of climate change. However, there is a scarcity of evidence-based research addressing the environmental and infrastructure factors that sustain cholera recurrence in Africa. This study adopts a statistical approach to investigate over two decades of endemic cholera outbreaks and their relationship with five environmental factors: water provision, sanitation provision, raising temperatures, increased rainfall and GDP. The analysis covers thirteen of the forty-two countries in the mainland sub-Saharan region, collectively representing one-third of the region's territory and half of its population. This breadth enables the findings to be generalised at a regional level. Results from all analyses consistently associate water provision with cholera reduction. The stratified model links increased water provision with a reduction in cholera risk that ranged from 4.2 % to 84.1 % among eight countries (out of 13 countries) as well as a reduction of such risk that ranged from 9.8 % to 68.9 % when there is increased sanitation provision, which was observed in nine countries (out of 13). These results indicate that the population's limited

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access to water and sanitation, as well as the rise in temperatures, are critical infrastructure and environmental factors contributing to endemic cholera and the heightened risk of outbreaks across the sub-Saharan region. Therefore, these are key areas for targeted interventions and cross-border collaboration to enhance resilience to outbreaks and lead to the end of endemic cholera in the region. However, it is important to interpret the results of this study with caution; hence, further investigation is recommended to conduct a more detailed analysis of the impact of infrastructure and environmental factors on reducing cholera risk.

1. Introduction

The world is currently facing its seventh cholera pandemic, with significant progress in controlling the disease achieved in most regions, including the Americas, Europe, Eastern Mediterranean, and Western Pacific. However, the African region presents a marked contrast, being considered the new epicentre of cholera (Gaffga et al., 2007), and exhibiting a consistent upward trend in cholera mortality over the past three decades (Ilic and Ilic, 2023). In 2021, the continent recorded a notable 2.9 % average case fatality ratio (CFR), and between 2000 and 2015, the sub-Saharan region alone accounted for 83 % of global cholera-related deaths (Lessler et al., 2018). Alarmingly, according to the WHO (2022), climate change is expected to accelerate the unprecedented surge of larger and deadlier cholera outbreaks worldwide. Specifically, January 2023 witnessed an exponential rise in cholera cases across Africa (WHO, 2023).

Furthermore, cholera is endemic in many African countries (Deen et al., 2020), persisting continuously, with outbreaks occurring either seasonally or sporadic. The endemicity and severity of outbreaks underscore the urgent need to address environmental conditions that facilitate cholera transmission in the region to strengthen community resilience. Given the limited economic resources of African countries, it is imperative to identify the most impactful factors justifying focused intervention efforts.

Although known environmental factors are linked to cholera incidence (see 'Background information' in Appendix A), most of the research has been conducted in Asia, particularly in the Ganges Delta (Islam et al., 1994; Faruque et al., 2003; Hashizume et al., 2008; Magny et al., 2008; Koelle, 2009; Magny et al., 2012; Islam et al., 2020). Therefore, the applicability of such findings in the African context is limited due to strain divergence and unique regional characteristics developed by autonomous *Vibrio Cholerae* strains in this geographical area (Johura et al., 2022).

Among African studies, several investigations have addressed water quality while examining environmental settings prone to cholera. Elevated cholera prevalence was observed in proximity to rivers and lakes, partly attributed to the abundant presence of phytoplankton and fishing activities (Nkoko et al., 2011). This pattern was further influenced by reliance on contaminated water sources for drinking and bathing within local communities (Acosta et al., 2001; Birmingham et al., 2008; Echenberg, 2011; Bompangue et al., 2012). Similarly, increased cholera cases were associated with contaminated water consumption near landfills, urban markets, and abattoirs (Olanrewaju and Adepoju, 2017), as well as industrial and agricultural activities introducing insoluble iron in the environment (Lipp et al., 2002). Water with high iron levels can enhance the longevity and virulence of *Vibrio Cholerae* (Patel et al., 2004). Additionally, elevated cholera rates attributed to poor water quality can be exacerbated by inadequate hygiene practices (Lemaitre et al., 2019), deforestation leading to soil degradation and reduced capacity to filter contaminants (Sena and Ebi, 2021), and climatic events such as floods and droughts (Farah, 2001; Bradley et al., 1996; Picarelli et al., 2017; Rieckmann et al., 2018; Suhr and Steinert, 2022). However, Perez-Saez et al. (2022) found a stronger correlation between cholera seasonality and precipitation than with flooding.

In studies examining other environmental settings in Africa, higher vulnerability to cholera was identified in coastal regions (Rebaudet et al., 2013), impoverished areas (Olago et al., 2007), densely populated urban settings (Zerbo et al., 2020), and zones of conflict (Echenberg, 2011). However, it is crucial to note that the dynamics of cholera outbreaks in these areas, as well as in the environmental settings described above, are intrinsically linked to specific local conditions and are hardly applicable to different scenarios. A similar approach is observed in numerous African studies focusing on local incidence, typically within the range of a town or a district (see Table S1 in Appendix A), limiting the generalisability of their findings to other geographical areas. Such studies usually collect data over short periods, rarely exceeding a couple of years, hindering the detection of patterns such as seasonality.

Moreover, data-driven studies have rarely addressed Africa's environmental factors at the multi-country level (see Fig. 1), failing to promote international coordination known to yield greater benefits in responding to infectious disease outbreaks (Jit et al., 2021). For instance, among all cholera studies in Africa, only Stoltzfus et al. (2014) employ quantitative methods to investigate water and sanitation provision factors beyond the provincial level. However, these authors' multivariate analysis found "*no detectable association between cholera and population density, poverty, availability of piped water, waste disposal methods, rainfall from January to March, or rainfall from July to September*." The overall scarcity of quantitative studies covering larger regions represents a missed opportunity to generate results that could inform government and funding institutions in their resource allocation and policy formulation processes. Conversely, organisations such as the WHO (2021), UNICEF (2016), and the World Bank (2018) advocate for an evidence-based decision-making approach for their members and associates.

Further research gaps include the under-explored relationship between cholera outbreaks and factors such as the African climate, socioeconomic indicators, and infrastructure (Jutla et al., 2015; Jutla et al., 2017; Girotto et al., 2021). Moreover, between 1995 and 2005, the Sub-Saharan region alone accounted for 66 % of global cholera outbreaks, amounting to 87.6 % of worldwide cholera cases. Remarkably, past research was unable to link more than half of these outbreaks to an identifiable risk factor (Bompangue et al., 2011). This highlights the need for further research aimed at delineating clearer parameters for the association of risk factors with cholera outbreaks.

Therefore, this study is dedicated to investigating the environmental factors (e.g., water provision, sanitation provision, temperatures, rainfall, and GDP) that contribute to the recurrence of endemic cholera outbreaks in the sub-Saharan area. These factors should not be exclusive to a specific geographical area and are not directly linked to any economic activity or cultural practices. This allows for the analysis to be carried out on variables and patterns that can be universally applicable to all countries in the study. Additionally, events linked to extreme conditions, such as floods, droughts, conflicts, etc., are not addressed in our analysis due to their extraordinary nature of occurrence. These events are more likely to act as triggers for an epidemic event rather than being responsible for sustaining the regular recurrence of outbreaks that characterize an endemic zone.

In line with this, our study explores how cholera risk is influenced by changes in water and sanitation provision, variations in rainfall and temperature, and economic growth as measured by GDP. These factors were chosen due to their known links with cholera and their capability of being compared between countries using international parameters and definitions. This scope was adopted aiming to detect the common barriers to endemic cholera control faced by multiple countries in the region. Such information facilitates collective efforts in searching for and implementing solutions, and promotes international collaboration in establishing policies and regulations.

Furthermore, the selected factors lack investigation using quantitative methods, especially for areas extending beyond country borders (see Fig. 1). Therefore, this study employs a comprehensive quantitative framework, leveraging previous research with over two decades of data collected across the region. In a pioneering effort, through the scrutiny of an exhaustive dataset, the analysis explores how cholera outbreaks in sub-Saharan countries are affected spatially (country-based) and temporally (annual-based) by environmental factors at a multi-country level.

The upcoming sections will provide a comprehensive examination of the data selection and analysis processes. The datasets underwent several processes, including descriptive, correlation, and visualisation analyses, before the final method, using a stratified Poisson-based multivariable generalised mixed linear regression model. This will be followed by the presentation of results and a discussion from each analysis, delving into the findings, elaborating on their broader implications and contextual significance. The concluding section will encapsulate the study's key findings and suggest potential avenues for future investigation.

2. Methodology

The methodology involved a discrete selection of variables and countries while keeping the sample size as large as possible for the analysis. A summary of the processes for variable selection, data, and analysis is illustrated in Fig. 2. The analysis followed the structure of an ecological study within a longitudinal framework, covering at least eighteen consecutive years of data collection for all variables. This approach allowed for an examination of the variation in cholera relative risk associated with the environmental factors.

