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Research Article

A Process for Determining the Environmental and the Sociological Factors That Influenced the Emergence of Ebola in Guinea

Michael Mbwille*

Trident University, California, USA

***Corresponding Author:** Michael Mbwille, Trident University, California, USA.

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Abstract

Ebola virus disease (EVD) outbreaks have been occurring intermittently in Central Africa since 1976. With the reemergence of Ebola in Guinea, there is evidence that climate change and sociological risk factors influenced the outbreak (along with outbreaks of other diseases in the region). In 2014, the initial outbreak in West Africa was reported in Guinea, followed by Liberia and Sierra Leone. A better assessment of culture and sociological risk factors can aid in further understanding the human-to-human EVD epidemics. The potential process through which culture and the socioeconomic environment have an influence on interspecies Ebola virus's infection is debated. Surveillance efforts should be reinforced to understand further Ebola virus transmission events between and within species. The aim of this study was to investigate the associations between demographic, sociological, and environmental factors that may have predisposed the emergence of Ebola in Guinea between the years of 2014 and 2015 inclusive. The number of confirmed cases of EVD (EVD-C) was the dependent variable of study. A quantitative, retrospective, longitudinal panel design was used to test the null hypotheses related to the two research questions. The study population included available information from the six districts of the country of Guinea that had data reported for at least one confirmed case of EVD during 2014 through 2015. Significance was found in the regression model for all predictors. The predictor of female education was associated with increases in EVD-C. The predictors of age greater than 39 years and urban population were associated with decreased EVD-C. The seasonal variables of 2015 were all associated with decreased EVD-C when compared to Season 4, the only seasonal variable representing 2014. The results of this research support the idea that associations among demographic, sociological, and environmental factors may have predisposed the emergence of Ebola in Guinea between 2014 and 2015.

Keywords: Ebola Virus Disease (EVD); Climate Change; Sociological Risk Factors; Interspecies Infection; Seasonal Variables

Abbreviations

CDC: Centers for Disease Control and Prevention: C DNA: A DNA that is complementary to a given RNA which serves as a template for synthesis of the DNA in the presence of reverse transcriptase; CC BY-ICO: Creative Commons Attribution for Intergovernmental Organizations; CFR: Case Fatality Rate; CI: A confidence interval for a parameter is a random interval constructed from data in such a way that the probability that the range contains the actual value of the parameter can be specified before the data are collected; DNA: Deoxyribonucleic acid, a self-replicating material which is present in nearly all living organisms as the main constituent of chromosomes; DRC: Democratic Republic of Congo; EID: Emerging Infectious Diseases; ECDC: The European Union agency aimed at strengthening Europe's defenses against infectious diseases; Epi week: An epidemiological week, commonly referred to as an epi week or a CDC week, is merely a standardized method of counting

weeks to allow for the comparison of data year after year; EVD: Ebola Virus Disease; EVD-C: Confirmed Ebola Virus Disease; GDL: Global Data Lab; HDX: Humanitarian Data Exchange; HF: Hemorrhagic fever; INDEX CASE: The first identified case in a group of related cases of a specific infectious or heritable disease; MEBOV: Mekona Ebola Virus; NHP: Non-Human Primates; OLS: Ordinary least squares is a type of linear least squares method for estimating the unknown parameters in a linear regression model; OR: Odds ratio; RQ1: Research question 1; RQ2: Research question 2; RNA: Ribonucleic acid, a nucleic acid present in all living cells. Its principal role is to act as a messenger carrying instructions from DNA for controlling the synthesis of proteins, although in some viruses RNA rather than DNA carries the genetic information; SES: Social, economical status; SEIR: Susceptible-exposed-infectious-recovered; SARS: An infectious disease with symptoms including fever and cough and, in some cases, progressing to pneumonia and respiratory failure. It is caused by a coronavirus; WHO: World Health Organization. The primary role is to direct international health within the United Nations' system and to lead partners in global health responses; WBDO: Waterborne disease outbreaks; ZEBOV: Zaire Ebola Virus.

Introduction

Background and Introduction

The reemergence of Ebola Virus Disease (EVD) in West African countries in 2014 suggests a connection to the climate changes afflicting the region in recent years. Researchers linked EVD and other infectious diseases to environmental changes decades ago [1]. Now, climate change increases the global challenge in the issues of ecology, economics, and sociology. Extrapolations suggest the environment alterations can increase chances of the spread of EVD and other zoonotic diseases [2].

Ebola is an emerging zoonotic infection that previously has appeared in remote villages of equatorial Africa. Ebola virus, related to a family of *Filoviridae*, consists of three types, the Ebola, Marburg, and Cueva viruses. It is among the most dangerous pathogens in humans [3]. First, the Ebola virus was recognized as causing the disease in human beings in the epidemic in the Democratic Republic of the Congo (DRC) and South Sudan in Central Africa in 1976. Five types of Ebola virus were identified before the West Africa outbreak in "Zaire, Bundibugyo, Sudan, Reston, and Taï Forest" [2]. But, the first three, Bundibugyo Ebola virus, Zaire Ebola virus, and Sudan Ebola virus have been associated with significant outbreaks in equatorial Africa [2].

In contrast, West African countries had never experienced an Ebola outbreak until recently. In 2014, EVD outbreak in Guinea was reported for the first time [4]. Afflicted individuals identified early in Liberia and Sierra Leone had traveled to Guinea [5,6] (see Appendix A for a map of West African countries that have had EVD outbreaks between 2014 and 2016). Furthermore, the current outbreak in West Africa is caused by a new strain of Ebola virus, designated Makona Ebola virus (MEBOV) which is 97% similar to Zaire Ebola virus. According to [7], the virus was first isolated in Guinea, triggering the West Africa epidemic in 2014. Most outbreaks originated in remote villages. This epidemic was the most EVD had spread in history [5]. It began in southeastern Guinea in December 2013 and continued for over two years, resulting in significant loss of life and social disruption across the region [8]. Presently, the epidemic is under control, but WHO has not yet declared the outbreak ended because there are still occasional flare-ups of EVD.

The suspected index case (first case) was a 2-year-old child who died in December 2013 in the southern part of Guinea, the village of Méliandou, Guéckédou. Initial case handling was poor, due to lack of resources, knowledge, and experience, which created fear among the general population. Most individuals believed that the deaths of their loved ones were posed by the supernatural, and they did not understand the real cause of the disease. During the outbreak, many people emigrated to other villages, and some people fled to the nearby countries of Liberia and Sierra Leone through open national borders. Their hope was to find care or escape from what they believed to be a curse from spirit [2]. Before Guinea, public health systems recognized there was a problem; the outbreaks had spread and involved three countries across different national health structures. However, the public health structures lacked resources and the ability to tackle the epidemic. These factors contributed to the initial misdiagnosis and inappropriate disease prevention and management approach in West Africa compared to Central Africa. Hence, the disease spread through the regions unexpectedly, and the epidemic became out of control, spreading to the metropolitan city of Conakry, the capital of Guinea and home to two million people [2].

In the past, outbreaks of Ebola virus in Equatorial Africa occurred mostly in rural areas, where there was a small population and only a few neighboring villages. This low population may be the reason the outbreaks were easily and quickly controlled. It also made it easy to establish effective isolation measures due to the small community size. Furthermore, in the West and Equatorial Africa, there is a widespread misunderstanding of the route of EVD transmission. The disease is caused by direct contact with infected bodily fluids or the dead body of an infected person or animal. However, cultural beliefs among the society have emphasized that EVD is caused instead by a supernatural power which in turn cannot be controlled by either hygienic precautions or is beyond the expertise of health care workers [2].

Government and medical officials were not prepared to respond to the new, unexpected disease outbreak and they failed to manage it effectively. The West African health care system also faced a major problem associated with inadequate financial resources. Compounding the problem was the lack of laboratories with the capacity to diagnose a patient specimen and inadequate facilities to handle the patients. Human-to-human transmission caused the majority of cases in West Africa through direct contact with an ill relative, friends, or the corpses of those who died from EVD [2]. Ebola virus can remain infectious in a dead body for an extended period. Traditional burial practices in West Africa, such as close contact with the corpse by kissing the body and hugging or bathing the body, makes it challenging to control despite knowing that most people have acquired the disease through these cultural practices [6]. Regardless of the ability of Ebola viruses to transmit between human and nonhuman species, only periodic epidemics have been identified, and most of them were restricted to Equatorial Africa. The outbreak of EVD outside Equatorial African countries to western Africa raised a concern regarding spreading to other nations because of the high number and ease of the population movement across borders.

Previously, Ebola viruses were known as "hemorrhagic fever viruses" (HF) because its clinical presentations included bleeding disorders and hypovolemic shock [9]. EVD is no longer referred to as HF because only a small percentage of individuals develop a significant hemorrhage, usually in the terminal phase of the disease and after developing severe hypovolemic shock. Current scientific evidence suggests that fruit bats are the host for the Ebola virus; these bats can be infected and asymptomatic [2]. Human and nonhuman primates (NHP) catch EVD when they come into contact with an infected bat's bodily fluids, and by direct or indirect contacts with infected people or animals. For instance, a leftover fruit eaten by an infected bat in the forest may drop to the ground, and another animal may eat it and become infected. Fruit bats sleep in trees. Therefore, there is a high probability that another forest animal's food may potentially become contaminated by bat excreta. When a cluster of bats is excreting in an area, other animals can be infected by eating the surrounding vegetation as the excreta becomes part of the forest floor [2].

