Water-borne Disease Prevalence and Water and Sanitation Infrastructure.

County by County Analysis of Kenya.

Author: Aoko

Level: Undergraduate Degree in statistics.

Institution: The Jomo Kenyatta University of Agriculture and Technology.

Year: 2023

Introduction

Waterborne diseases continue to be a significant menace to the general health of the people in Kenya, which is mostly brought about by lack of access to potable water and sanitation facilities. Contaminated water sources and poor hygiene practices are common ways of spreading diseases like diarrhea, cholera, dysentery, amoebiasis, and bilharzia (WHO, 2017; Olowe et al., 2016). According to previous research, the use of water and sanitation infrastructure can significantly decrease the proliferation of these diseases (Ferreira et al., 2021).

The prevalence of diseases in Kenya is widely distributed in geographic terms with most of the counties recording high prevalence rates in Turkana, Machakos, Kakamega, West Pokot, and other areas in western Kenya (KNBS Statistical Abstract, 2021). Irrespective of this difference, there has been paucity of research conducted nationally to determine whether such disease patterns in counties have a spatial dependence or not. This research paper fills this gap of studying how the prevalence of waterborne diseases is associated with a water and sanitation infrastructure in all 47 counties in Kenya by utilizing spatial analysis methods.

Objectives

Three objectives were used to guide the study:

1. To investigate the spatial dependence of prevalence of waterborne diseases in the counties of Kenya.
2. To determine geographic hot spots of significant waterborne diseases.
3. To estimate the correlation among water, sanitation service ladders and disease prevalence in the region, by means of spatial regression.

Data and Methodology

3.1 Data Sources

The research employed the secondary data which is clustered at the county level of:

Nigeria Demographic and Health Survey (Nigeria DHS) 2019/2020 (Nigeria DHS, 2020).

COVID-19 tracks and statistics in Kenya, 2021 (KNBS, 2021).

Some of the variables were the prevalence rates of diseases, household source of drinking water, level of sanitation services, water treatment as well as availability of adequate drinking water.

3.2 Analytical Approach

To describe geographic variance in disease prevalence, choropleth maps were used in the exploratory spatial analysis. The spatial dependence was measured by the Moran I statistic as the measure of the disease prevalence clustering (Hoffman & Kedron, 2023).

In a bid to capture spatial spillover effects, the Spatial Autoregressive (SAR) models were used. The SAR framework can contribute the effects of spatial interaction where one prevalence level in a county can affect another prevalence level in an adjacent county, whereas traditional regression models do not (Zhang et al., 2021). The Maximum Likelihood Estimation (MLE) was used to estimate the model parameters, which give effective and consistent estimates (Wen, 2015).

Results

4.1 The spatial dependence and Hotspots

The spatial dependency of all the major waterborne diseases was serious as analyzed. There were multiple instances of non-random geographic clustering as counties with high disease prevalence were often adjacent to other counties with high disease prevalence.

Hotspots of individual diseases were defined:

- Cholera: Machakos, Turkana and Marsabit.
- Diarrhea Kirinyaga, Elgeyo-Marakwet, Lamu, West Pokot, and Homa Bay.
- Dysentery: Migori
- Amoebiasis: Kirinyaga and Tharaka-Nithi.
- Bilharzia: Lami, Kilifi, Kwale and Mombasa counties located along the coast.

This can be attributed to the prior findings of regional vulnerability that is tied to lack of sanitation, urbanization, and limited access to water (Livingstone, 2021; Shusterman, 2020).

4.2 Ladder Effects Water and Sanitation Service.

The SAR models demonstrated that a better level of sanitation services was commonly linked with reduced incidence of diarrhea, cholera, and dysentery, which confirms the literature claim on the protective effect of sanitation infrastructure (Wolf et al., 2022; KDHS, 2023).

The water treatment methods and the source of household drinking water had different impacts on different diseases. Although untreated and surface water sources are commonly related to an increased risk of the disease (Magana-Arachchi and Wanigatunge, 2020; Manetu and Karanja, 2021), not all model coefficients were significant or had the same direction. These discrepancies indicate that the dynamics of disease transmission are complicated and affected by the local environmental and behavior influences (Daniel et al., 2021).

Discussion

The findings support the fact that there is a geographical concentration of waterborne diseases in Kenya and are not randomly distributed. The counties with high prevalence are often geographically clustered, which supports the significance of a spatially conscious approach to the implementation of public health. The detection of disease-specific hotspots is consistent with the previous studies of the informal settlements by urban areas, coastal exposure, and the regional disparities in sanitation (Osiemo et al., 2019; Livingstone, 2021).

Though enhanced sanitation services showed a protective effect at all times, the changing effect of water treatment techniques indicates the necessity of intervention-specific action. The results justify the need to develop policies based on geography instead of national approaches (Ferreira et al., 2021).

Conclusion

This research proves that the prevalence of waterborne diseases in Kenya is much spatially dependent and is correlated with water and sanitation infrastructure. Hotspots of diseases underscore the importance of focusing the intervention especially in the north, west, central and coastal areas. Better sanitation infrastructure is also a very important variable in decreasing disease burden, whereas the efficacy of water treatment practices is disease and location-specific. Altogether, spatial analysis can be useful in evidence-based resource distribution and health planning of the population.

References

CDC. (2022). *Household water treatment*. Centers for Disease Control and Prevention.

CDC. (2023). *World Water Day*. Centers for Disease Control and Prevention.

Daniel, D., Pande, S., & Rietveld, L. (2021). Socio-economic and psychological determinants for household water treatment practices. *Frontiers in Water, 3*.

Ferreira, D. C., et al. (2021). Investment in drinking water and sanitation infrastructure and its impact on waterborne diseases dissemination. *Science of the Total Environment, 779*.

Hoffman, T., & Kedron, P. (2023). Spatial autoregressive models. *GIS&T Body of Knowledge*.

KDHS. (2023). *Kenya Demographic and Health Survey 2022–Key Indicators Report*.

KNBS. (2021). *Statistical Abstract 2021*.

Livingstone, J. (2021). Urban water scarcity and disease outbreaks in Africa.

Magana-Arachchi, D. N., & Wanigatunge, R. P. (2020). *Ubiquitous waterborne pathogens*.

Manetu, W. M., & Karanja, A. M. (2021). Waterborne disease risk factors and intervention practices.

Olowe, B., Oluyege, J., & Famurewa, O. (2016). Prevalence of waterborne diseases and microbial assessment.

Osiemo, M. M., Ogendi, G. M., & M’Erimba, C. (2019). Microbial quality of drinking water and prevalence of water-related diseases.

Shusterman, J. (2020). Poor sanitation in Kenya leads to water-borne diseases.

WHO. (2017). *Diarrhoeal disease*. World Health Organization.

WHO. (2022). *Drinking-water*. World Health Organization.

Wolf, J., et al. (2022). Effectiveness of interventions to improve drinking water, sanitation, and handwashing. *The Lancet, 400*.

Wen, H. (2015). Properties of Maximum Likelihood Estimation (MLE).

Zhang, L., et al. (2021). Spatial distribution of rural population from a climate perspective. *PLOS ONE*.