2.1. Selection of cholera risk factors

Drawing on previous studies, we investigated selected environmental, infrastructure, and socio-economic factors associated with cholera outbreaks to determine the nature and extent of their influence on the incidence of cholera in Sub-Saharan Africa. The chosen factors include rainfall and temperature, associated with climate variabilities (Magny et al., 2007; Magny et al., 2012; Trærup et al., 2011, Nkoko et al., 2011; Picarelly et al. 2017; Pasetto et al., 2018; Lemaitre et al., 2019), infrastructure and their availability, such as the accessibility to clean water and adequate sanitation (Echenberg, 2011), and GDP, which represents the socio-economic status of a country and its population (Chireshe et al., 2020). This study excluded the analysis of complex factors such as armed conflicts, droughts, proximity to lakes, coastal and riverine areas, as these factors are highly specific to each context and may not be replicable in other areas. However, it is important to recognise that these factors can contribute to cholera outbreaks and should be taken into consideration when formulating public health policies.

2.2. Data collection

Data on rainfall, temperature, GDP, water and sanitation provision were collected for all African countries from several sources. Cholera cases were retrieved from the annual records produced and published by the WHO since 1926 (WHO, 2020). Each publication was downloaded, and records from individual countries were compiled to produce a series of tables to analyse cholera data incidence over time. Additional data on weekly cholera cases in Mozambique's regions of Cabo Delgado and Niassa and the cities of Beira, Inhambane, Maputo, Nampula, Pemba and Quelimane were also obtained by extracting values from Figs. 1 and 2 in Gujral et al. (2013) study entitled "Cholera Epidemiology in Mozambique Using National Surveillance Data". The data on countries' population, required to produce cholera rates, were obtained from the United Nations Population Division (United Nations, 2019) and GDP figures by the Statistics Division of the United Nations. The latest dataset

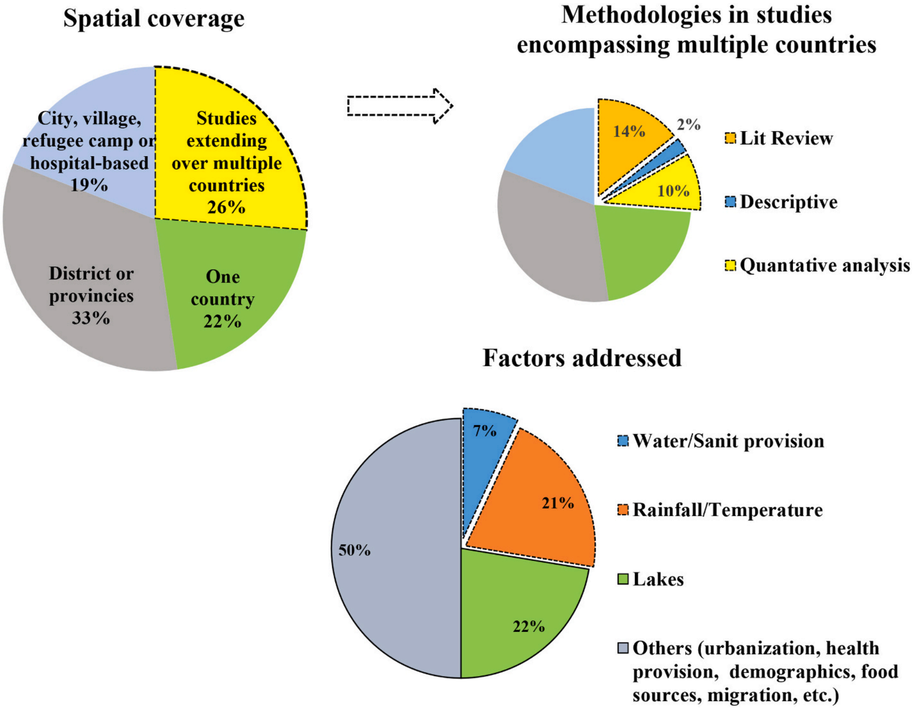


Fig. 1. Proportional distribution of African studies addressing cholera environmental factors.
(Source: Table S1 in Appendix A)

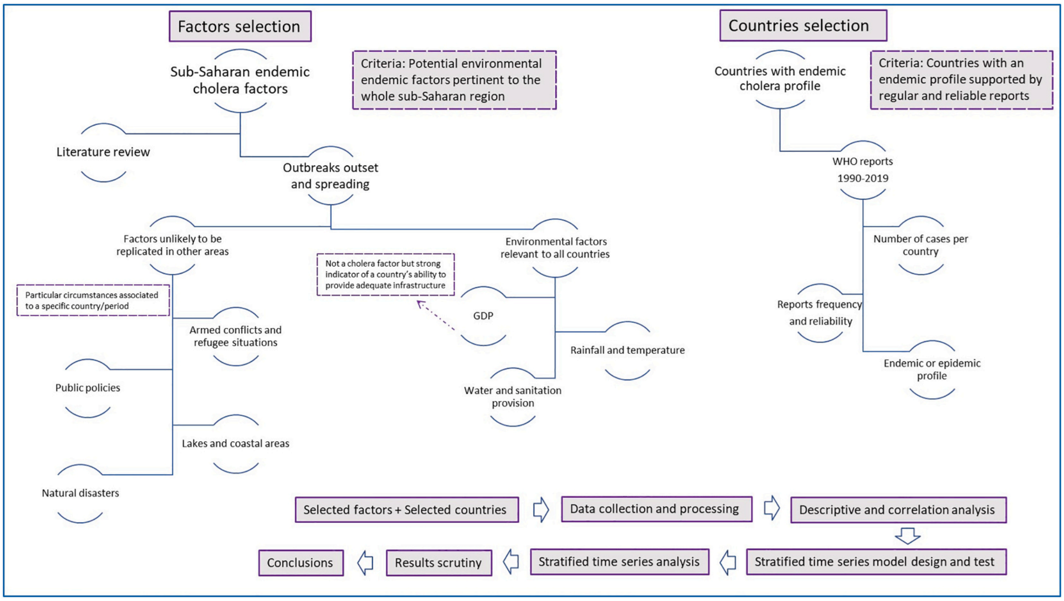
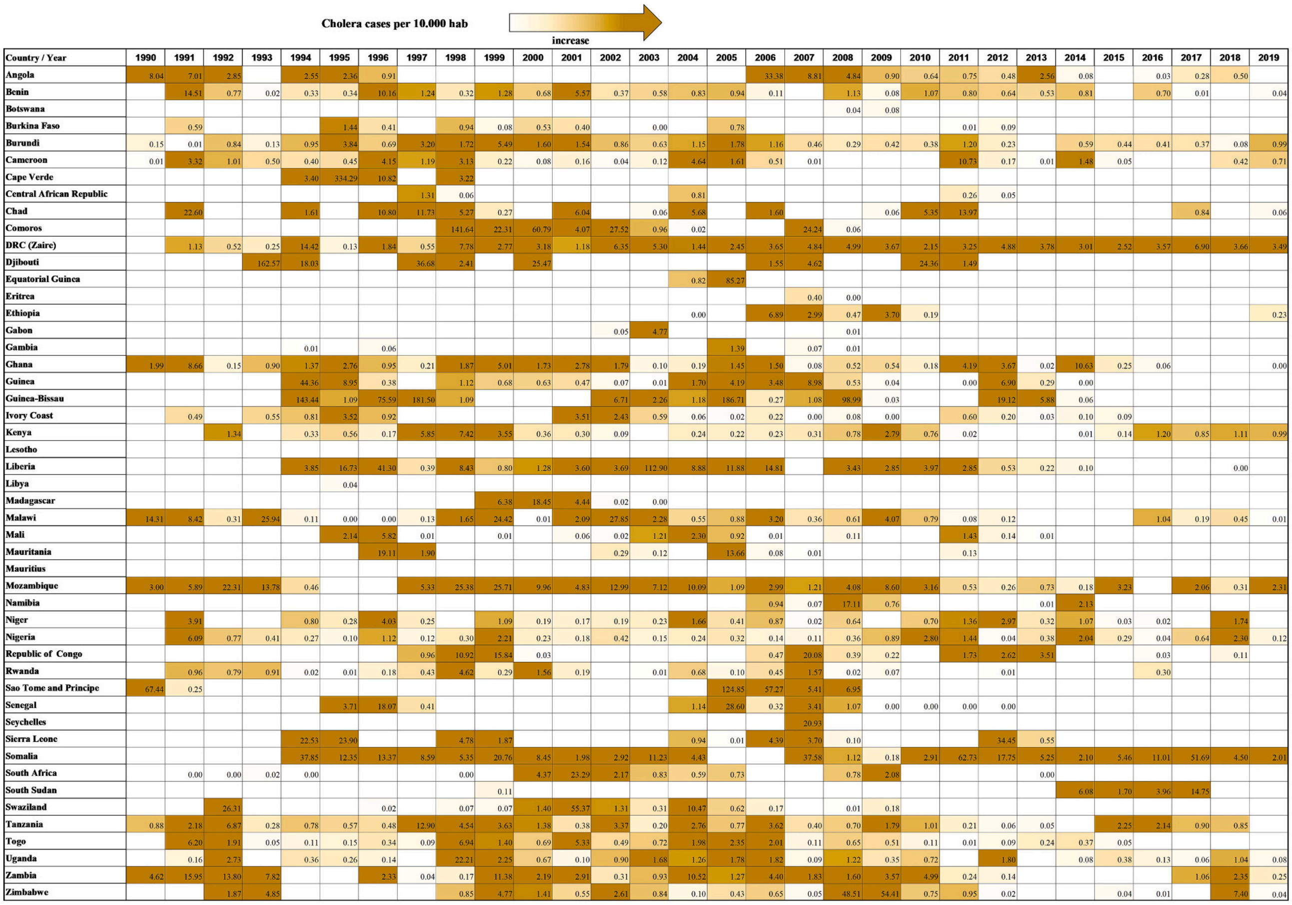