In the past, Ebola epidemics in Africa have been in Equatorial Africa, including the DRC, Congo, Gabon, and Uganda. Many Equatorial African outbreaks have been associated with people eating nonhuman primates by hunting for or finding dead animals. Many who consumed these animals carried the disease back to their villages and died from EVD. NHP and other wildlife are also prone to be infected with EVD, and both human and animal corpses can remain infectious for weeks [10].

To date, there is no evidence of chimpanzees or gorillas in Guinea, Liberia, or Sierra Leone that were affected. Also, there is no definite proof that humans have been infected by animals, just an assumption that bats initially infected individuals. The rationale behind this hypothesis is that in this part of West Africa people hunt and eat fruit bats. Particularly in Guinea and Equatorial Africa, two types of fruit bats often consumed by humans have been identified as carriers of Ebola virus and associated with the initial outbreak [11].

Although there are no epidemiological investigations yet that conclusively associate an epidemic to infection acquired from killing and or eating bats, it is a relatively logical assumption. However, to manage and evaluate the risk of a future potential outbreak, it is crucial to understand and learn whether bats in this region carry Ebola virus, and if so, which type of bats. Furthermore, understanding the impact of other factors such as social, cultural, and or climatic changes is invaluable and an important area of research. This research is intended to study further the relationship between Ebola and environmental factors associated with West Africa Ebola outbreaks. Despite years of Ebola infections, there is limited research linked to the sociological, economic, and cultural issues affecting Ebola.

Statement of the problem

There have been over 30 epidemics of EVD since the first Ebola outbreak in DRC and Sudan in 1976 [9]. The outbreak in Guinea caused the massive outbreak to spread to other West African countries. Still, few studies have focused on the relationship between Ebola and environmental risk factors. Previous Ebola outbreaks in Equatorial Africa have been related to hunting or eating bush meat, and they occurred in remote areas [9]. However, the outbreak patterns in Guinea and other West African countries are characteristically different from those in other parts of Africa. Most cases of EVD occurred to highly populated areas compared to Equatorial Africa where the disease occurred in remote regions.

Purpose of the study

The aim of this study was to investigate the associations between demographic, sociological, and environmental factors which may have predisposed the emergence of Ebola in Guinea between the years of 2014 and 2015 inclusive. The number of confirmed cases of EVD (EVD-C) was the dependent variable of study. This retrospective study was conducted to evaluate demographic, sociological, and environmental factors, to understand their contribution to the massive outbreak. The study allowed exploring the potential links to EVD and added to the broader efforts of preventing future epidemics. The following research questions and associated statistical hypotheses were investigated.

Research questions and hypotheses

- **RQ1:** Is there a relationship between environmental changes and EVD-C in Guinea during the years of 2014 and 2015?
- **$H1_0$:** None of the eight-dummy coded seasonal variables of the regression model will be statistically significant predictors of EVD-C.
- **$H1_{alt}$:** At least one of the eight dummy coded seasonal variables independent variables of the regression model will be statistically significant predictors of EVD-C.
- **RQ2:** Is there a relationship between the demographic and sociological independent variables and EVD-C in Guinea during the years of 2014 and 2015?
- **H2o:** There is no statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015.
- **$H2_{alt}$:** There is a statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015.

Materials and Methods

This retrospective study was conducted to investigate possible associations between demographic, sociological, and environmental factors as related to the number of confirmed cases of Ebola reported in the country of Guinea during the years of the Guinea outbreak (2014-2015). Findings from this study may allow stakeholders to explore potential links of factors to EVD more deeply as well as to add knowledge to the broader efforts of preventing future epidemics.

Research design

A quantitative, retrospective, longitudinal, panel design was used to test the hypotheses of this study. Panel data analysis is a form of longitudinal data analysis. A panel is a cross-section or group of variables surveyed periodically over a given timeframe. The repeated observations in a panel analysis allowed for the investigation of dynamics of change inside of short time intervals [12].

Study populations

The study population included available information from the six districts of the country of Guinea that had data reported for at least one confirmed case of EVD during 2014 to 2015 inclusive. Each year of data included 53 records, one record for each epi week. Thus, a total of 6 X 106 = 636 records were retrieved for use in this study.

Power analysis

The design of this study incorporated multiple regression frameworks with an assumed underlying Poisson distribution. Power formulas are not readily available from "out of the box" softwares such as GPower or PASS to compute a sample size for the model structure used in this study. Often rule of thumb or Monte Carlo simulations are reported in the literature to test different cross-sectional units (N; for this study N = 6, the 6 districts) X time (T; for this study, T = 106, the number of epi weeks) values and thus derive a sample size. Santos and Barrios made use of bootstrap techniques to test for asymptotic consistency as well as estimator bias with cross-sectional estimates ranging in value from N = 10 to N = 50,

and time values ranging from T = 3 to T = 50 [13]. They found that the time dimension affected consistency and bias between estimators more so than the number of cross-sectional units. The number of epi weeks, T = 106, is much larger than the maximum value of T = 50 tested by Santos and Barrios. Thus, the 636 records are more than sufficient for the use of the panel regression using a Poisson framework.

To assure the sample size was sufficient, GPower was used with OLS multiple regression criteria to calculate a priori sample size. The following parameters were used in the power analysis: alpha = 0.05, power = 0.80, and a medium effect size = 0.15. A minimum of N = 181 records was required. Therefore, the N = 636 records included in this study are more than sufficient to power the analysis.

Data collection methods

The data used in this study were readily available and open source. The data were retrieved from a data bank located on the Humanitarian Data Exchange website (HDX), located at https://data.humdata.org/. To facilitate data collection, keywords of Guinea and Ebola were used to locate 36 possible data sources located at the following link:

https://data.humdata.org/search?q=Guinea&ext_page_size=25&sort=score+desc%2C+metadata_modified+desc&tags=ebola#dataset-filter-start

A review of the data sources resulted in two datasets being secured for compilation and use in this study. The first dataset, entitled "Guinea EVD case numbers by District" were pulled from the link via a direct link to the WHO data base. The link returned a Comma Separated Variables (.csv) file with the number of probable, suspected, and confirmed cases for available districts in Guinea, for each epi week. Two records for each district, case type, and epi week were included in the database. The first record was taken from the Ministry of Health SitRep, also called the WHO situation report. The second record was made from the patient database maintained in Guinea. The situation report confirmed cases (EVD-C) data were used in this study.

The second dataset was obtained, which included the demographic and sociological data from 2012, the closest year to 2014 for which this type of data was available. The data were contributed to HDX by Global Data Lab (GDL; www.globaldatalab.org). This data were prepared by aggregating individual and household level survey data to the level of sub-national areas within Guinea. The demographic and sociological data used as predictor variables for each of the six districts (see Table 1) were derived from this dataset.

The HDX and the organizations that contributed the datasets to the HDX have an open initiative to provide free access to data banks, which can be downloaded, manipulated, used and reused with no restrictions. Also, the data can be used to create new and advanced solutions for global development, to help the control of global infectious disease, and to reduce poverty and improve global health. According to the Creative Commons Attribution for Intergovernmental Organizations (CC BY-ICO), data can be shared freely. The data can be copied and redistributed in any medium or format and can be used privately or commercially. The data can be adapted, transformed, or used to build upon the material in the datasets. Terms of the license are that the researcher must give appropriate credit, provide a link to the license, and indicate if changes were made. More information on the CC BY-ICO deed can be found at https://creativecommons.org/licenses/by/3.0/igo/. The license for the use of the datasets can be found at https://creativecommons.org/licenses/by/3.0/igo/legalcode.

Statistical analysis

A single panel regression model was used to test the hypotheses of both research questions of this study. The specifications of the panel regression model are presented in Figure 1. Table 1 presents the operationalization of each of the variables which will be included in the regression model. Stata v.14 software will be used for both descriptive and inferential analysis. A 95% level of significance was set for all inferential testing.

Figure 1: Complex system self-organized over time. The source of the diagram is by Hiroki Sayama, D.Sc. Collective Dynamics of Complex Systems Research Group at Binghamton University, State University of New York, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=12191267

Concept	Description	Relevance to spread of EVD
Social-Ecological System (SES)	The combined model of humans-in-nature identifying the description of social and ecological systems is unnatural and subjective (Berkes et al., 2003). There are depictions of collected empirical data about the activities of ecosystems and their sustainability (Berkes & Folke, 1998).	A common body of theory and model related to the SES outline provides multiple methodologies and procedures with the possibility of understanding EVDs. Sustainability mostly and operationally expressed regarding human health, is essential to control the emergence of infectious disease.
Resilience	The scale of a disruption that can be absorbed by the system devoid of the system undergoing a meaningful change (Holling & Gunderson, 2002).	Equally, social activities and environmental systems can show resilience regarding structural flexibility and adaptive organization for having the knowledge and the capacity of understanding the disruption of ecosystems. The impairment of natural resistance tends to increase vulnerability, which is likely to promote infection.
Concept	Description	Relevance to spread of EVD
Surprise	The disagreement perception between action and a priori expectation inherent in complex adaptive systems (Gunderson, 2003). Changed modes of surprise established in social-ecological systems are a local surprise, cross-scale surprise, and a real novelty.	EVDs fit this definition of surprise in that the presence of the current West Africa EVD trend was unexpected though the warning signs appeared apparent, retrospectively. This typology shows a potential advantage to understanding EVDs.
Barriers and bridges	Barriers characterized by the impairment of values and knowledge if the result from institutional constructions and created dysfunctions in a system. Connections are the links between activities and control that become possible through an integrated understanding of systems.	Understanding EVDs requires the collaboration of people from a broad range of disciplines, within and outside biomedicine. Managing EVDs and other infectious diseases in general and controlling specific diseases require similar collaboration among many sectors in addition to public health. A unified vision of "disease systems" is necessary to provide a "plan" for action.

