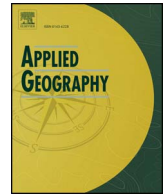




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An exploration of the spatiotemporal and demographic patterns of Ebola Virus Disease epidemic in West Africa using open access data sources

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ABSTRACT

The purpose of this study was to investigate the utility of exploratory analytical techniques using publically available data in informing interventions in case of infectious diseases outbreaks. More exactly spatiotemporal and multivariate methods were used to characterize the dynamics of the Ebola Virus Disease (EVD) epidemic in West Africa, and propose plausible relationships with demographic/social risk factors. The analysis showed that there was significant spatial, temporal, and spatiotemporal dependence in the evolution of the disease. For the first part of the epidemic, the cases were highly clustered in a few administrative units, in the proximity of the point of origin of the outbreak, possibly offering the opportunity to stop the spread of the disease. Later in the epidemic, high clusters were observed, but only in Liberia and Sierra Leone. Although not definitely factors of risk, in the setting in which the epidemic arose, our analysis suggests infrastructure, access to and use of health services, and connectivity possibly accelerated and magnified the spread of EVD. Also, the spatial, temporal, and spatiotemporal patterns of epidemic can be clearly shown – with evident application in the early stages of management of epidemics. In particular, we found that the spatiotemporal analytic tool SaTScan may be used effectively during the evolution of an epidemic to identify areas for targeted intervention. In the case of EVD epidemic in West Africa, better data and integration local knowledge and customs may have been more useful to recognize the proper response.

1. Introduction

The West African Ebola epidemic of 2014 - the largest in history - arose in a much different cultural setting than previous outbreaks. Previous outbreaks had occurred in isolated villages, whose people had experience with Ebola and were unlikely to travel great distances to seek medical care. In contrast, continuous movement of people from their villages (even while very sick), across borders from Guinea to either Sierra Leone or Liberia, and into urban centers, drove the rapid spread of Ebola to neighboring West African countries, into cities, in a matter of days (WHO, 2016a). Over three years, 28,616 confirmed, probable and suspected cases have been reported in West Africa, resulting in 11,310 deaths (WHO, 2016a). The magnitude of this epidemic and the difficulty containing it suggests the need for better understanding of dynamics of the EVD.

While it is well recognized that interventions such as isolation of patients and safe and sanitary funerals and burials played a vital role in controlling the epidemic, as did the people's own adaptation (Chowell & Nishiura, 2014; Richards, 2015; Rivers, Lofgren, Marathe, Eubank, & Lewis, 2014), the purpose of this study was to investigate if exploratory analytical techniques using publically available data can provide

insights into epidemic dynamics and propose plausible relationships with demographic/social risk factors. More exactly, principal components, spatial, temporal, and spatiotemporal analysis were used to assess the patterns of the EVD epidemic, identify the areas and time intervals of high risk, and identify the associated risk factors which can influence the risk of infection.

The analysis of spatiotemporal-distributed disease data can be used to identify the presence of absence of areas with significant differences in risk (Sherman et al., 2014), identify possible periodical patterns in the behavior of the disease (Marek, Tuček, & Pászto, 2015), and propose effective responses to outbreaks (Martins-Melo, Ramos, Alencar, Lange, & Heukelbach, 2012). However, these spatiotemporal analytic techniques cannot actually identify the factors leading to the observed patterns. Therefore, multivariate methods were used to explore if there are any patterns within the socio-demographic variables considered, and any relationship between these variables and the EVD case counts.

The paper is structured as follow: Section 2 describes the data processing and the statistical methodology. Section 3 presents the results of our analysis. Section 4 discuss the results, while section 5 contains the recommendations and conclusions.

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2. Methods

2.1. Data processing and description

To calculate the daily and weekly number of cases in each administrative district, a dataset provided by OCHA ROWCA on the Humanitarian Data Exchange (HDX, 2015), that compiled the number of cases released by various sources including the WHO, national health ministries, and other sources was used. The dataset recorded daily cumulative total, confirmed, probable and suspected cases, as well as new cases and the number of deaths from March 24, 2014, up to March 28, 2015. The records cover six countries in West Africa: Guinea, Liberia, Mali, Nigeria, Senegal, and Sierra Leone, at various administrative units' levels.

For the study, the most severely affected countries by the EVD epidemic were selected: Guinea, Liberia, and Sierra Leone, with a total of 63 administrative units. Additional data was collected from published reports (Fink & Sheri, 2014; HumanitarianResponse, 2016; WHO, 2016b). As a result, the coverage of the case counts was extended, and some of the missing entries (June 2014–August 2014), and errors (end of 2014 – beginning of 2015) were corrected. Fig. 1 shows the weekly case counts based on the original and appended datasets. Supplementary material file S1 describes briefly the method used in calculating the case counts. The final datasets had daily and weekly Ebola virus counts and rates for the three West African countries (aggregated over 63 administrative units) from December 06, 2013 to March 28, 2015.