Fig. 2. Diagrams of the variable's selection process and analysis flowchart.

found that includes figures for Somalia, as other official databases have no information since 1991 (United Nations National Accounts, 2020).

Information on rainfall and temperature was collected from Climate Change Knowledge Portal (World Bank Group, 2020) and the relevant data were downloaded for each country for the period between 1991 and 2016. Additional rainfall records were also provided by the National Centres for Environmental Information website (NOAA, 2020), which supplies daily records of rainfall collected by a vast network of weather stations distributed around the world.

Water and sanitation provision data were extracted from a


Cholera cases per 10.000 hab

increase

Country / Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Angola	8.04	7.01	2.85		2.55	2.36	0.91										33.38	8.81	4.84	0.90	0.64	0.75	0.48	2.56	0.08		0.03	0.28	0.50	
Benin		14.51	0.77	0.02	0.33	0.34	10.16	1.24	0.32	1.28	0.68	5.57	0.37	0.58	0.83	0.94	0.11		1.13	0.08	1.07	0.80	0.64	0.53	0.81		0.70	0.01		0.04
Botswana																			0.04	0.08										
Burkina Faso		0.59				1.44	0.41		0.94	0.08	0.53	0.40		0.00		0.78						0.01	0.09							
Burundi	0.15	0.01	0.84	0.13	0.95	3.84	0.69	3.20	1.72	5.49	1.60	1.54	0.86	0.63	1.15	1.78	1.16	0.46	0.29	0.42	0.38	1.20	0.23		0.59	0.44	0.41	0.37	0.08	0.99
Cameroon	0.01	3.32	1.01	0.50	0.40	0.45	4.15	1.19	3.13	0.22	0.08	0.16	0.04	0.12	4.64	1.61	0.51	0.01				10.73	0.17	0.01	1.48	0.05			0.42	0.71
Cape Verde					3.40	334.29	10.82		3.22																					
Central African Republic								1.31	0.06						0.81							0.26	0.05							
Chad		22.60			1.61		10.80	11.73	5.27	0.27		6.04		0.06	5.68		1.60			0.06	5.35	13.97						0.84		0.06
Comoros									141.64	22.31	60.79	4.07	27.52	0.96	0.02			24.24	0.06											
DRC (Zaire)		1.13	0.52	0.25	14.42	0.13	1.84	0.55	7.78	2.77	3.18	1.18	6.35	5.30	1.44	2.45	3.65	4.84	4.99	3.67	2.15	3.25	4.88	3.78	3.01	2.52	3.57	6.90	3.66	3.49
Djibouti				162.57	18.03			36.68	2.41		25.47						1.55	4.62			24.36	1.49								
Equatorial Guinea															0.82	85.27														
Eritrea																		0.40	0.00											
Ethiopia															0.00		6.89	2.99	0.47	3.70	0.19									0.23
Gabon													0.05	4.77					0.01											
Gambia					0.01		0.06									1.39		0.07	0.01											
Ghana	1.99	8.66	0.15	0.90	1.37	2.76	0.95	0.21	1.87	5.01	1.73	2.78	1.79	0.10	0.19	1.45	1.50	0.08	0.52	0.54	0.18	4.19	3.67	0.02	10.63	0.25	0.06			0.00
Guinea					44.36	8.95	0.38		1.12	0.68	0.63	0.47	0.07	0.01	1.70	4.19	3.48	8.98	0.53	0.04		0.00	6.90	0.29	0.00					
Guinea-Bissau					143.44	1.09	75.59	181.50	1.09				6.71	2.26	1.18	186.71	0.27	1.08	98.99	0.03			19.12	5.88	0.06					
Ivory Coast		0.49		0.55	0.81	3.52	0.92					3.51	2.43	0.59	0.06	0.02	0.22	0.00	0.08	0.00		0.60	0.20	0.03	0.10	0.09				
Kenya			1.34		0.33	0.56	0.17	5.85	7.42	3.55	0.36	0.30	0.09		0.24	0.22	0.23	0.31	0.78	2.79	0.76	0.02			0.01	0.14	1.20	0.85	1.11	0.99
Lesotho																														
Liberia					3.85	16.73	41.30	0.39	8.43	0.80	1.28	3.60	3.69	112.90	8.88	11.88	14.81		3.43	2.85	3.97	2.85	0.53	0.22	0.10				0.00	
Libya						0.04																								
Madagascar										6.38	18.45	4.44	0.02	0.00																
Malawi	14.31	8.42	0.31	25.94	0.11	0.00	0.00	0.13	1.65	24.42	0.01	2.09	27.85	2.28	0.55	0.88	3.20	0.36	0.61	4.07	0.79	0.08	0.12				1.04	0.19	0.45	0.01
Mali						2.14	5.82	0.01		0.01		0.06	0.02	1.21	2.30	0.92	0.01		0.11			1.43	0.14	0.01						
Mauritania							19.11	1.90					0.29	0.12		13.66	0.08	0.01				0.13								
Mauritius																														
Mozambique	3.00	5.89	22.31	13.78	0.46			5.33	25.38	25.71	9.96	4.83	12.99	7.12	10.09	1.09	2.99	1.21	4.08	8.60	3.16	0.53	0.26	0.73	0.18	3.23		2.06	0.31	2.31
Namibia																	0.94	0.07	17.11	0.76				0.01	2.13					
Niger		3.91			0.80	0.28	4.03	0.25		1.09	0.19	0.17	0.19	0.23	1.66	0.41	0.87	0.02	0.64		0.70	1.36	2.97	0.32	1.07	0.03	0.02		1.74	
Nigeria		6.09	0.77	0.41	0.27	0.10	1.12	0.12	0.30	2.21	0.23	0.18	0.42	0.15	0.24	0.32	0.14	0.11	0.36	0.89	2.80	1.44	0.04	0.38	2.04	0.29	0.04	0.64	2.30	0.12
Republic of Congo								0.96	10.92	15.84	0.03						0.47	20.08	0.39	0.22		1.73	2.62	3.51			0.03		0.11	
Rwanda		0.96	0.79	0.91	0.02	0.01	0.18	0.43	4.62	0.29	1.56	0.19		0.01	0.68	0.10	0.45	1.57	0.02	0.07			0.01				0.30			
Sao Tome and Principe	67.44	0.25														124.85	57.27	5.41	6.95											
Senegal						3.71	18.07	0.41							1.14	28.60	0.32	3.41	1.07	0.00	0.00	0.00	0.00							
Seychelles																		20.93												
Sierra Leone					22.53	23.90			4.78	1.87					0.94	0.01	4.39	3.70	0.10				34.45	0.55						
Somalia					37.85	12.35	13.37	8.59	5.35	20.76	8.45	1.98	2.92	11.23	4.43			37.58	1.12	0.18	2.91	62.73	17.75	5.25	2.10	5.46	11.01	51.69	4.50	2.01
South Africa		0.00	0.00	0.02	0.00				0.00		4.37	23.29	2.17	0.83	0.59	0.73			0.78	2.08				0.00						
South Sudan										0.11															6.08	1.70	3.96	14.75		
Swaziland			26.31				0.02		0.07	0.07	1.40	55.37	1.31	0.31	10.47	0.62	0.17		0.01	0.18										
Tanzania	0.88	2.18	6.87	0.28	0.78	0.57	0.48	12.90	4.54	3.63	1.38	0.38	3.37	0.20	2.76	0.77	3.62	0.40	0.70	1.79	1.01	0.21	0.06	0.05		2.25	2.14	0.90	0.85	
Togo		6.20	1.91	0.05	0.11	0.15	0.34	0.09	6.94	1.40	0.69	5.33	0.49	0.72	1.98	2.35	2.01	0.11	0.65	0.51	0.11	0.01	0.09	0.24	0.37	0.05				
Uganda		0.16	2.73		0.36	0.26	0.14		22.21	2.25	0.67	0.10	0.90	1.68	1.26	1.78	1.82	0.09	1.22	0.35	0.72		1.80		0.08	0.38	0.13	0.06	1.04	0.08
Zambia	4.62	15.95	13.80	7.82			2.33	0.04	0.17	11.38	2.19	2.91	0.31	0.93	10.52	1.27	4.40	1.83	1.60	3.57	4.99	0.24	0.14					1.06	2.35	0.25
Zimbabwe			1.87	4.85					0.85	4.77	1.41	0.55	2.61	0.84	0.10	0.43	0.65	0.05	48.51	54.41	0.75	0.95	0.02			0.04	0.01		7.40	0.04

