

Anticipatory decision-making for cholera in Malawi

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ABSTRACT Climate change raises an old disease to a new level of public health threat. The causative agent, *Vibrio cholerae*, native to aquatic ecosystems, is influenced by climate and weather processes. The risk of cholera is elevated in vulnerable populations lacking access to safe water and sanitation infrastructure. Predictive intelligence, employing mathematical algorithms that integrate earth observations and heuristics derived from microbiological, sociological, and weather data, can provide anticipatory decision-making capabilities to reduce the burden of cholera and save human lives. An example offered here is the recent outbreak of cholera in Malawi, predicted in advance by such algorithms.

KEYWORDS cholera, remote sensing, Malawi

Cholera remains a deadly waterborne diarrheal disease and is devastating for populations living in poverty and lacking access to safe water, sanitation, and hygiene (WASH) infrastructure. *Vibrio cholerae*, frequently linked to diarrheal illness and a causative agent of the cholera disease, thrives in regions where environmental, weather/climate, and societal vulnerabilities intersect. The continent of Africa is particularly vulnerable to cholera outbreaks, notably where there is a lack of access to WASH infrastructure and sufficient healthcare facilities. Figure 1 shows major cholera outbreaks occurring across Africa from 2017 to 2022. Apart from African countries, several other countries have reported cholera (1), e.g., Haiti (2010) and more recently in Yemen (2016) (2). Natural (earthquake in Haiti) and anthropogenic (civil unrest in Yemen) disasters have damaged WASH infrastructure (2, 3), resulting in massive cholera outbreaks.

Cholera is preventable by ensuring access to WASH and adequate medical infrastructure. Over the past 50 years, several major discoveries have been made, notably that *V. cholerae* is native to the aquatic environment where it proliferates when conditions for its growth are optimal (4–9). Proliferation of *V. cholerae* and related *Vibrio* spp. in the environment was shown to be driven by environmental factors, namely ambient weather and climatic processes, with coastal waters serving as an ecological niche for several pathogenic *Vibrio* spp., including *Vibrio parahaemolyticus*, *Vibrio vulnificus*, and *Vibrio cholerae* ([review provided by Brumfield et al. (10)]. Another important finding is that *Vibrio* spp. are commensal to copepods, zooplankton comprising a significant component of aquatic fauna that feed on phytoplankton in coastal waters (6, 11). In fact, copepods are a major host of *V. cholerae* (12). A single copepod can harbor up to 10^4 *V. cholerae* cells (9); hence, ingestion of untreated water containing a small number of copepods can promote disease (13–15), a sufficiently significant activity for the copepod to be concluded a vector (16). Studies by Huq et al. and Colwell et al. (14, 15) demonstrated that employing simple sari-cloth filtration prior to consumption of water effectively removed zooplankton and particulate matter from drinking water and significantly reduced the number of cholera cases in Bangladesh villages. In total, these findings demonstrated vibrios in the environment to be strongly associated with ecological and climate/weather processes (e.g., flooding [17, 18], sea surface temperature [19, 20],