Table 1: The Concept of Complex and System Theory Ebola Vulnerability.

Before testing the hypotheses of this study, descriptive statistics were presented at the population and district level. The independent variables are in summary form in the datasets. Therefore, only percentages and mean values of the independent variables are presented without measures of dispersion. The dependent variable of EVD-C were disaggregated at the district and seasonal levels and when possible measures of dispersion were reported, including when possible standard deviations, mean, medians, and ranges of the counts of confirmed cases of Ebola virus disease.

Assumptions for the panel regression model within the Poisson framework do not include the need for normality on the EVD-C variable. Rather, a check for over-dispersion will be performed to be certain that the EVD-C variable is not zero-inflated. Zero-inflation happens when there are numerous zero counts in a dataset such that the variance is inflated and much higher than the mean. If over-dispersion was indicated, a negative binomial model was used in lieu of the Poisson model. The negative binomial model does not require adjustments for over dispersion [14].

The dependent variable of confirmed EVD cases is a count variable and not at the interval level. Therefore, a generalized regression model was used for analysis in this study. A Poisson regression was used for the analysis. However, if the model was zero-inflated, i.e. there were a high number of zeros representing the incidence of EVD in the districts over many time intervals, then other models, such as a negative binomial regression, were considered for use. In any case, a regression framework incorporating the panel data design was utilized for this study. The EVD incident data were aggregated at the seasonal level. Thus 8 dummy coded time points were included as seasonal time series variables in the analysis. A total of six districts (Boke, Conakry, Faranah, Kankan, Kindia, & N'Zerekore) were included as the main units of analysis.

In statistics, the fixed district effects estimator is an estimator for the coefficients in panel data analysis. If fixed district effects were assumed, time-independent effects were imposed for each district. Fixed effects models assist in controlling for unobserved heterogeneity when this heterogeneity is constant over time. To this end, the significant advantage of using the fixed effects model is that error terms are "permitted" to be correlated with the individual effects. The fixed district effects estimator could also be used to control for the endogeneity of the predictor variables.

A fixed seasonal effect was used to control for time specific effects that are the same for each of the six districts, which is why all the demographic and sociological predictor variables were measured at only one time, for 2012, which was the last year before 2014 in which the demographic and sociological predictor variable data were collected. Many of the observed seasonal variables in the time series were necessarily correlated to some degree or other (i.e., multicollinearity). However, this need not be of concern unless the standard errors are particularly large in the model. Figure 3 presents the specifications of the regression model proposed to test both hypotheses in this study. Table 2 presents the variable names, source names, and operationalization for the specified model.

Variable Name	HDX Dataset Variable Name	Description	Type	Operationalization
Dependent Variable (criterion)				
EVD-C	Numeric	The number of confirmed cases of EVD for the epi-week	Count	A value from 0 to a larger integer number
Panel Variable				
District	Location	A total of 6 districts in Guinea which had confirmed cases of EVD during 2014-1015 will be included as panel variables	Categorical	The "xt" panel data commands in the Stata software require the six districts to be numerically coded for identification in the model. The districts will be coded as follows: Boke = 1 Conakry = 2 Faranah = 3 Kankan = 4 Kindia = 5 N'Zerekore = 6
Time Variable for Panel				
Time	Epi week	The epidemiological week for each year of the study. The first epi week of the year ends, by definition, on the first Saturday of January, as long as it falls at least four days into the month. Each epi week begins on a Sunday and ends on a Saturday.	Ordinal time series	The dataset has 53 sequentially numbered epi weeks for each year of the study (2014, 2015). The data will be operationalized into a continuous time series from Time = 1, to Time = 106.

Independent Variables (predictors)				
Wealth	iwi	The mean International Wealth Index Score (IWI) for each district. The IWI is a comparable asset-based wealth index for measuring household wealth in low and middle-income countries (Smits & Steendijk, 2014)	Continuous	Wealth for each district will be represented by the value of IWI from 2012, the most recent year before 2014 that the IWI was recorded. Values of the wealth variable will range from 0 to 100, with higher numbers associated with greater wealth.
Age < 9 years	Age09	Percentage of population aged 0-9 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 10-19 years	age10-19	Percentage of population aged 10-19 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 20-29 years	age20-29	Percentage of population aged 20-29 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 30-39 years	age30-39	Percentage of population aged 30-39 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 40-49 years	age40-49	Percentage of population aged 40-49 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 50-59 years	age50-60	Percentage of population aged 50-59 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 60-69 Years	age60-69	Percentage of population aged 60-69 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed as decimal notations.
Age 70-79 Years	age70-79	Percentage of population aged 70-79 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age 80-89 Years	age80-79	Percentage of population aged 80-89 years in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Age ≥ 90 years	age90hi	Percentage of population aged 90 years or older in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Female Education	edyr_fem	Mean years of education of women aged 20-49 in a given district	Continuous	The average number of years of education for women aged 20-49 in each district.
Male Education	edyr_male	Mean years of education of men aged 20-49 in a given district	Continuous	The average number of years of education for men aged 20-49 in each district.
Urban Area	Urban	The percentage of the population living in an urban area in a district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.

Agricultural Worker	wrk_agr	The percentage of married men aged 20-49 years working in an agricultural occupation in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Household = small	Small_ house	The percentage of households with none or one sleeping room in a district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Household = large	large_house	The percentage of households with three or more sleeping rooms in a district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Water-piped	tap_water	The percentage of households with piped water in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Water-bad	bad_water	The percentage of households with a bad quality water supply in a given district	Continuous (percentage)	The possible values of the variable are between 0 and 1 expressed in decimal notation.
Households	Nhh	Number of households in a district	Count	The number of households in a given district. This variable has a theoretical range from 0 to infinity.
Time Series Seasonal Variables				
Season 1	---	Derived variable representing the year 2014, epi weeks 1-14	Indicator	1 = record from 2014, epi weeks 1-14 = otherwise
Season 2	---	Derived variable representing the year 2014, epi weeks 15-27	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 3	---	Derived variable representing the year 2014, epi weeks 28-40	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 4	---	Derived variable representing the year 2014, epi weeks 41-53	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 5	---	Derived variable representing the year 2015, epi weeks 1-14	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 6	---	Derived variable representing the year 2015, epi weeks 15-27	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 7	---	Derived variable representing the year 2015, epi weeks 28-40	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise
Season 8	---	Derived variable representing the year 2015, epi weeks 41-53	Indicator	1 = record from 2014, epi weeks 1-14 0 = otherwise

Note: HDX = Human Data Exchange; EVD-C = Confirmed Cases of Ebola Virus Disease.

Table 2: Operationalization of Study Variables.

Figure 2: Complex and system theory chart of Ebola transmission.

GENERALIZED PANEL REGRESSION MODEL

(1) $EVD\text{-}C = f\,(W + A_1 + A_2 + A_3 + A_4 + A_5 + A_6 + A_7 + A_8 + A_9 + A_{10} + F + M + U + G + H_1 + H_2 + P + B + N + S_1 + S_2 + S_3 + S_4 + S_5 + S_6 + S_7 + S_8) + \alpha_d + \varepsilon$

Or more formally:

(2) $EVD\text{-}C_{d,t} = \beta_0 + \beta_1 W_{d,t} + \beta_2 A_{1,d,t} + \beta_3 A_{2,d,t} + \beta_4 A_{3d,t} + \beta_5 A_{4d,t} + \beta_6 A_{5d,t} + \beta_7 A_{6d,t} + \beta_8 A_{7d,t} + \beta_9 A_{8d,t} + \beta_{10} A_{9d,t} + \beta_{11} A_{10d,t} + \beta_{12} F_{d,t} + \beta_{13} M_{d,t} + \beta_{14} U_{d,t} + \beta_{15} G_{d,t} + \beta_{16} H_{1d,t} + \beta_{17} H_{2d,t} + \beta_{18} P_{d,t} + \beta_{19} B_{d,t} + \beta_{20} N_{d,t} + \beta_{21} S_{1,d,t} + \beta_{22} S_{2,d,t} + \beta_{23} S_{3d,t} + \beta_{24} S_{4d,t} + \beta_{25} S_{5d,t} + \beta_{26} S_{6d,t} + \beta_{27} S_{7d,t} + \beta_{28} S_{8d,t} + \varepsilon_{d,t}$

Where:

$EVD\text{-}CP_{d,t}$ = # of confirmed cases of EVD in a district *d*, in a given epi week, *t*.
W = The International Wealth Index for the district
$A_{1,d,t}$ = % of population aged 0-9 years.