Fig. 3. Cholera rates per 10.000 habitants in sub-Saharan countries from 1990 and 2019. The intensity of cell shading increases with higher rates. (Data source: WHO, 2020)

publication by the Center for International Earth Science Information Network (CIESIN), which reports on natural resource preservation levels and child health indicators, including extensive information on "*at least basic sanitation*" and "*at least basic water*" provision levels in Africa (CIESIN, 2019). The term "*basic sanitation*" is defined as "use of improved facilities that are not shared with other households", and "*basic water*" is defined as "drinking water from an improved source, provided collection time is not more than 30 minutes for a round trip, including lining up and waiting" (UNICEF/WHO, 2019). Complementary sources of water and sanitation figures used in this study include the Joint Monitoring Programme (JMP) progress reports on drinking water and sanitation provision from years 2000 to 2017 (UNICEF/WHO, 2019), and the non-partisan polling organisation Afrobarometer that conducted household surveys in Africa from 2000 to 2018 (Afrobarometer, 2019).

2.3. Selection of datasets

The next stage of the methodology involved assessing the consistency and reliability of the collected data, which are essential prerequisites for ensuring a sample that accurately reflects the reality of cholera outbreaks in Africa. During this phase, the cholera dataset was transformed into an incidence rate per 10,000 population and limited to the years between 1995 and 2019 due to significant data discrepancies before 1995.

A thorough examination of the dataset, depicted in Fig. 3, revealed numerous years with no recorded cholera cases. This absence of records could be attributed to two reasons: either the country was cholera-free, or there were failures to report cases, which is common in regions facing challenges in collecting and processing cholera data (Griffith et al., 2006). However, solely relying on the dataset makes it impossible to determine which scenario is accurate. Consequently, the study encountered difficult in relying on information from countries with prolonged periods or multiple years without cholera cases, especially those inconsistent with the country's historical records. To address this issue, countries with a high number of unreported years were excluded, as there is a genuine possibility that cholera reports are inconsistent and do not reflect the country's reality. Thus, countries with no reports in over two-thirds or 20 years of the period between 1990 and 2019 were excluded.

As a result, 18 countries remained for further analysis to classify endemic and epidemic cholera incidence based on the regularity and severity of the outbreaks. The WHO (2022) stipulates a minimum requirement of three consecutive years of confirmed cholera detection to classify an endemic area. Examination of the records revealed that most countries displayed regularly distributed outbreaks with reasonable variance in case numbers over time, as expected in endemic settings. However, some countries exhibited clear epidemic patterns, with isolated years of sudden and extraordinary peaks in cholera cases that returned to regular levels in subsequent years. For example, neighbouring countries Mozambique and Zimbabwe, with similar average cholera cases, displayed contrasting patterns. While Mozambique showed a smooth transition with almost uniform case distribution throughout the study period, Zimbabwe reported low cholera rates for seven years, followed by extraordinary numbers in 2008 and 2009 before returning to the previous levels (Fig. S1 in Appendix A). Such disparity suggests a relationship between factors and cholera outbreaks that differs from the endemic profile, prompting the use of another filter to exclude datasets likely to contain extreme or frequent epidemic outbreaks, which could destabilise the analysis of endemic risk factors.

Therefore, countries with isolated peaks representing a highly abnormal number of cases were considered likely to be reporting an epidemic or acute episode, typically caused by a particular agent or circumstance, and may not share the same factors as an endemic profile. The criteria for an "abnormal peak" were established based on the observation of each country's historical average cases. If a peak represented more than ten times the average of cases in the country measured before and after the peak, the entire dataset for the country needed exclusion from the subsequent analysis. The filtering process resulted in a selection of thirteen countries: Benin, Burundi, Democratic Republic of Congo (DRC), Ghana, Ivory Coast, Kenya, Malawi, Mozambique, Niger, Nigeria, Somalia, Tanzania, and Togo. The period between 2000 and 2017 was chosen for data collection based on data availability for all variables.

2.4. Statistical analysis

The statistical analysis was tailored according to the features of each factor and database to extract the most relevant information from various combinations of datasets. Preliminary descriptive analysis was conducted using tools and applications of the IBM SPSS Statistics v26 software to identify the properties of the datasets. Initially, a quantile-quantile (Q-Q) plot was created to visualise the data distribution compared to the expected normal distribution. This was followed by Pearson and Spearman Rho correlation tests to assess the strength and direction of the relationship between the variables. By utilizing both correlations, it becomes possible to offset any potential shortcomings of normality tests (Rovetta, 2020; Van den Heuvel and Zhan, 2022). Also, Spearman's rank correlation coefficient (Spearman Rho) can better accommodate the non-parametric properties of the cholera dataset.

Next, the factors were divided and analysed using cholera datasets tailored to each factor. To investigate the impact of water and sanitation provision, the study observed changes in cholera rates following improvements in provision between 2000 and 2017 in each country. The role of climatic factors was evaluated through graphical visualization of trends in rainfall and temperature, as provided by NOAA (2020), alongside the corresponding weekly cholera cases from several locations in Mozambique, retrieved from Gujral et al. (2013). Although these datasets were too small to determine endemic incidence, they did offer an opportunity to observe lag times and seasonality patterns, which would not have been possible using the annual records from WHO (2020).

Finally, the main analysis was conducted, taking into account all factors. It utilized a stratified Poisson-based multivariable generalised mixed linear regression model (Famoye, 2015) to examine the influence of environmental factors on the relative risk of cholera in each country. Implementing a time-series-based Poisson mixed model was deemed appropriate for this study because our objective was to model the incidence counts of cholera cases, which demonstrated a time-varying distribution (Frome, E. L., & Checkoway, H., 1985. The models, based on Mantel and Haenszel (1959), Sheppard and Prentice (1995) Rao and Rao (2012), and Stroup (2012), were stratified by each country on the thirteen selected countries: Benin, Burundi, Democratic Republic of Congo (DRC), Ghana, Ivory Coast, Kenya, Malawi, Mozambique, Niger, Nigeria, Somalia, Tanzania, and Togo (see Section 2.3). Additionally, all models were mutually adjusted for the following a priori socioeconomic and climate-related confounding variables: annual GDP, annual average temperature, and annual average precipitation. When analysing the influence of water provision or basic sanitation services on incident cholera, the effects of residual confounding were statistically controlled with the inclusion of our aforementioned set of a priori socioeconomic and climate-related risk factors to the stratified Poisson regression model (McNutt et al., 2003).

The models were stratified for each country to account for cross-country variability and to derive parameter estimates that were country-specific. The mathematical formula for modelling the relationship between our primary variables of interest and the outcome is as follows (Famoye, 2015):

$$y_{[m,c],t} \sim \text{Poisson}\left(\lambda_{[m,c],t}\right) \tag{1}$$

$$\lambda_{[m,c],t} = \alpha_{[m,c]} + \sum_{k=1}^{4} \beta_{[m,c],k} X_{[m,c],k,t} + log\left(P_{[c],t}\right) \tag{2}$$

where:

$m = 1$ and 2
$c = 1, 2, 3, \ldots$ and 11
$t = 2001, 2002, 2003, \ldots$ and 2017
$k = 1, 2, 3$ and 4

The model parameter $\lambda_{[m,c],t}$ represents the conditional mean incidence rate, typically reflecting the incidence of cholera in a country (c). The terms m and c, enclosed in square brackets in Eqs. (1) and (2), serve as mathematical identifiers denoting the model type and the country [$c =$ (1) Benin, (2) Burundi, (3) Democratic Republic of Congo (DRC), (4) Ghana, (5) Ivory Coast, (6) Kenya, (7) Malawi, (8) Mozambique, (9) Niger, (10) Nigeria, (11) Somalia, (12) Tanzania, and (13) Togo], respectively. We employed two model types ($m = 1$ and 2), where the first version was adjusted for basic sanitation along with our defined a priori confounders, while the second version was adjusted for water provision with the same confounders. This approach was necessary due to severe multicollinearity between basic sanitation and water provision variables. The symbol $\alpha_{[m,c]}$ represents the overall country-specific average incidence rates of cholera when all other factors are held constant. In this model, we assume $P_{[c],t}$ is the offset variable at the country-level, representing the reference population at risk of cholera at each specific time point (year) t for each country c. Our time-varying independent variables are represented as $X_{[m,c],k,t}$ where $k = 1, 2, 3$ and 4. It is important to note that when the model type m was 1, we used a model containing the following independent variables: basic sanitation $\left(X_{[m,c],1,t}\right)$ with a priori confounders [i.e., annual GDP $\left(X_{[m,c],2,t}\right)$, annual average temperature $\left(X_{[m,c],3,t}\right)$, and annual average precipitation $\left(X_{[m,c],4,t}\right)$]. Conversely, when m was 2, the model contained water provision with the same a priori confounders.