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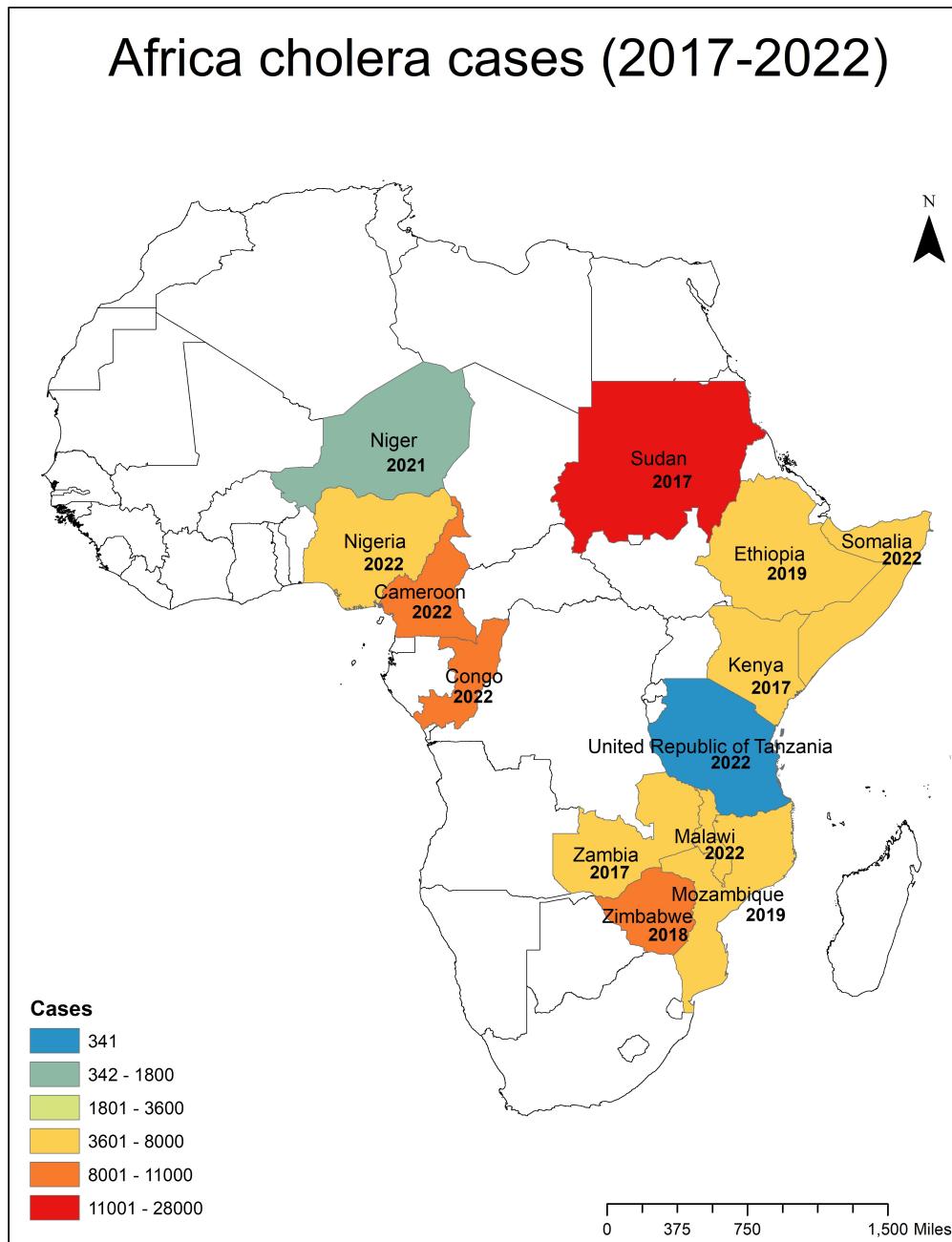


FIG 1 Cholera outbreaks reported in Africa from 2017 to 2022.

zooplankton blooms [12, 14], and salinity [21] and regional hydrology (e.g., river flows [22], coastal plankton ecology [23], ambient temperature [24], and precipitation [25, 26]).

Previous research demonstrated that cholera outbreaks occur in two modes (27–31): epidemic, which is the sudden occurrence of cholera in a region where societal disturbance results in a lack of access to safe drinking water and appropriate sanitation, and endemic, which is a continuous occurrence of cholera cases in human population with quasi-predictable seasonality. The cholera epidemic mode can evolve to become endemic if WASH access is not ensured. A cholera outbreak requires distinct trigger and transmission mechanisms (29, 30, 32), where the trigger is defined as conditions that initiate an outbreak driven by social and environmental dynamics and transmission as spreading of infection into human communities. While the origins of the cholera trigger

have been debated (28, 30), the interaction of humans with an environmental reservoir of *V. cholerae* has been linked with outbreaks of cholera (12, 23, 33, 34).

Given the spatial uncertainty of cholera in vulnerable regions with poor WASH infrastructure, a key challenge is determining when and where to introduce mitigation action to prevent an outbreak. One solution is anticipatory decision-making, a framework that uses predictive intelligence based on knowledge derived from field surveillance and mathematical models (30). A 3-year, near real-time model validation applied in Yemen yielded 72% accuracy in forecasting the risk of the likelihood of cholera (30). It was the first study to highlight the use of environmental, climate, and weather information integrated with microbiological and sociological data to estimate the risk scores for cholera.