$A_{1,d,t}$ = % of population aged 0-9 years.
$A_{2,d,t}$ = % of population aged 10-19 years.
$A_{3,d,t}$ = % of population aged 20-29 years.
$A_{4,d,t}$ = % of population aged 30-39 years.
$A_{5,d,t}$ = % of population aged 40-49 years.
$A_{6,d,t}$ = % of population aged 50-59 years.
$A_{7,d,t}$ = % of population aged 60-69 years.
$A_{8,d,t}$ = % of population aged 70-79 years.
$A_{9,d,t}$ = % of population aged 80-89 years.
$A_{10,d,t}$ = % of population aged 90 years or greater.
$F_{d,t}$ = Average number of years of education for women aged 20-49.
$M_{d,t}$ = Average number of years of education for men aged 20-49.
$U_{d,t}$ = % of population living in urban areas.
$G_{d,t}$ = % of married men aged 20-49 years who are agricultural workers.
$H_{1d,t}$ = % of households with none or one sleeping rooms.
$H_{2d,t}$ = % of households with three or more sleeping rooms.
$P_{d,t}$ = % of households with piped water.
$B_{d,t}$ = % of households with a bad quality water supply.
$N_{d,t}$ = Number of households.
$S_{1,d,t}$ = dummy coded variable for Season 1 (2014 epi-weeks 1-14).
$S_{2,d,t}$ = dummy coded variable for Season 2 (2014 epi-weeks 15-27).
$S_{3,d,t}$ = dummy coded variable for Season 3 (2014 epi-weeks 28-40).
$S_{4,d,t}$ = dummy coded variable for Season 4 (2014 epi-weeks 41-53).
$S_{5,d,t}$ = dummy coded variable for Season 5 (2015 epi-weeks 1-14).
$S_{6,d,t}$ = dummy coded variable for Season 6 (2015 epi-weeks 15-27).
$S_{7,d,t}$ = dummy coded variable for Season 7 (2015 epi-weeks 28-40).
$S_{8,d,t}$ = dummy coded variable for Season 8 (2015 epi-weeks 41-52).
$\varepsilon_{d,t}$ = error term, distribution is assumed normal.

Figure 3: Model specification for testing the hypotheses of the study.

Figure 4: Measures of Central Tendency and Variability for the Number of Confirmed EVD.

Figure 5: EVD-C Frequency Across Districts by Season.

Using a generalized regression model and fixed effects, the quantitative analysis tested whether there are associations between demographic, sociological, and environmental factors, which may have predisposed the emergence of Ebola in Guinea between the years of 2014 and 2015 inclusive. The number of confirmed cases of EVD (EVD-C) will be the dependent variable of study. Predictor variables include wealth (W), age < 9 years (A_1), age 10-19 years (A_2), age 20-29 years (A_3), age 30-39 years (A_4), age 40-49 years (A_5), age 50-59 years (A_6), age 60-69 years (A_7), age 70-79 years (A_8), age 80-89 years (A_9), age ≥ 90 years (A_{10}), female education (F), male education (M), urban area (U), agricultural worker (G), household=small (H_1), household=large (H_2), water-piped (P), water-bad (B), households (N), and eight seasonal dummy coded time series variables (S_1 through S_8).

Results and Discussion

The results are divided into four sections: (a) descriptive findings, (b) investigation of assumptions as they relate to inferential analysis, (c) statistical analysis of the panel regression model, and (d) model findings as they relate to each statistical hypothesis. Stata v.14 software was used for all descriptive and inferential analyses. A 95% confidence level ($p < .05$) was set for all inferential tests.

This retrospective study was conducted to investigate possible associations among demographic, sociological, and environmental factors as related to the number of confirmed cases of Ebola Virus Disease (EVD-C) reported in the country of Guinea during the years of the Guinea outbreak (2014-2015). Findings from this study may allow stakeholders to explore potential links of factors to Ebola Virus Disease (EVD) more deeply as well as to add knowledge to the broader efforts of preventing future epidemics.

Population and descriptive findings

The study population included available information from the six districts of the country of Guinea that had data reported for at least one confirmed case of EVD during 2014 through 2015. Each year of data included 53 records, one record for each epi week. Thus, a total of 6 X 106 = 636 records were retrieved for use in this study. However, upon the inspection of the dataset, it was found that confirmed cases of EVD were not reported for the six districts in Guinea in either the WHO situation or patient reports until 2014, epi-week 38 (the week of September 15 through 21, 2014). A large number of hidden cases in Sierra had ignited a fiery outbreak back in Guinea and Liberia. The number of unknown EVD cases was extremely high and the spread became uncontrollable between Guinea, Liberia and Sierra Leone. It took more than two months for WHO to declare the EVD epidemic is "a Public Health Emergency of International Concern (PHEIC)" [15]. Unfortunately, no data were available until September 2014 (see Appendix B; Guinea Ebola timeline 2014-2015.) The number of confirmed cases of EVD was used as the dependent variable in hypothesis testing for this study. Therefore, the epi-weeks from 1 to 37, 2014, in the data set were not usable.

Eight dummy-coded seasonal variables were planned for use as predictors to address the hypotheses of RQ1. The elimination of 2014 epi-weeks 1 through 37 resulted in the full elimination of Seasons 1 and 2 from the data. Season 3 included 2014 epi-weeks 28 through 40. Inclusion of Season 3 in the analysis would have resulted in only 4 weeks of data for Season 3. It was decided that records pertaining to Seasons 1 through 3 would be removed from the analysis and that the study would include only the data from 2014 epi-week 41 through 2015 epi-week 53. Season 4 was the only representative season for 2014. The year 2015 included Seasons 5 through 8. A total of 390 records were retained for analysis in this study, which included a total of 65 epi-weeks for each of the six districts.

A total of 735 confirmed cases of EVD were reported for the N = 390 records retained for analysis. The number of confirmed cases of EVD for each epi-week ranged from 0 to 29 (M = 1.88 cases/epi-week, SD = 4.74 cases/epi-week, Mdn = 0 cases/epi-week). However, n = 280 records (71.8% of all records) had zero confirmed cases of EVD for the respective epi-week. Table 3 includes a presentation of the frequency counts of EVD-C, and measures of central tendency and variability for the number of EVD-C each epi-week, by district and season. The largest number of EVD-C occurred in the district of Conakry (392 cases, 53% of all cases). The district of Kindia reported the lowest number of EVD-C (20 cases, 3% of all cases). Except for the district of Boke, the largest average number of EVD-C per epi-week were in Season 4 (2014 epi-weeks 41-52, which represented October 6, 2014 through December 28, 2014 inclusive), and then decreased in number from Seasons 5 through 8. The largest number of EVD-C per epi-week for the district of Boke was in Season 6, which included the 2015 epi-weeks of 15 through 27, representing April 6, 2015 through July 5, 2015 inclusive.

A fixed seasonal effect was used to control for time specific effects that were the same for each of the six districts. Demographic and sociological predictor variables were measured at only one time for 2012, which was the last year before 2014 in which the demographic and sociological predictor variable data were collected. Demographic variables included measurements of percentages of age group membership (Table 4) and average education levels by gender (Table 5). Table 6 presents the sociological fixed-effect variables of number of households, wealth index, urban area, agricultural workers, small households, large households, water-piped, and water-bad, measured in percentages.

	Total Number	EVD-C per Epi-Week			
District/ Season	**of EVD-C**	**M**	**SD**	**Mdn**	**Range**
Boke					
All Seasons	32	0.49	1.67	0.00	0 – 10
Season 4	1	0.08	0.29	0.00	0 – 1
Season 5	0	N/A	N/A	N/A	N/A
Season 6	31	2.38	3.15	1.00	0 – 10
Season 7	0	N/A	N/A	N/A	N/A
Season 8	0	N/A	N/A	N/A	N/A
Conakry					
All Seasons	392	6.03	7.54	2.00	0 – 26
Season 4	160	13.33	6.88	15.00	1 – 26
Season 5	182	13.00	7.09	12.00	4 – 25
Season 6	13	1.00	1.63	1.00	0 – 6
Season 7	36	2.77	3.88	1.00	0 – 13
Season 8	1	0.08	0.28	0.00	0 – 1
Faranah					
All Seasons	45	0.69	2.44	0.00	0 – 16
Season 4	39	3.25	4.94	1.50	0 –16
Season 5	6	0.43	1.09	0.00	0 – 4
Season 6	0	N/A	N/A	N/A	N/A
Season 7	0	N/A	N/A	N/A	N/A
Season 8	0	N/A	N/A	N/A	N/A
Kankan					
All Seasons	31	0.48	1.38	0.00	0 – 7
Season 4	27	2.25	2.45	1.00	0 – 7
Season 5	4	0.29	0.73	0.00	0 – 2
Season 6	0	N/A	N/A	N/A	N/A
Season 7	0	N/A	N/A	N/A	N/A
Season 8	0	N/A	N/A	N/A	N/A
Kindia					
All Seasons	77	1.18	2.84	0.00	0 – 16
Season 4	55	4.58	5.16	3.50	0 – 16
Season 5	20	1.43	1.60	1.00	0 – 5
Season 6	2	0.15	0.38	0.00	0 – 1
Season 7	0	N/A	N/A	N/A	N/A
Season 8	0	N/A	N/A	N/A	N/A
N'Zerekore					
All Seasons	158	2.43	6.10	0.00	0 – 29
Season 4	154	12.83	8.45	10.50	2 – 29
Season 5	4	0.29	0.61	0.00	0 – 2
Season 6	0	N/A	N/A	N/A	N/A
Season 7	0	N/A	N/A	N/A	N/A
Season 8	0	N/A	N/A	N/A	N/A

Table 3: Frequency Counts of EVD-C, and Measures of Central Tendency and Variability for the Number of EVD-C Each Epi-Week, by District and Season.

Note: EVD-C = Confirmed Cases of Ebola Virus Disease; M = Mean; SD = Standard Deviation; Mdn = Median; N/A = Not Applicable, no EVD-C reported for the season.