The country-specific coefficients in Eqs. (1) and (2), denoted as $\beta_{[m,c],k}$, represent the estimated parameters $\beta_{[m,c],1}$, $\beta_{[m,c],2}$, $\beta_{[m,c],3}$ and $\beta_{[m,c],4}$ for the primary independent variables: basic sanitation or water provision (depending on m), GDP, temperature, and precipitation, respectively. These coefficients are reported as relative risk ratios (RR) by exponentiating them and providing 95 % confidence intervals (95 % CI). Statistical significance is assessed based on 95 % CI, considering significance if the interval excludes the null value of 1. Geographical mapping of these model estimates (i.e., RR and 95 % CI) for the 13 sub-Saharan African countries with complete WHO data allows for the interpretation of cholera risk. An RR greater than 1 implies an increased risk, deemed "significantly increased" if both limits of the 95 % CI are above 1. Conversely, an RR less than 1 signifies a protective effect (or decreased risk), considered "significantly decreased" if both limits of the 95 % CI are below 1. If the null value (1) falls between the lower and upper limits of the 95 % CI, the RR estimate is considered "not significant". The statistical analysis was conducted in RStudio using the Generalised Linear Mixed Models (glmmTMB) and Template Model Builder (TMB) (Liboschik et al., 2017). It is essential to note that the main cholera dataset (WHO, 2020) has coarse spatial and temporal resolution, offering information solely on the total annual reported cholera cases for each country. This consideration is crucial for the accurate interpretation of the results.

3. Results and discussion

3.1. Descriptive and multivariable correlation analysis

In the descriptive analysis, the variables of rainfall, temperature, GDP, access to water and sanitation provision were treated as continuous, numerical, and non-negative values. Cholera cases were considered integers and displayed a non-normal, positively skewed distribution in the Q-Q plots.

Two correlation tests were conducted on a sample size of 229 for most variables (216 for rainfall and temperature). A Pearson's correlation test examined the possibility of a linear relationship between cholera and the other variables, while Spearman's Rho test, chosen for the non-parametric properties of the cholera dataset, assessed non-linear relationships. Both tests produced coefficients ranging from −1 to 1, with correlation strength increasing from 0 to −1 and 0 to 1. The significance of the findings is assessed using a *p*-value of 0.05 or lower, with increased significance as the p-value approaches 0.00. It is important to note that the negative sign in the correlation coefficients signifies an inverse relationship between independent and dependent variables.

The results of both tests are presented in Table 1. The Spearman test showed a strong and significant negative correlation between cholera rates and water provision levels (−0.463) and GDP (−0.478), with no significant results for the other variables. Similarly, Pearson's test revealed a significant correlation between water provision, rainfall, and GDP levels and cholera cases, with coefficients of 0.233, −0.176 and −0.243, respectively. However, these values are below the threshold of 0.5, indicating a relatively weak association.

The higher correlation coefficient observed in the Spearman test compared to the Pearson test suggests a non-linear association between cholera outbreaks and environmental factors. Non-linear relationships are more challenging to detect, as observed in most factors in this analysis. However, the Spearman revealed a strong connection between cholera outbreaks and two factors: water access and GDP. In both cases, the correlation is highly significant, suggesting that an increase in water provision or higher GDP corresponds to lower cholera rates, and vice-versa. These findings are noteworthy, particularly given that previous studies did not establish a relationship between cholera rates and piped water in Tanzania (Penrose et al., 2010; Stoltzfus et al., 2014) or with gross national product in Latin America (Ackers et al., 1998).

3.2. Climate and cholera cases - sample time-trend analysis

The following analysis explores the role of rainfall and temperature in cholera incidence in Mozambique. The results depicted in Fig. 4 illustrate the variations in rainfall and temperature, along with the recorded weekly cholera cases, in two regions and four cities in Mozambique between 2009 up to 2011. The graphs for the cities of Beira, Nampula, Pemba and Quelimane, as well as the regions of Cabo Delgado and Niassa, show a higher number of cholera cases occurring during or after periods of heavy rainfall and high temperature. While similar pattern is noticed in Maputo and Inhambane in 2009, it is not repeated in 2010.

The analysis revealed a clear pattern of surge and rise in cholera cases during or just after periods of intense rainfall and high temperatures, with almost no cholera incidence during cooler and drier periods. The observed pattern between rainfall and weekly cholera cases closely resembles the patterns detected by two previous studies that employed a similar method in Uganda (Bwire et al., 2017) and the Accra region in Ghana (Moore et al., 2018). Such findings underscore the importance of

Table 1
Pearson's and Spearman's Rho correlation coefficient between factors and cholera rates.

	Pearson's	Spearman's Rho
	Correlation coefficient	
Water provision	−0.233*	−0.463*
Basic sanitation	0.055	−0.091
Rainfall increase	−0.176*	−0.11
Temperature rise	0.024	−0.113
GDP	−0.243**	−0.478**