A climate-driven, sociological hypothesis states that if a region experiences above-average air temperature, followed by heavy precipitation, and considerable damage to water and sanitation infrastructure, human behavior will change with respect to consumption of water, rendering the region to high risk of cholera (details of the model are provided in previously published studies [23, 28, 31, 35]). The potential of a cholera outbreak will remain low if any of these conditions are not met. A data-driven,

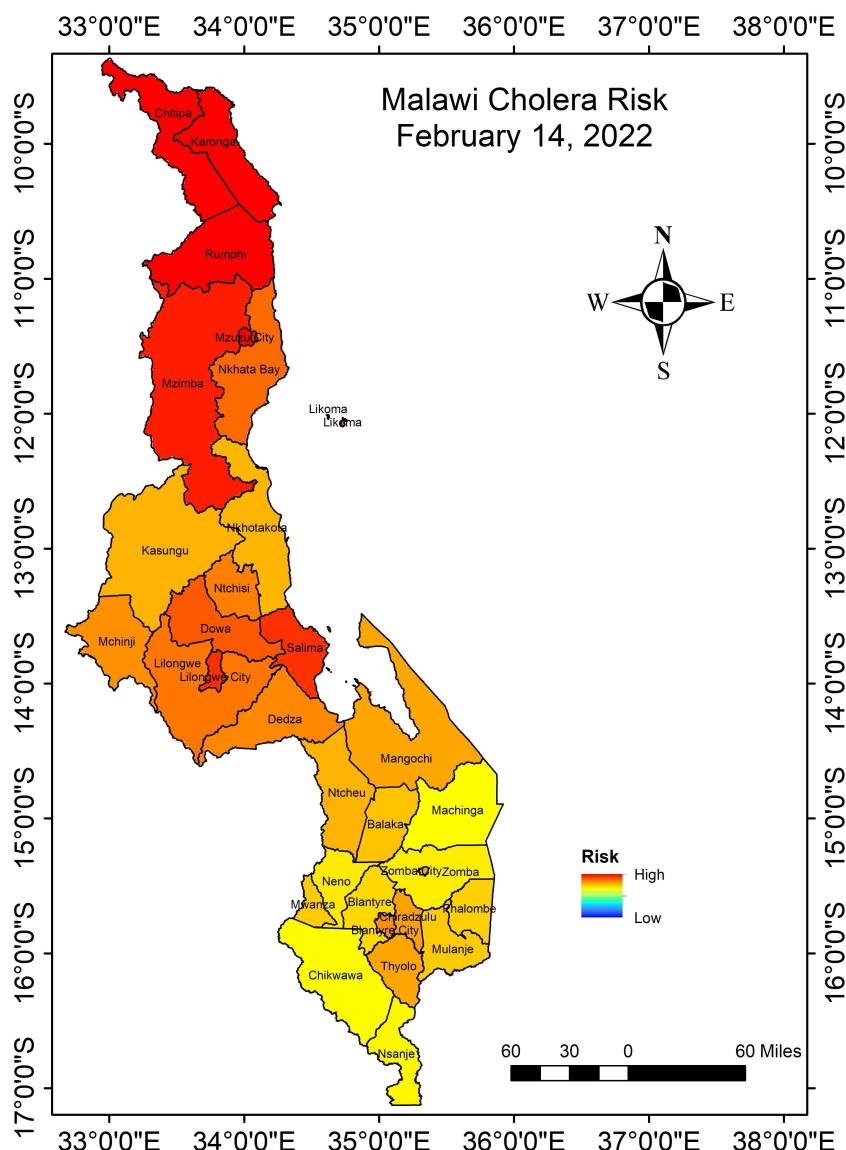


FIG 2 Cholera risk for Malawi 14 February 2022, valid for the following 4 weeks.

score-based mathematical algorithm developed over the past decade provides a reliable lead time of 4 weeks for the risk of cholera (28, 30, 31, 36) (a web hub is currently in beta phase and is available at <https://vibrio-prediction-ufl.hub.arcgis.com/>). The algorithm provides risk values (high, medium, and low) at 1 km × 1 km pixel scale and employs earth observations, including precipitation, temperature, population density, sociological factors (e.g., access to drinking water and sanitation), and *Vibrio spp.* growth parameters. The output of the algorithm and the validation of the hypothesis have been demonstrated for Zimbabwe (35) and subsequently for Nepal (31) and Haiti (28) and, more recently, for Yemen (30, 36).