Variable/District	**Percent (%) of Population**
Age < 9 years: Percentage of population aged 0-9 years in a given district.	
Boke	31.20
Conakry	25.30
Faranah	35.20
Kankan	36.50
Kindia	34.20
N'Zerekore	34.10
Average (%) of all districts combined	32.75
Age 10-19 years: Percentage of population aged 10-19 years in a given district.	
Boke	24.50
Conakry	26.40
Faranah	25.30
Kankan	23.80
Kindia	23.20
N'Zerekore	23.90
Average (%) of all districts combined	24.52
Age 20-29 years: Percentage of population aged 20-29 years in a given district.	
Boke	12.70
Conakry	19.80
Faranah	11.00
Kankan	12.00
Kindia	12.50
N'Zerekore	12.90
Average (%) of all districts combined	13.48
Age 30-39 years: Percentage of population aged 30-39 years in a given district.	
Boke	8.70
Conakry	11.00
Faranah	9.00
Kankan	9.40
Kindia	9.60
N'Zerekore	9.60
Average (%) of all districts combined	9.55
Age 40-49 years: Percentage of population aged 40-49 years in a given district.	
Boke	6.90
Conakry	6.80
Faranah	7.90
Kankan	7.00
Kindia	6.60
N'Zerekore	7.40
Average (%) of all districts combined	7.10
Age 50-59 years: Percentage of population aged 50-59 years in a given district.	
Boke	8.10
Conakry	5.70
Faranah	5.90

Kankan	5.60
Kindia	6.00
N'Zerekore	5.50
Average (%) of all districts combined	6.13
Age 60-69 years: Percentage of population aged 60-69 years in a given district.	
Boke	4.50
Conakry	3.50
Faranah	3.90
Kankan	3.60
Kindia	4.40
N'Zerekore	4.10
Average of all districts combined	4.00
Age 70-79 years: Percentage of population aged 70-79 years in a given district.	
Boke	2.50
Conakry	1.10
Faranah	1.30
Kankan	1.50
Kindia	2.50
N'Zerekore	5.50
Average (%) of all districts combined	1.78
Age 80-89 years: Percentage of population aged 80-89 years in a given district.	
Boke	0.80
Conakry	0.40
Faranah	0.40
Kankan	0.50
Kindia	0.70
N'Zerekore	0.50
Average (%) of all districts combined	0.55
Age ≥ 90 years: Percentage of population aged 90 years or older in a given district	
Boke	0.10
Conakry	0.10
Faranah	0.10
Kankan	0.10
Kindia	0.20
N'Zerekore	0.10
Average (%) of all districts combined	0.12

Table 4: Fixed-Effects Demographic Variables for Age Groups By District.

Note: Fixed-effects percentage data were collected for the 2012 calendar year, which was that last year prior to 2014 in which the data were available.

Table 4 presents the demographic fixed-effect variables for age, by age group, measured in percentages. Most of the population of the six districts combined were under 19 years of age (57%; N = 390). And four-fifths of the population (80%) were under 40 years of age. The six districts were distributed similarly across all age groups.

Table 5 includes the demographic information for the average years of education for both males and females, according to the six districts, and overall. On average, for all six districts combined, males had twice the education (4.60 years) of females (2.10 years). The population of the district of Conakry had the most educated individuals of both genders, with males having 9 years of education on average, and females averaging 5.7 years of education. Males were the least educated, on average, in the district of Kindia (1.5 years). Females in the district of Kankan were the least educated, less than one year on average (0.7 years).

Variable/District	Average Education (in years)
Female Education: The average number of years of education for women aged 20-49 in each district.	
Boke	2.20
Conakry	5.70
Faranah	0.80
Kankan	0.70
Kindia	1.70
N'Zerekore	1.50
Average of all districts combined	2.10
Male Education: The average number of years of education for men aged 20-49 in each district.	
Boke	4.70
Conakry	9.00
Faranah	3.10
Kankan	2.40
Kindia	1.50
N'Zerekore	4.50
Average of all districts combined	4.60

Table 5: Fixed-Effects Demographic Variables for the Level of Education of the Population Aged 20-49, By Gender and District.

Note: Fixed-effects data were collected for the 2012 calendar year, which was that last year prior to 2014 in which the data were available.

Table 6 includes the sociological fixed-effect variables of this study, measured in counts or percentages, as retrieved from the WHO and HDX databases. Five of the six districts had similar measurements on all the variables. The district of Conakry differed from the other five districts. The population of Conakry was wealthier, with an International Wealth Index Score (IWI) of 73%. The IWI value for Conakry was much higher than the other five districts and for the average index of all six districts combined (38%). The population of Conakry was more urban than the other five districts. One hundred percent of the population of Conakry was urban, compared with the average for all districts of 34%. Only 4% of the married men aged 20 to 49 years were agricultural workers in the district of Conakry, compared to over half of the married men aged 20-49 being classified as agricultural workers in each of

the other five districts. Conakry has a larger percentage of smaller households (13%) than the other five districts, and therefore a smaller percentage of larger households (57%) than the other five districts. Water quality was also much better in Conakry. Eighty-five percent of the households in Conakry had piped water, and less than 1% of the households had bad water quality. Kindia had a larger number of households with poor water quality (47%) when compared to the other districts. However, N'Zerekore had the lowest percentage of households with piped water (2%), as well as a low percentage of the population living in an urban setting (15%).

Variable / District	Population Measurement
Households: The number of households in the district	
Boke	841.00
Conakry	1251.00
Faranah	565.00
Kankan	954.00
Kindia	1038.00
N'Zerekore	1144.00
Average (count) of all districts combined	965.50
Wealth: The mean International Wealth Index Score (IWI) for each district. The IWI is a comparable asset-based wealth index for measuring household wealth in low and middle-income countries (Smits & Steendijk, 2014)	
Boke	36.30
Conakry	72.60
Faranah	26.30
Kankan	31.00
Kindia	34.10
N'Zerekore	28.00
Average (index) of all districts combined	38.05
Urban: The percentage of the population living in an urban area in a district	
Boke	34.20
Conakry	100.00
Faranah	19.40
Kankan	13.70
Kindia	23.10
N'Zerekore	14.90
Average (%) of all districts combined	34.22
Agricultural worker: The percentage of married men aged 20-49 years working in an agricultural occupation in a given district.	
Boke	63.70
Conakry	3.70
Faranah	69.00
Kankan	76.40
Kindia	58.10
N'Zerekore	72.00
Average (%) of all districts combined	57.15
Household = small: The percentage of households with none or one sleeping room in a district.	
Boke	8.50
Conakry	12.70
Faranah	7.30
Kankan	6.10
Kindia	9.90
N'Zerekore	6.40
Average (%) of all districts combined	8.48
Household = large: The percentage of households with three or more sleeping rooms in a district.	
Boke	70.70
Conakry	56.80
Faranah	70.30
Kankan	74.30
Kindia	73.10
N'Zerekore	73.70
Average (%) of all districts combined	69.82
Water-piped: The percentage of households with piped water in a given district.	
Boke	25.80
Conakry	84.70
Faranah	3.20
Kankan	8.00
Kindia	11.10
N'Zerekore	2.10
Average of all districts combined	22.48
Water-bad: The percentage of households with a bad quality water supply in a given district.	
Boke	29.70
Conakry	0.90
Faranah	22.90
Kankan	19.60
Kindia	46.50
N'Zerekore	17.10
Average (%) of all districts combined	22.78

Table 6: Fixed-Effects Sociological Variables Reported by District and for All Districts Combined

Note. Fixed-effects Population Measurement for the sociological data was collected for the 2012 calendar year, which was that last year prior to 2014 in which the data were available.

The variable of Households was measured in counts. The variable of Wealth was measured by an index between 0 and 100, with higher values indicative of greater wealth. All other variables were measured as the percentage of the population.

Assumptions

The mean values of EVD-C per epi-week were lower than the standard deviations for all six districts (see Table 3). Additionally, the number of records with an EVD-C of zero was very large, with n = 280 records (71.8% of all records) containing zero confirmed cases of EVD for the respective epi-week. A histogram of the EVD-C variable indicated a long positive skew, with most values close to the lower end of the scale, and with a few values of EVD-C dispersed at the high end of the range. The data were count data, and the distribution was Poisson. It was determined that the data could be zero-inflated. Also, of concern were the mean to variance numbers for the dependent variable of EVD-C. The variance (s2 = 22.45) was almost 12 times larger than the mean (M = 1.88), indicating over-dispersion of the data points for the EVD-C variable. The zero inflation and over-dispersion of the EVD-C variable indicated that a negative binomial regression may be a better choice than Poisson regression for modeling the data. A Poisson regression model was tested with the full model specifications as defined in the Methods chapter, and the model failed to converge. A negative binomial regression model was tested with the full specifications and did converge. However, many variables were omitted from the model due to multicollinearity.

Zero-inflation and over-dispersion were present, and the Poisson model failed to converge. The negative binomial model converged, although with multicollinearity issues. It was determined that a negative binomial regression would be used to test the regression models hypothesis testing, as the negative binomial distribution allows for a variance with a larger value than the mean. The STATA command for a negative binomial regression model with panel data "xtnbreg" was used to fit a negative binomial model to the dataset, with the autoregressive (AR1) correlation option chosen due to the repeated measures nature of the data. The multicollinear variables were investigated further with bi-variate assessments via Spearman's rank order correlation coefficients. The findings of the correlational analyses as well as the revised model specifications are presented in the next section.

Correlational analyses

Correlational analysis was performed on the full dataset prior to performing the negative binomial regression analysis. Because a negative binomial regression was being modeled for this study, normality was not needed or assumed for any of the variables in the data. Also, linearity was not needed or assumed. Spearman's rho correlations are based on a rank order of data values and not on a normal distribution, and they can be used with count, percentage, and ordinal data. Therefore, this nonparametric alternative was chosen for use in this study to maintain a conservative approach to assessing correlation significance.

The five seasonal variables were correlated with the age groups variables such that all bivariate relationships between Seasons X Age Groups returned a correlation coefficient of 1. It was decided that the age groups would be aggregated into a single variable, "age > 39 years," which was coded as the percentage of the population over 39 years of age in each district.