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

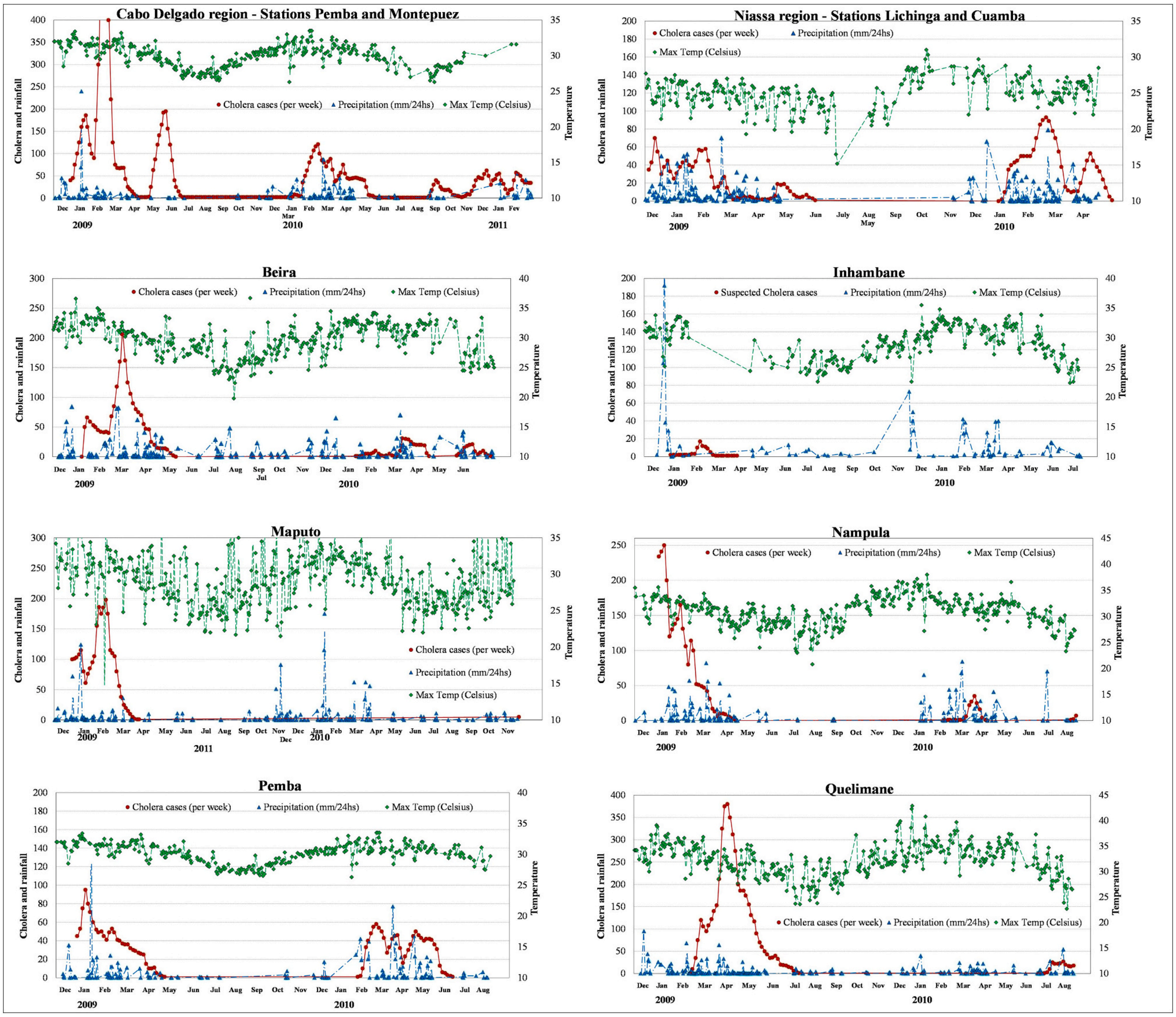


Fig. 4. Time-trend analysis of daily rainfall (blue triangles), maximum daily temperature (green diamonds), weekly cholera cases (red circles) for two regions and six cities in Mozambique. Cholera cases data retrieved from the Figs. 1 and 2 produced by Gujral et al. (2013), rainfall and temperature data from NOAA (2020). For better visualisation of the patterns, Y-axis values are limited to certain thresholds in some figures. Cholera data points represents number of cases per week, rainfall in mm/day and temperature in ^{0}C.

Table 2
Improvements in water and sanitation provision from 2000 to 2017 and respective changes in cholera rates.

Country	Basic water provision		Basic sanitation provision		Cholera cases / 10.000 habit (5-year average)		Improvements 2000–2017		Reduction in average cholera rates
	2000 (%)	2017 (%)	2000 (%)	2017 (%)	1998–2002	2015–2019	Water (%)	Sanitation (%)	Absolute (percentage)
Benin	61	66	8.6	16	1.6	0.15	5.0	7.85	1.5 (90 %)
Burundi	51	61	45	46	2.2	0.46	10	0.61	1.8 (80 %)
DRC	34	43	21	20	4.3	4.0	9.3	−0.95	0.23 (5 %)
Ghana	64	81	8.6	18	2.63	0.06	17	10	2.6 (97 %)
Ivory Coast	71	73	21	32	1.2	0.02	2.1	11	1.2 (98 %)
Kenya	47	59	34	29	2.3	0.86	12	−4.5	1.5 (63 %)
Malawi	53	69	21	26	11	0.34	16	5.4	11 (97 %)
Mozambique	20	56	11	29	16	1.6	36	19	14 (90 %)
Niger	36	50	5.1	14	0.37	0.36	15	8.5	0.00 (0 %)
Nigeria	48	71	30	39	0.69	0.68	23	9.7	0.00 (0 %)
Somalia	20	52	20	38	7.9	15	33	19	−7.0 (90 %)
Tanzania	27	57	4.3	30	2.7	1.2	29	26	1.4 (54 %)
Togo	46	65	10	16	3.0	0.01	19	6.2	3.0 (99 %)

(Data source: WHO, 2020; UNICEF/WHO, 2019) continuous monitoring and detailed recording of cholera cases to better understand the dynamics between climate and endemic outbreaks.

3.3. Analysis of long-term effects of water and sanitation improvements on cholera rates

The observational analysis, as presented in Table 2, illustrates the improvements in water and sanitation provision between 2000 and 2017 in each country and compares with changes in the average number of cholera cases. To minimise distortion from potential transient factors in any given year, the cholera incidence before and after the infrastructure changes was calculated as the mean number of cases over a 5-year interval, spanning from 1998 to 2002 and 2015 to 2019.

The analysis results reveal that all countries improved population

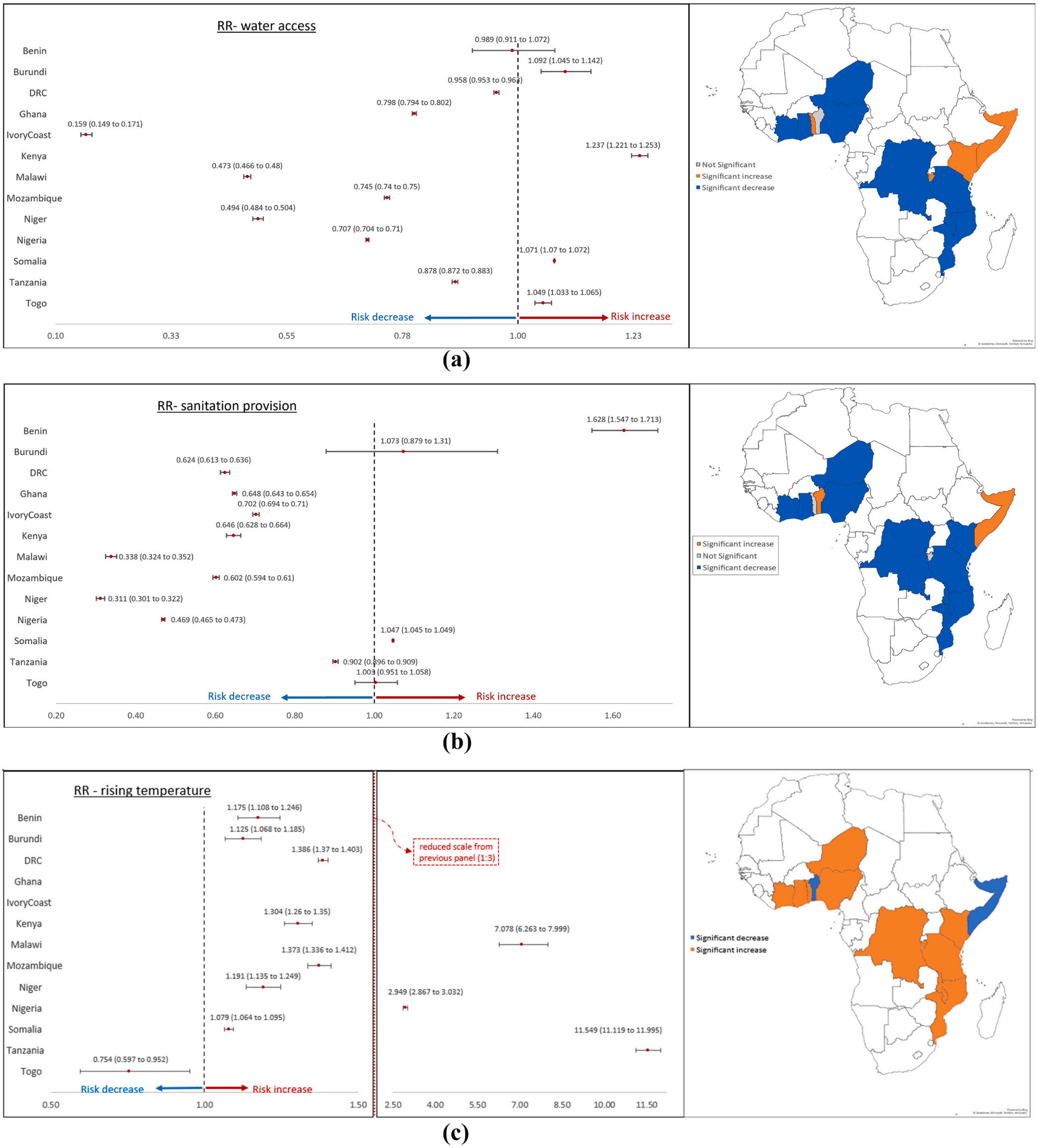


Fig. 5. Left side: graphical representation of the stratified time-series analysis results displaying relative risk values and respective 95 % confidence intervals. Right side: Map visualisation of results where countries with significant cholera relative risk decreases are coloured blue, countries with no significant findings are coloured grey, and countries with significant relative risk increases are coloured orange. Environmental factors considered in the analysis: improved water provision (a), improved sanitation provision (b), rising temperatures (c), rainfall increase (d) and GDP increase (e). RR = relative risk ratio (dimensionless).