The cholera algorithm, focusing on the trigger mechanism, was implemented in Malawi in February 2022, in the middle of the rainy season. However, the region recorded both anomalous conditions of warm temperatures and high precipitation. Heightened risk of cholera, on a district scale, for the country was predicted (see Fig. 2) with a 4-week lead time. Medium risk, as shown in Fig. 2, indicates that if conditions became amplified (in this case, damage and/or lack of access to WASH infrastructure), the region would experience cholera within 4 weeks of forecast. In fact, the first confirmed case of cholera was reported in Malawi on 2 March 2022 (37), leading the Ministry of Health to declare an outbreak the following day. The cholera cases decreased with the onset of dry months (May to October). Cholera risk, as computed by the algorithm, increased again in October 2022 and peaked in January 2023 (Fig. 3) by which time the outbreak had affected all districts of the country, with case numbers and case fatality surpassing Malawi's previous worst outbreak 20 years earlier. Cholera risk algorithm produce a time series of risk scores interpreted as a rate of increase (risk value consistently increased over the previous forecasted risk value) (details in references 30, 36). Figure 3 shows the consistent increase in cholera risk from October 2022, hence favored increased odds of cholera.

Geophysical processes have only recently been established for deducing and forecasting the behavior of a pathogen. Therefore, it is crucial to provide a comprehensive, data-driven, and adaptable understanding of an infectious disease that is influenced by weather and climate to achieve reliable decision-making. It is essential to differentiate between reactive and anticipatory decision-making. Most decision-making, with respect to infectious diseases, remain reactive, with intervention and mitigation initiated after

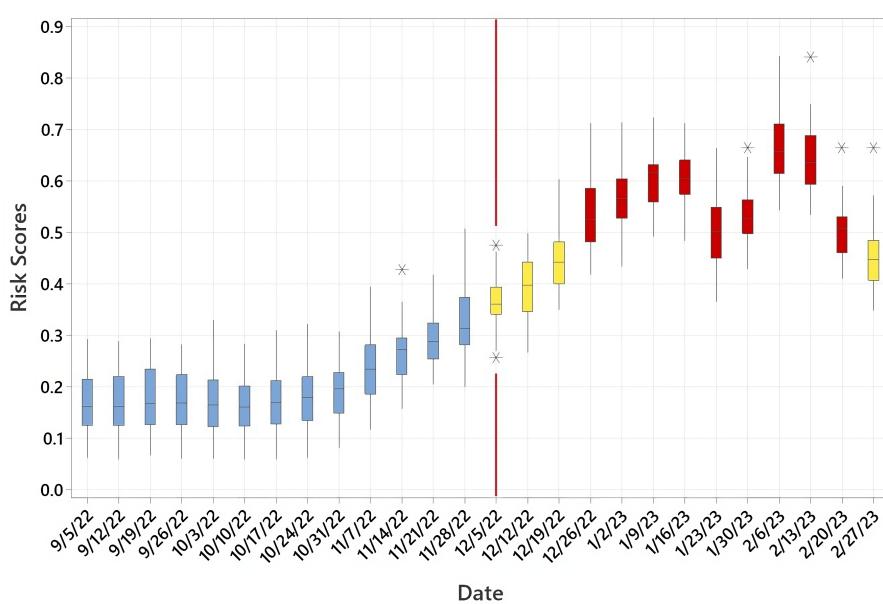


FIG 3 Boxplot for an entire Malawi cholera risk time series (values greater than 0.34 represent medium risk, in yellow color; values greater than 0.50 represent a high risk, in red color, of cholera). Line shows probable time when cholera was acknowledged by the health agencies.