Table 7 presents the bi-variate correlations between the dependent variable of EVD-C, the demographic variables of (a) age > 39 years, (b) female education and (c) male education, and the set of sociological variables (see Table 4). Many of the bi-variate associations were multicollinear, meaning that the correlation coefficient was positive and above a value of .700 [16]. The variable of female education had multicollinearity with male education (r = .943, p < .0005). The increases in female education levels would have more of an association with the dependent variable of EVD-C, which was because many care givers in the community were women with higher education levels, and these women were in direct contact more often with EVD patients than males with higher education levels. Therefore, the variable of male education was excluded from the negative binomial regression model.

The variable of urban indicated multicollinearity with the predictors of female education (r = .943, p < .0005), male education (r = .839, p < .005), wealth (r = .771, p < .0005), household = small (r = .943, p < .0005), and water-piped (r = .829, p < .0005). The variable of urban also had very strong negative correlations with the variables of agricultural worker (r = -.943, p < .005) and household = large (-.829, p < .0005). It was determined that female education was important to the study and would be retained as a variable in the regression model. However, the strong associations between urban and the other variables, positive and negative, indicated redundancy. For example, urban areas are associated with greater education, greater wealth, smaller households (and conversely not with larger households), more piped water and less bad water, and fewer agricultural workers. Also, the smaller households and more people in an urban area suggest that the variable of number of households would not add any more information to the regression model over the urban variable. Therefore, it was decided by the researcher to remove the variables redundant with the variable of urban, namely (a) households, (b) agricultural worker, (c) household = small, (d) household = large, (e) water-piped, and (f) water- bad.

Variable		1	2	3	4	5	6	7	8	9	10	11
1.	EVD-D											
2.	Age > 39 years	-.274**										
3.	Female education	.287**	.116*									
4.	Male education[a]	.278**	.029	.943**								
5	Households[a]	.350**	-.493**	.486**	.543**							
6.	Wealth[a]	.273**	-.058	.829**	.714**	.486**						
7.	Urban	.265**	.116*	.943**	.829**	.257**	.771**					
8.	Agricultural worker[a]	-.299**	-.058	-.886**	-.714**	-.371**	-.714**	-.943**				
9.	Household = small[a]	.299**	.058	.886**	.714**	.371**	.714**	.943**	-1.00			
10.	Household=large[a]	-.239**	.116*	-.657**	-.600**	-.029	-.371**	-.829**	.771**	-.771**		
11.	Water-piped[a]	.252**	-.058	.771**	.600**	.257**	.943**	.829**	-.771**	.771**	-.543**	
12.	Water-bad[a]	-.264**	.841**	-.086	-.314**	-.600**	-.086	.029	-.086	.086	.143**	.029

* p < .05; **p < .001

[a] Variable was removed from the negative binomial regression analysis due to multicollinearity or redundancy.

Note. EVD-C = Confirmed Cases of Ebola Virus Disease.

Table 7: Correlations for Bi-Variate Relationships of Dependent, Demographic, and Sociological Variables of Study.

The variable of wealth indicated multicollinear relationships like the variable of urban. As such, it was assumed that only one of the two variables should be included in the model. Wealth had a slightly stronger correlation with the dependent variable of EVD-C ($r = .273$, $p < .0005$) than did urban ($r = .265$, $p < .0005$). However, the urban variable had a larger range of values (13.7% - 100%) than the wealth variable (index scores from 26.3 to 72.6, see Table 4). Also, the urban variable was expressed in percentages rather than an index, which were the same measurement units as the other retained predictors in the regression model. Therefore, the researcher decided to retain the variable of urban for the regression model and discarded the wealth variable.

Inferential analysis and findings

One negative binomial regression model was developed to test both null hypotheses of this study. The dependent variable of confirmed EVD cases (EVD-C) was a count variable and not measured at the interval level. Therefore, a generalized regression model was used for analysis in this study. A Poisson regression was planned for the analysis. However, the model was zero-inflated (i.e., there were a high number of zeros representing the incidence of EVD-C in the districts over the epi-weeks, and the negative binomial regression was used to model the regression because the negative binomial model is not as sensitive to zero-inflation and the over-dispersion that was also present in the distribution of the EVD-C variable.

The negative binomial regression was modeled with a panel data design. Eight dummy- coded seasonal variables were planned for use as predictors to address the hypotheses of RQ1. The elimination of 2014 epi-weeks 1 through 37 resulted in the full elimination of Seasons 1 and 2 from the data. Season 3 included 2014 epi-weeks 28 through 40. Inclusion of Season 3 in the analysis would have resulted in only four weeks of data for Season 3. It was decided that records pertaining to Seasons 1 through 3 would be removed from the analysis and that the study would include only the data from 2014 epi-week 41 through 2015 epi-week 53. Season 4 was the only representative season for the year of 2014 and was used as the reference season in the regression model. The year 2015 included Seasons 5 through 8. A total of 390 records were retained for analysis in this study, which included a total of 65 epi-weeks for each of the six districts [17].

Predictor variables included (a) age > 39 years, (b) female education, and (c) urban. The findings of the regression are presented in Table 8 and include the Beta coefficients, odds ratios, and stan-

dard errors for the model predictors, as well as the test statistics (z) and p-values. All the model predictors were statistically significant. Increases in the percentage of the population over the age of 39 were significantly associated with decreases in EVD-C (β = - 0.29, SE β = 0.07; OR = 0.75, SE OR = 0.05; p < .0005). The odds ratio of 0.75 suggested that members of the population over 39 years of age were 25% less likely to be EVD-C.

Variable	*B*	*SE B*	*OR*	*SE OR*	*z*	*p*
Age > 39 years	-0.29	0.07	0.75	0.05	3.98	<.0005
Female education	1.50	0.37	4.48	1.65	4.06	<.0005
Urban	-0.07	0.02	0.94	0.02	3.21	.001
Season 5	-0.84	0.19	0.43	0.08	4.39	<.0005
Season 6	-2.14	0.27	0.12	0.03	7.93	<.0005
Season 7	-2.51	0.33	0.08	0.03	7.59	<.0005
Season 8	-5.06	1.01	0.01	0.01	5.02	<.0005
Constant	4.48	1.50	88.31	132.74	2.98	.003
Wald χ^2 = 280.37						
p < .0005						

Table 8: Negative Binomial Regression Coefficients, Odds Ratios, and Test Statistics for EVD-C Regressed on Predictors and Seasonal Variables (N = 390).

Note: EVD-C = Confirmed Cases of Ebola Virus Disease. Reference group for Season = Season 4.

Increases in female education were significantly associated with increases of EVD-C (β = 1.50, SE β = 0.37;OR = 4.48, SE OR = 1.65; p < .0005). The odds ratio of 4.48 suggested that each one-year increase in the level of education for females was associated with an approximately 350 times greater likelihood of EVD-C. The predictor of urban was significantly associated with decreases in EVD-C (β = -0.07, SE β = 0.02; OR = 0.94, SE OR = 0.02; p = .001). Each one percent increase in the urban population was associated with a 6% reduction in the likelihood of EVD-C.

The seasonal variables were modeled in reference to Season 4, which was the only season that included the year 2014. Decreases in EVD-C were found over all seasons. The model findings for Season 5 (β = -0.84, SE β = 0.19; OR = 0.43, SE OR = 0.08; p = < .0005), suggested that EVD-C was approximately 57% less likely in Season 5 when compared to Season 4. The model findings for Season 6 (β = -2.14, SE β = 0.27; OR = 0.12, SE OR = 0.03; p = < .0005), suggested that EVD-C was approximately 88% less likely in Season 6 when compared to Season 4. The model findings for Season 7 (β = -2.51, SE β = 0.33; OR = 0.08, SE OR = 0.03; p = <0005), suggested that EVD-C was approximately 92% less likely in Season 7 when compared to Season 4. And finally, the model findings for Season 8 (β = -5.06, SE β = 1.01; OR = 0.01, SE OR = 0.01; p = < .0005), suggested that EVD-C was approximately 99% less likely in Season 8 when compared to Season 4.

Inferential analysis and findings

The results of the negative binomial regression model were used to address the two null hypotheses of the study. The findings and conclusions for each of the hypothesis tests are presented according to each research question and associated statistical hypotheses.

Hypothesis test for research question 1

- RQ1: Is there a relationship between environmental changes and EVD-C in Guinea during the years of 2014 and 2015?
- $H1_0$: None of the eight-dummy coded seasonal variables of the regression model will be statistically significant predictors of EVD-C.
- $H1_{alt}$: At least one of the eight dummy coded seasonal variables independent variables of the regression model will be statistically significant predictors of EVD-C.

Eight dummy-coded seasonal variables were planned for use as predictors to address the null hypothesis of RQ1. However, upon the inspection of the dataset, it was found that confirmed cases of EVD were not reported for the six districts in Guinea in either the WHO situation or patient reports until year 2014, epi-week 38 (the week of September 15 through 21, 2014). The elimination of 2014 epi-weeks 1 through 37 resulted in the full elimination of Seasons 1 and 2 from the data. Season 3 included 2014 epi-weeks 28 through 40. Inclusion of Season 3 in the analysis would have resulted in only four weeks of data for Season 3. It was decided that records pertaining to Seasons 1 through 3 would be removed from the analysis and that the study would include only the data from 2014 epi-week 41 through 2015 epi-week 53. Season 4 was the only representative season for the year of 2014 and was used as the reference season in the regression model. The year 2015 included Seasons 5 through 8.