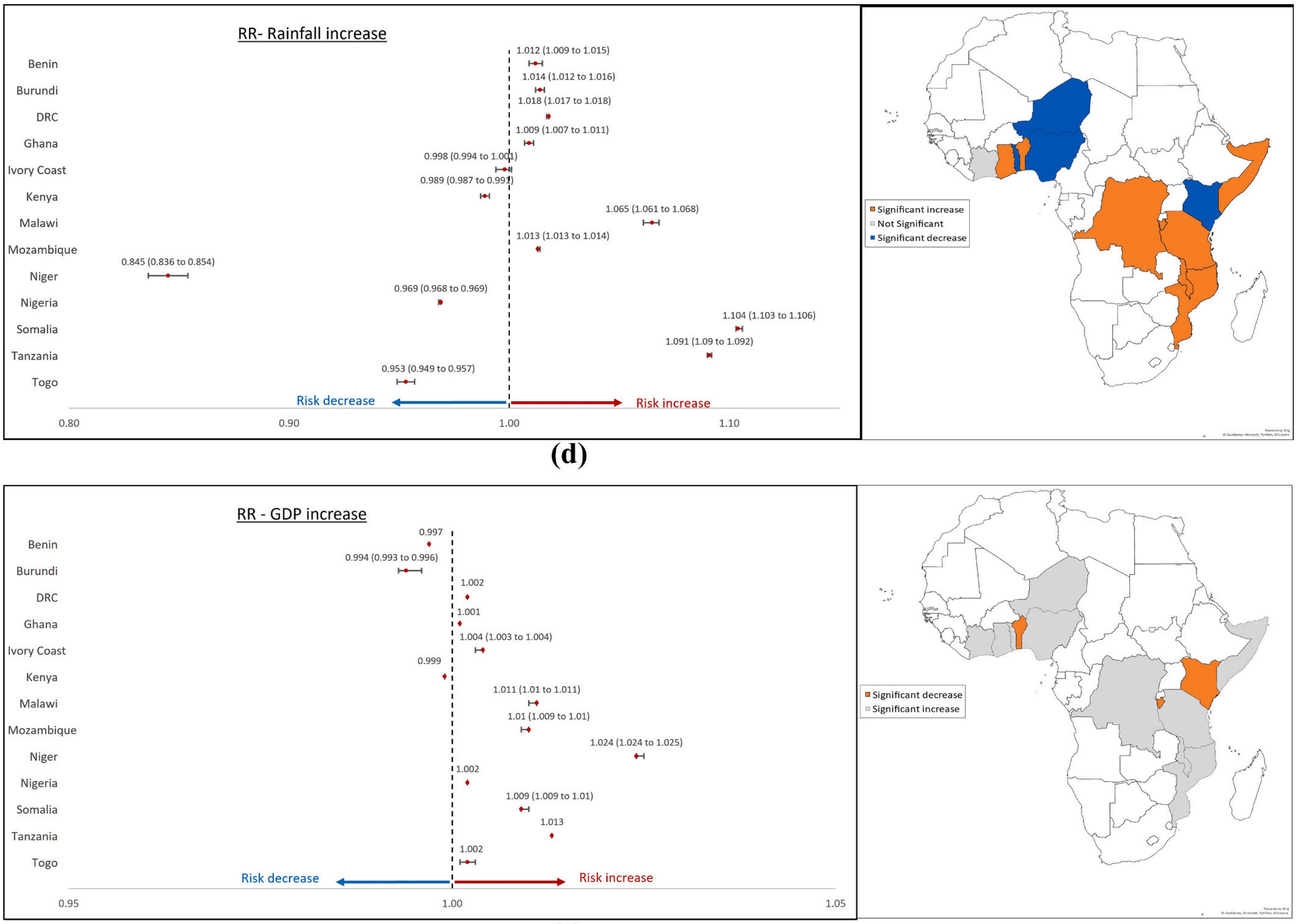


Fig. 5. (*continued*).

access to water, with only two countries, DRC and Kenya, having a reduction in sanitation access. However, the changes in cholera rates are influenced not only on the increase or reduction in access but also by the baseline level of provision and the initial cholera rates. For example, similar reduction rates of 1.49 and 1.43, respectively, represents a 90 % reduction in cholera rates in Benin, but only a 54 % reduction in Tanzania. Despite Benin modestly increasing water provision by around 5 % and sanitation provision by around 8 %, Tanzania increased both by over 25 %. However, compared with the remaining countries, in 2000, the level of water provision in Tanzania was very low (27 %), while Benin had one of the highest rates (61 %). Higher percentage change in cholera rates (above 90 %) was also observed in countries with initially higher water provision (Ghana, Ivory Coast) and in Mozambique, the country with the highest increase in provision by 2017.

The effects on cholera rates associated with improved sanitation are harder to estimate from this analysis, especially because sanitation provision, which was very low in 2000, remained below 46 % in all countries by 2017. Furthermore, Somalia stands out as the only country with a 90 % increase in cholera rates despite significant improvements in water and sanitation. However, Somalia faces unique challenges, which will be discussed in the following sections. For a clearer visualisation of the changes over time, a graphical illustration can be found in Fig. S2.

While our results suggest a strong link between the provision of water and basic sanitation and the reduction of cholera risk, we emphasize the importance of understanding the underlying mechanisms. For instance, gaining a more detailed understanding of factors such as the efficiency of water treatment at the source, household water treatment practices, hygiene behaviour, and enhancements to water and sanitation infrastructure (Taylor et al., 2015) may help elucidate the mechanisms behind the reduced cholera risk associated with improved water and sanitation provision.

3.4. Results from stratified multivariable Poisson regression model in assessing the geospatial risk of cholera

The results of the stratified model are presented on the left side of Fig. 5, displaying the estimated relative risk and respective 95 % confidence intervals (CI). On the right side of Fig. 5, the maps show countries in blue where the relative risk of cholera has decreased, in orange where the risk has increased, and in grey where findings are non-significant. The first model, using Set 1, assessed the impact of increased water access on cholera risk. This model yielded significant results in all countries except for Bening, as shown in Fig. 5(a). Among these, eight countries experienced a significant reduction in the relative cholera risk ranging between 4.2 % and 84.1 %, with the lowest and highest reduction observed in Democratic Republic of the Congo (DRC) and Ivory Coast, respectively. Meanwhile, the remaining countries, namely Burundi, Kenya, Somalia, and Togo, showed an increase in cholera risk. Transposing the outcomes onto the maps in Fig. 5(a) reveals a pronounced predominance of blue areas, indicating that improvements in basic water provision decrease the relative risk of cholera at cross-border levels. This suggests access to safe water as a protective factor for endemic cholera outbreaks occurrence in the region.

Comparable results are observed in Fig. 5 (b) for Set 2 i.e., the model considering sanitation provision improvements. Somalia and Benin experienced a significant rise in cholera risk, while nine other countries (i.e., DRC, Ghana, Ivory Coast, Kenya, Malawi, Mozambique, Niger, Nigeria, and Tanzania) exhibited a significant reduction in relative risk that ranged from 9.8 % to 68.9 %, indicating that improved sanitation provision is also a protective factor for endemic outbreaks.

Such findings reinforce the critical importance of ensuring ample access to adequate water and sanitation across the sub-Saharan region to enhance its resilience to endemic cholera outbreaks. Specifically, water supply should be readily available, of acceptable quality, affordable, and free from health hazards (Scanlon et al., 2004). Meanwhile, sanitation facilities should be accessible, effectively preventing human contact with excreta and contamination of food and water sources (United Nations, 2010). Despite some progress, achieving such standards remains a challenge for the sub-Saharan region, with only 34 % of the population having access to basic drinking water and 17 % having access to basic sanitation, as of 2017 (UNICEF/WHO, 2019). Most urban residents in the region rely on onsite sanitation facilities, such as pit latrines and septic tanks, sparsely distributed and often not connected to a sewerage system. The task of emptying latrines is typically performed manually by residents (Weststrate et al., 2019). The extent to which countries can meet these standards often varies based on the availability of resources for funding infrastructure projects. Nevertheless, given that water and sanitation provision are recognised as a human right, this responsibility transcends national boundaries.

Fig. 5(c) displays the model outcomes in response to increasing annual average temperatures. All results were significant. Only two countries, Somalia and Benin, showed a small decreased risk, while the remaining eleven countries observed an increase in the relative risk of cholera ranging from 11 % to 250 %. The high consistency and significance of the results can corroborate climate change as a threat to cholera control. This threat is attributed to its role in raising temperatures, as demonstrated by the analysis, which increases the risk of endemic cholera outbreaks. Similarly, Fig. 5(d) illustrates an increase in the relative risk of cholera in eight countries when considering rising rainfall. The exceptions include the Ivory Coast, with no significant result, along with Togo, Niger, Nigeria, and Kenya, for which the relative risk of cholera decreased. However, the accuracy of this analysis is most certainly affected by the wide spatial and temporal resolution in the cholera dataset. At the country level, the number of cases does not permit the detection of variations in the occurrence and severity of outbreaks within specific regions of the country, while the annual time frame precludes the identification of seasonal patterns.

Finally, when considering the stratified model accounting for the GDP factor, there was minimal variation in the relative risk among all countries, as shown in Fig. 5(e). These results suggest that GDP fluctuations had no significant influence on cholera risks throughout the entire period. This finding is somewhat unexpected and calls for further investigation in future studies.