For demographic and health information about West Africa, datasets provided by USAID on the Demographic and Health Surveys (DHS) Program website (USAID, 2016) were used. DHS collects, analyzes, and disseminates population, health, HIV, and nutrition data in over 90 countries. More details about the data collected in West Africa can be found in the DHS reports specific to each country (INS, 2013; LISGIS, 2014; SSL, 2014). For this research, the focus was on surrogate variables for factors hypothesized to be possible risk factors in the transmission of diseases: having access to bicycles, motorcycles or cars, women having a hospital delivery, women having a doctor or medical professional present at birth, education level, literacy, and reading newspapers, listening to radio or watching TV, sharing a toilet with other households, number of children living at home, and the mean number of STD and sexual partners. These factors represent access to information, transportation, healthcare, and behavior that might modify risk of exposure. The data was aggregated to the administrative unit, and variables were expressed as a percent of respondents having that attribute.

2.2. Spatial analysis

Spatial analysis methods were used to evaluate the geographical

distribution of the weekly Ebola infection rates. The administrative units from which the case counts were recorded were considered the units for the analysis.

The presence of spatial dependence was assessed using Global and Local Moran's I indexes for each of the 70 weeks of the epidemic considered in our dataset. The rates of infection were used instead of case counts since, generally, the number of cases is correlated to the underlying population size, and sometimes spatial autocorrelation may be detected only as an artifact of the spatial distribution of the population (Bivand, Pebesma, & Gomez-Rubio, 2008). For the local Moran's I analysis, Holm p-value adjustments were used to assess the significance of each test (Brunsdon & Comber, 2015).

In the analysis, three distance measures were considered: first two are commonly used in spatial analysis: a *contiguity based neighbors matrix*, and a *centroid based distance matrix* (Bivand et al., 2008). Since it was suggested that the dispersal of Ebola virus is supported by the proximity of infected people to main roads (Hui-Jun et al., 2015), a *population-weighted road distance matrix* (Mitze, 2012) was also considered. To calculate the population-weighted road distance matrix, a list of major cities with their complementary population sizes for the three states considered was compiled from various internet sources (Brinkhoff, 2015; Wikipedia, 2015), but not limited to them. The web-based information available for these countries is scarce, inconsistent, and the town names were often different from source to source. In the end, a list of 83 cities from across all administrative units was compiled. The road-based distances (in km) between all them was calculated using the ggmap function in R (Kahle & Wickham, 2013) and Google Maps for the city pairs unrecognized by the R package. The population-weighted distances between administrative units were calculated as described by Mitze (Mitze, 2012).

The contiguity based weight matrix was row-standardized, and inverse-distance weight matrices were generated for the centroid and road distances. The analysis was conducted in R-language (R Core Team, 2016), using the R packages PBS mapping, spdep, and ape (Bivand & Piras, 2015; Paradis, Claude, & Strimmer, 2004; Schnute, Boers, & Haigh, 2015).

2.3. Temporal analysis

To test for temporal dependence, a multivariate ARMAX model was considered (Shumway & Stoffer, 2011). The multivariate ARMAX model expressed the counts of new Ebola cases, in a given administrative unit, as a linear combination of the trend and past counts of Ebola cases in all the other administrative units.

The case counts at time t were expressed as:

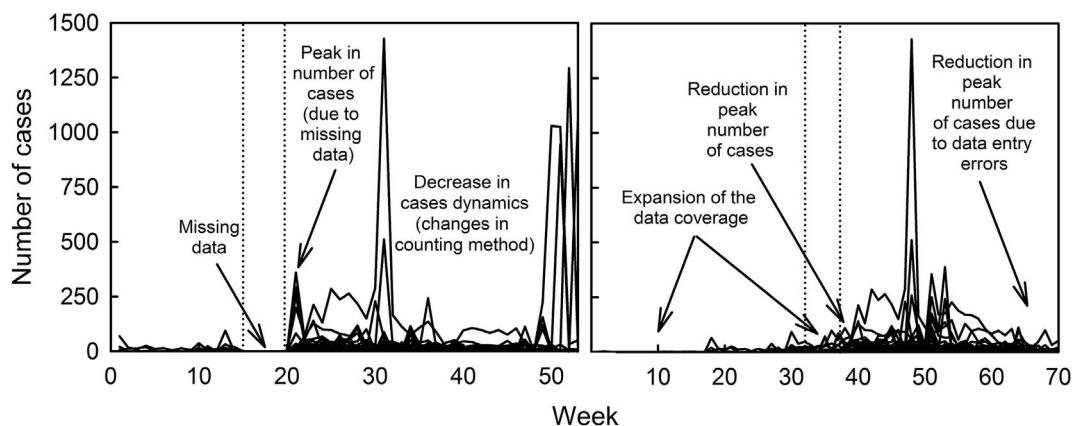


Fig. 1. Weekly case counts calculated from the original dataset (left), and calculated from the appended dataset (right).

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