TABLE 1 Recommended preemptive actions

	Preemptive interventions	Preference	Source
Safe water	Sealed and bottled water	1	(40)
	Water treatment	2	(41, 42)
	Boiling water	3	(43)
Safe defecation	Limit open defecation	1	(44, 45)
	Chemical treatment of fecal matter	2	(46)
	No defecation near/in a water body	3	(47)
Hand wash	Ensuring proper hand washing principles	1	(48, 49)
	Washing hands before and after cooking and eating	2	(47, 49)
	Washing hands when treating sick patients	3	(50)
Eating habits	Thoroughly cooking and preparing food	1	(49)
	Avoiding seafood during disease outbreaks	2	(49)
	Encouraging peeled vegetables and fruits	3	(42, 49)
Oral cholera vaccine	Before exposure (7–10 days before infection)	1	(51)

an outbreak has begun. Earth observation data, if sociological processes and microbial processes are included, can provide anticipatory decision-making. Frameworks to guide anticipatory decision-making should be developed to support Ministries of Health and other agencies to translate risk data into effective action. This is important in places such as Malawi which are highly vulnerable to increasingly climate-related public health shocks yet with limited resources to respond. For Malawi, anticipatory intervention to limit spread of cholera could have contributed to improving targeted distribution of water safety kits, stockpiling, and ensuring availability of antibiotics, timely vaccination, and education of the local population on handling water drawn from ponds and rivers in conflicted regions. Anticipatory, risk-based intervention in February 2022 could have contributed to preventing or limiting the spread of the initial outbreak that occurred in March 2022, as well as made best use of limited vaccine stocks (38) (given the global shortage) and other interventions by focusing on at risk populations. Thus, country-wide spread of disease that occurred later in 2022 and led to nearly 60,000 cases and over 1,700 deaths could have been prevented. It could also have been helpful to identify when the risk was reducing to inform decisions on when and where to scale down interventions. Internet or data transmission will be effective and helpful in implementing surveillance systems for reporting cholera cases. Table 1 lists some proactive measures that can be employed to prevent major outbreaks of cholera, adapted from reference 39. Reliability of predictive intelligence for infectious diseases generated by mathematical algorithms that integrate earth observations and geophysical processes into disease models is a new field with a powerful future.

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REFERENCES

1. Khouri P. 2023. Cholera is back but the world is looking away. *BMJ* 380:141. <https://doi.org/10.1136/bmj.p141>
2. Camacho A, Bouhenia M, Alyusfi R, Alkohlani A, Naji MAM, de Radiguès X, Abubakar AM, Almoalmi A, Seguin C, Sagrado MJ, Poncin M, McRae M, Musoke M, Rakesh A, Porten K, Haskew C, Atkins KE, Eggo RM, Azman AS, Broekhuijsen M, Saatcioglu MA, Pezzoli L, Quilici M-L, Al-Mesbahy AR, Zagaria N, Luquero FJ. 2018. Cholera epidemic in Yemen, 2016–18: an analysis of surveillance data. *6. Lancet Glob Health* 6:e680–e690. [https://doi.org/10.1016/S2214-109X\(18\)30230-4](https://doi.org/10.1016/S2214-109X(18)30230-4)
3. Hasan NA, Choi SY, Eppinger M, Clark PW, Chen A, Alam M, Haley BJ, Taviani E, Hine E, Su Q, Tallon LJ, Prosper JB, Furth K, Hoq MM, Li H, Fraser-Liggett CM, Cravioto A, Huq A, Ravel J, Cebula TA, Colwell RR. 2012. Genomic diversity of 2010 haitian cholera outbreak strains. *Proc Natl Acad Sci USA* 109:E2010–7. <https://doi.org/10.1073/pnas.1207359109>
4. Choopun N, Louis V, Huq A, Colwell RR. 2002. Simple procedure for rapid identification of *Vibrio cholerae* from the aquatic environment. *Appl Environ Microbiol* 68:995–998. <https://doi.org/10.1128/AEM.68.2.995-998.2002>
5. Kaneko T, Colwell RR. 1973. Ecology of *Vibrio parahaemolyticus* in Chesapeake Bay. *J Bacteriol* 113:24–32. <https://doi.org/10.1128/Jb.113.1.24-32.1973>
6. Kaneko T, Colwell RR. 1975. Adsorption of *Vibrio parahaemolyticus* onto chitin and copepods. *Appl Microbiol* 29:269–274. <https://doi.org/10.1128/am.29.2.269-274.1975>
7. West PA, Lee JV. 1982. Ecology of *Vibrio* species, including *Vibrio cholerae*, in natural waters in Kent, England. *J Appl Bacteriol* 52:435–448. <https://doi.org/10.1111/j.1365-2672.1982.tb05074.x>
8. Xu HS, Roberts N, Singleton FL, Attwell RW, Grimes DJ, Colwell RR. 1982. Survival and viability of nonculturable *Escherichia coli* and *Vibrio cholerae* in the estuarine and marine environment. *Microb Ecol* 8:313–323. <https://doi.org/10.1007/BF02010671>
9. Colwell RR, Spira WM. 1992. The Ecology of *Vibrio cholerae*, p 107–127. In cholera. Springer. <https://doi.org/10.1007/978-1-4757-9688-9>
10. Brumfield KD, Usmani M, Chen KM, Gangwar M, Jutla AS, Huq A, Colwell RR. 2021. Environmental parameters associated with incidence and transmission of pathogenic *Vibrio* spp. *Environ Microbiol* 23:7314–7340. <https://doi.org/10.1111/1462-2920.15716>
11. Tamplin ML, Gauzens AL, Huq A, Sack DA, Colwell RR. 1990. Attachment of *Vibrio cholerae* serogroup O1 to zooplankton and phytoplankton of Bangladesh waters. *Appl Environ Microbiol* 56:1977–1980. <https://doi.org/10.1128/aem.56.6.1977-1980.1990>
12. Huq A, Small EB, West PA, Huq MI, Rahman R, Colwell RR. 1983. Ecological relationships between *Vibrio cholerae* and planktonic crustacean copepods. *Appl Environ Microbiol* 45:275–283. <https://doi.org/10.1128/aem.45.1.275-283.1983>
13. Cash RA, Music SI, Libonati JP, Snyder MJ, Wenzel RP, Hornick RB. 1974. Response of man to infection with *Vibrio cholerae*. I. clinical, serologic, and bacteriologic responses to a known inoculum. *J Infect Dis* 129:45–52. <https://doi.org/10.1093/infdis/129.1.45>
14. Huq A, Xu B, Chowdhury MA, Islam MS, Montilla R, Colwell RR. 1996. A simple filtration method to remove plankton-associated *Vibrio cholerae* in raw water supplies in developing countries. *Appl Environ Microbiol* 62:2508–2512. <https://doi.org/10.1128/aem.62.7.2508-2512.1996>
15. Colwell RR, Huq A, Islam MS, Aziz KMA, Yunus M, Khan NH, Mahmud A, Sack RB, Nair GB, Chakraborty J, Sack DA, Russek-Cohen E. 2003. Reduction of cholera in Bangladeshi villages by simple filtration. *Proc*