Results were significant for Seasons 5, 6, 7, and 8 when compared to Season 4. Decreases in EVD-C were found over all seasons. The model findings for Season 5 (β = -0.84, SE β = 0.19; OR = 0.43, SE OR = 0.08; p = < .0005), suggested that EVD-C was approximately 57% less likely in Season 5 when compared to Season 4. The model findings for Season 6 (β = -2.14, SE β = 0.27; OR = 0.12, SE OR = 0.03; p = < .0005), suggested that EVD-C was approximately 88% less likely in Season 6 when compared to Season 4. The model findings for Season 7 (β = -2.51, SE β = 0.33; OR = 0.08, SE OR = 0.03; p = < .0005), suggested that EVD-C was approximately 92% less likely in Season 7 when compared to Season 4. And finally, the model findings for Season 8 (β = -5.06, SE β = 1.01; OR = 0.01, SE OR = 0.01; p = < .0005) suggested that EVD-C was approximately 99% less likely in Season 8 when compared to Season 4.

The conclusion as related to Null Hypothesis 1 is that Null Hypothesis 1 was rejected. There is sufficient evidence to indicate that at least one of the five dummy coded seasonal variables, independent variables of the regression model were a statistically significant predictor of EVD-C.

Hypothesis test for research question 2

- RQ2: Is there a relationship between the demographic and sociological independent variables and EVD-C in Guinea during the years of 2014 and 2015?
- H2o: There is no statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015.
- $H2_{alt}$: There is a statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015.

The demographic variables of (a) age > 39 years, and (b) female education were statistically significant for the dependent variable of EVD-C. Increases in the percentage of the population over the age of 39 were significantly associated with decreases in EVD-C (β = -0.29, SE β = 0.07; OR = 0.75, SE OR = 0.05; p < .0005). The odds ratio of 0.75 suggested that members of the population over 39 years of age were 25% less likely to be EVD-C. Increases in female education were significantly associated with increases of EVD-C (β = 1.50, SE β = 0.37; OR = 4.48, SE OR = 1.65; p < .0005). The odds ratio of 4.48 suggested that each one-year increase in the level of education for females was associated with an approximately 350 times greater likelihood of EVD-C.

The sociological predictor of urban was significantly associated with decreases in EVD-C (β = -0.07, SE β = 0.02; OR = 0.94, SE OR = 0.02; p = .001). Each one percent increase in the urban population was associated with a 6% reduction in the likelihood of EVD-C.

In the conclusion as it relates to null hypothesis 2, the hypothesis was rejected. There is sufficient evidence to indicate that there is a statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015.

Summary

The methods section began with a description of the data set and addresses deviations from the planned methods. Descriptive information on the study demographic variables and sociological variables were then presented in tables. Following the descriptive reporting, assumptions for the inferential analyses were then presented and discussed. Issues of multicollinearity and redundancy between variables were addressed and remedies were undertaken to reduce the model for convergence and proper fit. Following the descriptive and assumption sections, a negative binomial regression was performed to investigate the two research questions of study.

Significance was found in the regression model for all predictors. The predictor of female education was associated with increases in EVD-C. The predictors of age > 39 years and urban were associated with decreased in EVD-C. The seasonal variables of the year 2015 were all associated with decreased EVD-C when compared to Season 4, the only seasonal variable representing the year 2014.

A discussion of the results as well as implications of the findings as it relates to the literature review and further research is presented in the results section.

Summary of research

The following section is the discussion section. A brief of the research is presented, and findings of the study are discussed and interpreted. The significance of this research underlines the associations between demographic, sociological, and environmental factors which may have predisposed the emergence of Ebola in Guinea. At the end of the section are the recommendations for further research on this topic. The extent of the following conclusions

is limited because of the nature of the study; however, applied to other situations, these conclusions yield correct predictions. Still, these conclusions are significant in understanding the social, demographic and environmental influence on the emergency of EVD in Guinea.

Discussion and interpretation of findings

The research objective was to investigate the associations among demographic, sociological, and environmental factors which may have predisposed the emergence of Ebola in Guinea between the years of 2014 and 2015.

The conclusion can be drawn from the result and analysis presented in Chapter 4, which pertains to the objective of this study. The study population included available information from the six districts: Boke, Conakry, Faranah, Kankan, Kindia, and N'Zerekore of the country of Guinea that had data reported for at least one confirmed case of EVD between 2014 and 2015. Each year of data included 53 records, one record for each epi week. Thus, a total of 636 records were retrieved for use in this study. However, upon the inspection of the dataset, it was found that confirmed cases of EVD were not reported for the six districts in Guinea in either the WHO situation or patient reports until the year 2014, epi-week 38 (the week of September 15 through 21, 2014). The number of confirmed cases of EVD was used as the dependent variable in hypothesis testing for this study. Therefore, the epi-weeks from 1 to 37, 2014, in the data set were not usable.

It have been documented that WHO and Ministry of Health (MOH) in Guinea knew the Ebola is confirmed in Guinea as of March 23, 2014. However, the notification was delayed because of miscalculations that they thought the disease would be over soon, also other issue is related to the political and economic environment by withholding warnings because of fear from international communities. However, the miscalculations of local public health officials and WHO by expecting the disease could be over within three months when they thought the disease could be controlled and opted to delay taking action. The WHO under The Director-General was avoiding past mistake during swine flu pandemic when it was declared the "highest alert" and accused of alarmism by a pundit [15]. The number of new case of EVD was not reported and was claimed to be stable. Until on May 25, 2014, when neighboring countries of Sierra Leone and Liberia also notified cases of EVD [15].

The WHO implemented this declaration unrestricted in its statements. But, later confirm to be the major mistakes at the beginning of the outbreak. The disease was already disseminated in Sierra Leone during the early period of epidemic. A large number of hidden cases in Sierra Leone had ignited a fiery outbreak back in Guinea and Liberia. The number of unknown EVD cases was extremely high and the spread became uncontrollable between Guinea, Liberia and Sierra Leone. But still, it took more than two months for WHO to declare the EVD epidemic is "a Public Health Emergency of International Concern (PHEIC)" [15].Unfortunately no data where available until September 2014 [15]. Subsequently,the affirming a PHEIC, the WHO Director-General assigns a specific Emergency commission and releases a "temporary recommendations" to the way the outbreak to be handled. The WHO is responsible to counter check the data given by individual countries through investigations and confirm the nature and the spread of an infectious agent [15]. Even though the endorsements are not legally compulsory, the statement of a PHEIC applies significant political burden between the countries affected by the EVD or other infectious disease to oblige and on other countries to offer financial assistance. Hence, the initial plan of the WHO is to take the expertise in combating the outbreak. But not the case the WHO responded to late because of fatal miscalculations from the beginning of the outbreak in Guinea and other western African countries of Liberia and Sierra Leone.

The representative of WHO to the West African countries had good reason to a expect the outbreak to be controlled early as to previous outbreak in equatorial Africa [15]. The governments of Guinea, Liberia and Sierra Leone also had less interest in their part as being an economic challenge as it will cause trade and traveling restriction. Consequently, they notified fewer numbers of EVD to WHO in Geneva for an extended period and also announced the disease is controlled. All this is because of local interest of affected governments and WHO country representatives but resulted to into regional and global disaster, ended to very high price for the extended period., Eventually on Agust 8,2014, WHO declared " EVD epidemic a Public Health Emergency of International Concern" [15].

Eight dummy-coded seasonal variables were planned for use as predictors to address the hypotheses of RQ1, which was looking for a relationship between environmental changes and EVD-C in Guinea during the years of 2014 and 2015. There is a possibility of the emergence of EVD is closely related to ecological factors, but in this study, there is no clear evidence of Ebola seasonality in Guinea, there is sufficient evidence to indicate that at least one of the five dummy coded seasonal variables independent variables of the regression model were a statistically significant predictor of EVD-C. However, the study seasonal variables related to the quarterly season of the year rather than the seasonal pattern of the year in Guinea such as wet and dry season. Results were significant for Seasons 5, 6, 7, and 8 when compared to Season 4. The seasonal variables were modeled about Season 4, which was the only season that included the year 2014. Decreases in EVD-C were found overall seasons. The model findings for Season 5 which is from January 2015 to March 2015; OR = 0.43 suggested that EVD-C was approximately 57% less likely in Season 5 when compared to Season 4. The model findings for Season 6 April to June 2015; OR = 0.12 suggested that EVD-C was approximately 88% less likely in Season 6 when compared to Season 4. The model findings for Season 7 July to September 2015; OR = 0.08, suggested that EVD-C was approximately 92% less likely in Season 7 when compared to Season 4. Also, finally, the model findings for Season 8 October to December 2015; OR = 0.01, suggested that EVD-C was approximately 99% less likely in Season 8 when compared to Season 4. The study was observation yet if it is evident that seasons influence our activities, but, more studies will be needed to establish the relationship between seasons and EVD. Eight Ebola epidemics during 1994-2002 and uncovered relationships involving drier than the typical weather at the end of the rainy season [18].

The reemergence of EVD in West African countries in 2014 suggests a connection to the climate changes afflicting the region in recent years. Researchers linked EVD and other infectious diseases to environmental changes. After analyzing the data, this study observed the significant social and ecological, demographic activities that can manifest in spreading EVD to some communities. Before Guinea EVD outbreaks in 2014, over 30 epidemics occurred since the first Ebola outbreak in DRC and Sudan. The EVD in Guinea caused the massive epidemic to spread to other West African countries. Previous Ebola outbreaks in Equatorial Africa have been related to hunting or eating bush meat, and they occurred in remote areas. However, the outbreak patterns in Guinea and other West African countries are characteristically different from those in other parts of Africa. It is clear there was no evidence of animal to human transmission, which was confirmed. Also, most cases of EVD occurred in highly populated areas compared to Equatorial Africa where the disease occurred in remote regions.