3.5. Overall deliberations

This study encompasses thirteen countries geographically dispersed from West to East Africa, covering one-third of the sub-Saharan mainland area and half of the region's population (United Nations World Population Prospects, 2019). These countries were chosen for analysis due to their distinctive patterns in endemic cholera outbreaks. However, cholera occurrences are observed in several other countries (see Fig. 3), which could not be categorised as either endemic or non-endemic due to uncertainties in the datasets. Moreover, certain countries (e.g., Cameroon, Liberia, Uganda, Zambia, Zimbabwe) likely to exhibit endemic characteristics were excluded from the analysis due to extreme epidemic episodes in their data. These episodes had the potential to distort the analysis of endemic factors. Nevertheless, the selected countries provide extensive territorial coverage and represent a significant portion of the population. This extensive and representative sample, along with the consistency observed in the results across multiple analyses, supports the applicability of our findings to the entire region.

The strength of the results was partially challenged by a few anomalies, such as those observed in Somalia and Benin, which consistently deviated from the trends seen in other countries across all stratified analyses, and in countries like Togo and Burundi, where results were non-significant. In seeking an explanation, we considered the possibility of issues within the data or methodology, but the revision of the datasets and analysis did not uncover any significant issues. However, the reliability of cholera records can vary due to common issues such as incomplete data and underreporting, as highlighted by the WHO (2022). While the explanation for these discrepancies is not definitive, it is worth mentioning that Benin, Togo, and Burundi are among the countries with the smallest area and population among those analysed (United Nations, 2019), reducing their impact on the overall assessment. Therefore, further investigation is recommended to explore these discrepancies.

Somalia, on the other hand, serves as an extreme example of a complex cholera scenario that would require an entirely new study for a comprehensive understanding. For instance, Somalia has been classified as a 'failing state' (Shay, 2017), lacking an effective central government since 1991, which, according to Guha-Sapir and Ratnayake (2009), has hindered progress towards health improvements. The impact of such circumstances on cholera incidence is evident in our analysis.

Similarly, the inconclusive results obtained considering the GDP factor may suggest a more complex relationship with endemic cholera risk. However, it is reasonable to anticipate and acknowledge some level of discrepancy in a study with such broad spatial and temporal coverage, particularly when considering the intricate interplay of numerous factors influencing endemic cholera risk. These factors are dynamic in their roles and may also be influenced by underlying conditions such as local conflicts, population density, healthcare accessibility, human mobility, urbanisation, and many others. This represents major limitation of this study, which the authors acknowledge, namely our inability to include meaningful covariates to our models to mitigate potential confounding between the outcome and main exposure (i.e., basic water and sanitation services). The lack of such crucial adjustments in our stratified model will inevitably result in residual confounding in our analysis.

Despite its challenges, comprehending the patterns within the relationship linking environmental factors and endemic cholera in sub-Saharan Africa holds paramount significance for outbreaks prevention and mitigating outbreaks. For instance, Pasetto et al. (2018) employed rainfall predictions to forecast the spatial incidence of cholera in Haiti up to a month in advance. Similarly, in Yemen, Usmani et al. (2023) used information on water, climate, and environmental processes to estimate cholera risk four weeks ahead. At regional scale, early detection of cross-border cholera risks, such as droughts, facilitates multi-country responses, including agreements on water use, management, resource sharing, and rapid assistance during outbreaks (Charnley et al., 2022).

Finally, cholera's ability to rapidly cross borders, combined with its endemic presence sustained by the factors identified in our study, poses a permanent threat of outbreaks to the entire sub-Saharan region. Addressing the environmental and infrastructure factors is challenging for most countries in Sub-Saharan due to limited resources. This challenge requires international cooperation to increase the chances of success. Therefore, leveraging wide data coverage and rigorous analysis, this study was designed to draw international attention, inform evidence-based decision-making, guide resource allocation, drive policy changes, and promote collective collaboration to address these crucial factors for effectively tackling cholera in Sub-Saharan Africa.

4. Research limitations

The main limitations of this study were related to the availability and quality of the data. To comprehensively understand the dynamics and robustness of the relationship between cholera outbreaks and regional environmental and infrastructure factors, regular and reliable cholera records collected with great spatial and temporal granularity are essential. These elements are crucial for identifying high-risk areas and seasonal patterns, enabling the implementation of targeted interventions, and yielding improved outcomes within the available resources.

Unfortunately, this study was unable to access cholera datasets with such a level of information for any African country. While we were able to obtain detailed data on variables such as rainfall and temperature from online daily records provided by stations located in numerous urban areas in the region, there was no corresponding data available for cholera cases. Therefore, the inability to obtain comprehensive cholera records restricted the inclusion of other countries and limited the in-depth scrutiny of the factors like rainfall. However, the results from the data gathered from Mozambique highlight missed opportunities to identify similar relationships between cholera and climate variables in other countries using data at the appropriate granular level.

In addition, the study design relies on retrospective longitudinal data analysed within an ecological study framework. The data used in this study were significantly coarse at a country-level, which means that interpreting the results requires consideration of the ecological fallacy. The statistical methodology faced limitations on two fronts: (1) If the data were available at a higher geographic resolution, such as the implementation health unit (i.e., geographic health areas used in the surveillance of neglected tropical diseases by the WHO in sub-Saharan Africa) (WHO, 2018) we would have sought to implement a spatial-temporal model within a Bayesian framework, which may have yielded more promising results (Morris et al., 2019). (2) Alternatively, a multilevel multivariable Poisson regression model could have been a viable approach for this dataset's structure. However, we encountered convergence issues and multicollinearity between our main exposure variables (i.e., water and basic sanitation), leading us to discard this approach in favour of using a stratified modelling framework.

We acknowledge these as severe limitations, whereby the existing approach limits the internal validity of this study. Perhaps a hierarchical model executed within a Bayesian framework would have provided a solution over the initial frequentist approach, requiring only the same usage of the above model to be specified as the likelihood function. However, specifying priors for our main exposure (i.e., water and sanitation services) and confounding variables (i.e., temperature, rainfall, and GDP) was not a straightforward process, and we opted to avoid this minefield. This proposed approach could certainly be explored in future research.

Finally, the authors recognise that the study design restricts the analysis to only 13 sub-Saharan African countries with complete case data on cholera. Consequently, this limitation inherently restricts the generalizability of the results, primarily applying to the African countries included in this study with complete data.

5. Conclusions

This investigation contributes to public health research by identifying pivotal factors for regional action, facilitating targeted interventions, coordinated efforts, and cross-border strategies to enhance the region's resilience to endemic cholera outbreaks. Based on the research analyses conducted, the following key findings can be obtained in this study:

- The Spearman test showed a stronger correlation than the Pearson test between cholera outbreaks and environmental factors, suggesting a non-linear relationship. Specifically, it suggests a significant connection between cholera outbreaks and two factors: water access and GDP. Higher water provision and GDP corresponded to lower cholera rates, highlighting their importance in cholera prevention.
- Water access, sanitation provision, rising temperatures, and increased rainfall were identified as crucial factors contributing to endemic cholera incidence in the sub-Saharan region. These factors, when combined, are likely to influence cholera risk in specific countries such as the Democratic Republic of Congo (DRC), Ghana, Ivory Coast, Malawi, Mozambique, Niger, Nigeria, and Tanzania. Moreover, they have the potential to impact the risk of cholera across sub-Saharan countries. Therefore, making widespread access to clean water a primary goal in the sub-Saharan region could be the focal point of efforts to minimise the risk of endemic cholera outbreaks. This consistently emerged as a factor that reduces cholera risk in all analyses. Following this, the expansion of sanitation provision, which is also a mitigating factor, should be prioritised to prevent the contamination of water sources.
- Increased rainfall and rising temperatures significantly increased the risk of endemic cholera outbreaks. These factors transcend geographical borders and are expected to be intensified due to climate change, posing a substantial health risk that necessitates an integrated regional response.

However, the opportunity to comprehend the precise mechanisms involved in these relationships is being missed due to the low level of detail in cholera datasets, necessitating further investigation. Additionally, despite most of the countries have suggested strong link between water access and sanitation basic provision with reduced cholera risk, because a stratified analysis by region paired with Poisson regression was applied for estimating relative risk between factors and cholera, we recommend to repeat the analysis using a multilevel multivariable Poisson regression model to better understand the link of these infrastructure factors with cholera risk reduction.

Finally, we advocate for the establishment of stronger cholera surveillance systems across the region, incorporating continuous monitoring, meticulous record-keeping, and regular publication of data reports. This initiative can potentially serve as a crucial tool in addressing the substantial challenges posed by climate change.

CRediT authorship contribution statement

Cristiane D. Girotto: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Kourosh Behzadian:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Anwar Musah:** Writing – review & editing, Software, Methodology, Formal analysis. **Albert S. Chen:** Writing – review & editing, Funding acquisition. **Slobodan Djordjevic:** Writing – review & editing. **Gordon Nichols:** Writing – review & editing. **Luiza C. Campos:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.171896.

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