Natl Acad Sci USA 100:1051–1055. <https://doi.org/10.1073/pnas.0237386100>

16. Colwell RR. 1996. Global climate and infectious disease: the cholera paradigm. *Science* 274:2025–2031. <https://doi.org/10.1126/science.274.5295.2025>

17. Khan R, Usmani M, Akanda A, Palash W, Gao Y, Huq A, Colwell R, Jutla A. 2019. Long-range river discharge forecasting using the gravity recovery and climate experiment. *J Water Resour Plann Manage* 145:06019005. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0001072](https://doi.org/10.1061/(ASCE)WR.1943-5452.0001072)

18. Koelle K, Rodó X, Pascual M, Yunus M, Mostafa G. 2005. Refractory periods and climate forcing in cholera dynamics. *Nature* 436:696–700. <https://doi.org/10.1038/nature03820>

19. Constantin de Magny G, Murtugudde R, Sapiano MRP, Nizam A, Brown CW, Busalacchi AJ, Yunus M, Nair GB, Gil AI, Lanata CF, Calkins J, Manna B, Rajendran K, Bhattacharya MK, Huq A, Sack RB, Colwell RR. 2008. Environmental signatures associated with cholera epidemics. *Proc Natl Acad Sci USA* 105:17676–17681. <https://doi.org/10.1073/pnas.0809654105>

20. Lobitz B, Beck L, Huq A, Wood B, Fuchs G, Faruque AS, Colwell R. 2000. Climate and infectious disease: use of remote sensing for detection of *Vibrio cholerae* by indirect measurement. *Proc Natl Acad Sci U S A* 97:1438–1443. <https://doi.org/10.1073/pnas.97.4.1438>

21. Miller C, Drasar B, Feachem R. 1982. Cholera and estuarine salinity in Calcutta and London. *Lancet* 1:1216–1218. [https://doi.org/10.1016/s0140-6736\(82\)92340-6](https://doi.org/10.1016/s0140-6736(82)92340-6)

22. Akanda AS, Jutla AS, Islam S. 2009. Dual peak cholera transmission in Bengal Delta: a hydroclimatological explanation. *Geophys Res Lett* 36. <https://doi.org/10.1029/2009GL039312>

23. Jutla A, Whitcombe E, Hasan N, Haley B, Akanda A, Huq A, Alam M, Sack RB, Colwell R. 2013. Environmental factors influencing epidemic cholera. *Am J Trop Med Hyg* 89:597–607. <https://doi.org/10.4269/ajtmh.12-0721>

24. Speelmon EC, Checkley W, Gilman RH, Patz J, Calderon M, Manga S. 2000. Cholera incidence and El Niño-related higher ambient temperature. *JAMA* 283:3072–3074.

25. Hashizume M, Armstrong B, Hajat S, Wagatsuma Y, Faruque ASG, Hayashi T, Sack DA. 2008. The effect of rainfall on the incidence of cholera in Bangladesh. *Epidemiology* 19:103–110. <https://doi.org/10.1097/EDE.0b013e31815c09ea>

26. Pascual M, Bouma MJ, Dobson AP. 2002. Cholera and climate: revisiting the quantitative evidence. *Microbes Infect* 4:237–245. [https://doi.org/10.1016/s1286-4579\(01\)01533-7](https://doi.org/10.1016/s1286-4579(01)01533-7)

27. Codeço CT. 2001. Endemic and epidemic dynamics of cholera: the role of the aquatic reservoir. *BMC Infect Dis* 1:1. <https://doi.org/10.1186/1471-2334-1-1>

28. Khan R, Anwar R, Akanda S, McDonald MD, Huq A, Jutla A, Colwell R. 2017. Assessment of risk of cholera in haiti following hurricane matthew. *Am J Trop Med Hyg* 97:896–903. <https://doi.org/10.4269/ajtmh.17-0048>

29. Usmani M, Brumfield KD, Jamal Y, Huq A, Colwell RR, Jutla A. 2021. A review of the environmental trigger and transmission components for prediction of cholera. *Trop Med Infect Dis* 6:147. <https://doi.org/10.3390/tropicalmed6030147>

30. Usmani M, Brumfield KD, Magers BM, Chaves-Gonzalez J, Ticehurst H, Barciela R, McBean F, Colwell RR, Jutla A. 2023. Combating cholera by building predictive capabilities for pathogenic *Vibrio cholerae* in Yemen. *Sci Rep* 13:2255. <https://doi.org/10.1038/s41598-022-22946-y>

31. Khan R, Nguyen TH, Shisler J, Lin L-S, Jutla A, Colwell R. 2018. Evaluation of risk of cholera after a natural disaster: lessons learned from the 2015 Nepal earthquake. *J Water Resour Plann Manage* 144. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000929](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000929)

32. Jutla AS, Akanda AS, Islam S. 2010. Tracking cholera in coastal regions using satellite observations. *JAWRA J Am Water Resour Assoc* 46:651–662. <https://doi.org/10.1111/j.1752-1688.2010.00448.x>

33. Alam M, Hasan NA, Sadique A, Bhuiyan NA, Ahmed KU, Nusrin S, Nair GB, Siddique AK, Sack RB, Sack DA, Huq A, Colwell RR. 2006. Seasonal cholera caused by *Vibrio cholerae* serogroups O1 and O139 in the coastal aquatic environment of Bangladesh. *Appl Environ Microbiol* 72:4096–4104. <https://doi.org/10.1128/AEM.00066-06>

34. Singleton FL, Attwell RW, Jangi MS, Colwell RR. 1982. Influence of salinity and organic nutrient concentration on survival and growth of *Vibrio cholerae* in aquatic microcosms. *Appl Environ Microbiol* 43:1080–1085. <https://doi.org/10.1128/aem.43.5.1080-1085.1982>

35. Jutla A, Aldaach H, Billian H, Akanda A, Huq A, Colwell R. 2015. Satellite based assessment of hydroclimatic conditions related to cholera in Zimbabwe. *PLoS One* 10:e0137828. <https://doi.org/10.1371/journal.pone.0137828>

36. Barciela R, Bilge T, Brown K, Champian A, Sarran C, Shields M, Ticehurst H, Jutla A, Usmani M, Colwell R. 2021. Early Action for Cholera Project Yemen Case Study. Met Office.

37. WHO. 2022. Cholera-Malawi

38. WHO. 2022. Shortage of cholera vaccines leads to temporary suspension of two-dose strategy, as cases rise worldwide

39. Usmani M, Brumfield KD, Magers BM, Huq A, Barciela R, Nguyen TH, Colwell RR, Jutla A. 2022. Predictive intelligence for cholera in Ukraine? *Geohealth* 6:e2022GH000681. <https://doi.org/10.1029/2022GH000681>

40. McLennan JD. 2016. Did point-of-use drinking water strategies for children change in the dominican republic during a cholera epidemic? *Public Health* 138:57–62. <https://doi.org/10.1016/j.puhe.2016.03.012>

41. Sinyange N, Brunkard JM, Kapata N, Mazabu ML, Musonda KG, Hamoonga R, Kapina M, Kapaya F, Mutale L, Kateule E, Nanzaluka F, Zulu J, Musyani CL, Winstead AV, Davis WW, N'cho HS, Mulambya NL, Sakubita P, Chewe O, Nyimbili S, Onwuekwe EVC, Adrienne N, Blackstock AJ, Brown TW, Derado G, Garrett N, Kim S, Hubbard S, Kahler AM, Malambo W, Mintz E, Murphy J, Narra R, Rao GG, Riggs MA, Weber N, Yard E, Zyambo KD, Bakayita N, Monze N, Malama K, Mulwanda J, Mukonka VM. 2018. Cholera epidemic - lusaka, zambia, october 2017–may 2018. *MMWR Morb Mortal Wkly Rep* 67:556–559. <https://doi.org/10.15585/mmwr.mm6719a5>

42. Taylor DL, Kahawita TM, Cairncross S, Ensink JHH. 2015. The impact of water, sanitation and hygiene interventions to control cholera: a systematic review. *PLoS One* 10:e0135676. <https://doi.org/10.1371/journal.pone.0135676>

43. Lantagne D, Yates T. 2018. Household water treatment and cholera control. *J Infect Dis* 218:S147–S153. <https://doi.org/10.1093/infdis/jiy488>

44. Cowman G, Otipo S, Njeru I, Achia T, Thirumurthy H, Bartram J, Kioko J. 2017. Factors associated with cholera in Kenya, 2008–2013. *Pan Afr Med J* 28:101. <https://doi.org/10.11604/pamj.2017.28.101.12806>

45. Montgomery M, Jones MW, Kabole I, Johnston R, Gordon B. 2018. No end to cholera without basic water, sanitation and hygiene. *Bull World Health Organ* 96:371–371A. <https://doi.org/10.2471/BLT.18.213678>

46. Appiah-Effah E, Duku GA, Dwumfour-Asare B, Manu I, Nyarko KB. 2020. Toilet chemical additives and their effect on faecal sludge characteristics. *Heliyon* 6:e04998. <https://doi.org/10.1016/j.heliyon.2020.e04998>

47. Deoshatwar A, Salve D, Gopalkrishna V, Kumar A, Barve U, Joshi M, Katendra S, Dhembre V, Maheshwari S, Viswanathan R. 2021. Evidence-based health behavior interventions for cholera: lessons from an outbreak investigation in India. *Am J Trop Med Hyg* 106:229–232. <https://doi.org/10.4269/ajtmh.21-0625>

48. Htin Y, Luby S, Paquet C. 2003. A large cholera outbreak in Kano city, Nigeria: the importance of hand washing with soap and the danger of street-vended water. *J Water Health* 1:45–52.

49. Rabbani GH, Greenough WB. 1999. Food as a vehicle of transmission of cholera. *J Diarrhoeal Dis Res* 17:1–9.

50. Snow J. 1856. On the mode of communication of cholera. *Edinb Med J* 1:668–670.

51. Song KR, Lim JK, Park SE, Saluja T, Cho S-I, Wartel TA, Lynch J. 2021. Oral cholera vaccine efficacy and effectiveness. *Vaccines* 9:1482. <https://doi.org/10.3390/vaccines9121482>