The understanding of the emergence of EVD is imperative to the current intervention in health care as well as the prevention of more epidemics. For assessment and proper knowledge of demographic, sociological, and environmental factors that could have predisposed the emergence of EBOV in West Africa, the overall behavior of people in the affected area can also be reviewed. Because of these factors, understanding can be gained from the experience of this epidemic and assessment of the proper way of management of potential risks from Ebola across the complex urban and countryside that describe modern Africa.

Although there are no epidemiological investigations yet that conclusively associate an epidemic of infection spillover from killing and or eating bats, it is a relatively logical assumption. However, to manage and evaluate the risk of another potential outbreak happening, it is crucial to understand and learn whether bats in this region carry Ebola virus, and if so, which type of bats. Furthermore, understanding the impact of other factors such as social, cultural, and or climatic changes is invaluable and an essential area of research.

The second question is if there a relationship between the demographic and sociological independent variables and EVD-C in Guinea during the years of 2014 and 2015. The study shows there is sufficient evidence to indicate that there is a statistically significant relationship between demographic and sociological factors that might have contributed to the emergence of Ebola in Guinea between 2014 and 2015. The demographic review includes the average years of education for both males and females, according to the six districts, and overall. On average, for all six districts combined, males had twice the education (4.60 years) than females (2.10 years). The population of the district of Conakry had the most educated individuals of both genders, with males having 9 years of education on average, and females averaging 5.7 years of schooling.

Men were the least educated, on average, in the district of Kindia (1.5 years). Women in the district of Kankan were the least literate, less than one year on average (0.7 years).

The odds ratio of 4.48 suggested that each one-year increase in the level of education for females was associated with an approximately 350 times greater likelihood of EVD-C. Women play a significant role in epidemics, and other emergencies, The majority of a nurse, midwifery, tribal birth attendants and traders are women also some women practice as traditional healers. Other study which was conducted by WHO in 2015, indicates a high population of nurses and nurse's aide have been affected by Ebola. Almost more than 50% of all health worker contacted the disease (n= 373/718). Other affected includes health workers such as medical workers 12%, laboratory worker other basic workers such as cleaners and maintenance 7% [8]. Also, the mortality of Ebola has been extremely high among health care workers. By May 2015, about 0·02% of Guinea's population had died due to EVD, compared with 1·45% of doctors, nurses/midwives [19].

Women being a mother; they have a responsibility to care for their children and other family members. Also, as a neighbor, they care for the sick in the neighborhood. As caregivers, they will take responsibility to take care of sick individuals. Let us not to forget, if someone dies, there are frontier sympathizers. The outbreak in Guinea and other West African countries affected women enormously, because of the primary role they play as caregivers, health workers, small business owners, and farmers [20]. As of December 2014, women were 62% of the sick in Guéckédou, Guinea where the first case of EVD occurred and 74% in Télémilé, north of the capital Conakry.

Also, women have a significant risk of acquiring EVD through sexual contacts. Few studies showed the previous epidemics confirmed that Ebola could be identified, by polymerase chain reaction (PCR), in the semen and vaginal fluid of EVD survivors after clearance of virus in blood stream. Ebola virus was identified in 80% of 15 men tested and 4% of 26 women tested [21]. Before the western Africa Ebola outbreak, the virus was identified by PCR in semen up to 101 days once the beginning of symptoms related to EVD [21]. WHO, CDC researchers and the Sierra Leone Ministry of Health found that 49% of 93 of male survivors of EVD in that country who were within 10 months of release from a treatment center had Ebola virus detected by PCR in their genital fluids, also100% in 9 samples donated between 2 to 3 months once the beginning of sickness [22]. Other studies find Ebola virus detected from survivors between 4-6 months and in a few patients, the virus was identified in semen up to 9 months to one year after recovery from EVD, which shows that safe sex within three months after discharge from treatment centers is not enough to prevent sexual transmission of Ebola.

The sociological predictor of urban was significantly associated with decreases in EVD-C, each one percent increase in the urban population was associated with a 6% reduction in the likelihood of EVD-C. Significance was found in the regression model for all predictors. The predictor of female education was associated with increases in EVD-C. The predictors of age > 39 years and urban were associated with a decrease in EVD-C. The seasonal variables of 2015 were all associated with decreased EVD-C when compared to Season 4, the only seasonal variable representing 2014. The author in a study of the unprecedented scale of the West African EVD outbreak found it was due to ecological, and sociological factors, not individual attributes of the currently circulating strain of the virus [23].

Significance

Gender roles facilitating human-to-human transmission of EVD

The study observed women with education in Guinea were more infected with EVD, which need to be concerned. The problem may be related to occupation as most nurses, midwifery and nursing aides are women. Lack of resource, knowledge and availability of personal protective equipment its major challenge. Also, most women are thought to be primary caregivers taking care sick individuals [24]. Because of fulling gender roles, women are more likely to nurse sick children and care for their sick husbands, brothers, and sisters as well entire family. In comparing to men, it is unusual to find men take care of their wives or another family member when their sick. Because the role which women have in the community, make them at higher risk of exposure to EVD and other infectious disease. Liberian health officials reported that three-quarters of EVD-infected individuals are women because of their primary caretaking roles. Many lives were lost in Guinea, Liberia, Sierra Leone and Nigeria [24].

Human mobility

Movement of people is a major concern during an outbreak of any infectious disease, and mainly in the disease spread involves human-to-human contact, like EVD. During Guinea and other West African Ebola EVD outbreak in 2014-15, movement of people within and between urban and rural areas was a major challenge for the disease. Even with the attempt to control border crossings, and movement of people to another area, but attempts proved unsuccessful. The factor which encourages human mobility includes culture activities, social and family connections, fear, looking for better life and stability.

Traditional medicine and cures

Traditional medicine practitioners in Guinea and another part of West Africa are highly respected and influential in society. They can provide a significant impact on health-seeking behavior in the community. Thus, they can play a role in controlling the spread of Ebola and another infectious disease if healthcare officials can invite them and educate the proper methods of handling, detection, and notification of cases. Traditional practitioners do not have formal training but do acquire knowledge from a family member who practices. Also is experience gained through beliefs, skills, and practice that arise from theories. The practical applications are not uniform, and they differ according to culture. Traditional medicine represents the old system of care, which involves the establishment of customarily implementing specific techniques for preventing and diagnosing of diseases, involving caring for people for centuries. Therefore, proper training of traditional practitioners in infectious disease prevention and distribution of public health information might be an essential tool to reach healthcare information to local communities and sustain lessening the risk of transmission of Ebola [25].

Stigmatization and the outcome of EVD outbreak control

Healthcare related stigmas can impact the social behavior of individuals infected with Ebola and also a person not affected by this virus or other infectious diseases. This can create obstacles to implementing rapid outbreak teams; thus, hypothetically changing the pathogen spread, as well as disrupting social cohesion. There is a good example provided during the HIV/AIDS pandemic where understanding influences of health-linked to stigma, and public resentment during the control of outbreak, emphasizing the entire demand to reflect these foundations in public health policy establishment and implementation [26]. EVD Ebola perhaps offered a more radical situation. Healthcare workers were tirelessly involved in the care of the patient, but they have been inhospitably denounced during EVD outbreaks, excluded by their families, friends, and communities, even assaulted by their fellow citizens because people thought they were part of problem and responsible for spreading infection [27].

Overall these beliefs impeded health-seeking behavior by increasing the fear of being infected by EVD from healthcare providers, influencing the decision to pursue assistance. In turn, shame can bring fear and affect disease reporting of new patients or contacts to health care teams of possible infection because of an adverse reaction from their neighbors and entire society [28]. Survivors can also be outcast by their community; often their possessions are vandalized, and they are prohibited from sharing public services. Stigmatization can go far beyond victims' family members. Because stigma is not always localized and sometimes extend beyond the country where the disease prevails, fear may affect the global response and impact the reporting data related to the outbreak. The stigma associated with health was a significant problem in Guinea and another part of West Africa [28] and likely a contributor to the difficulties identified in containing the epidemic.

Education, predicting, control, and future requirements

To date, the Ebola is under control in Guinea and another part of West Africa. However, the effort still requires further mobilization of the resource, such as health educators, medical personnel, and supplies such as food, water, and other commodities. There remains a need for addressing how best to prepare other countries for the likelihood of introduction of Ebola and other infectious disease or emergency. Next, are some recommendations for helping preparedness in Africa and other countries.

Organized outbreak response strategies

Coordinated development of communication strategies and surveillance partnerships across the region will be needed. Governments outside the outbreak region will need to be actively included and assisted as is necessary to develop national detection and response strategies and protocols. To establish sustained partnerships across Africa, the global community will be vital for our capability to contain these and future outbreaks.

Outbreak response in resource-poor settings

Data gathering and communication still will challenge low-income poor resource situations and the precise policies required should be established to allow quick detection and intervention within the parameters and limits recognized in the area environment. Unified methods involving public health and veterinarians must develop the protocol that engages in research, environmental policy, and notification within local settings.

Broad establishment of alert systems and preparedness policies

While global and local efforts in modeling provide essential implements for predicting risk zones, community-based surveillance will be necessary to efficiently identify Ebola emergence in wildlife (detection of death and sickness) before outbreaks occur at the local level. Public health education will be crucial in reducing behaviors that increase the risk of spillover from wildlife sources. Application of Health education is essential of controlling many problems related to Ebola outbreaks, such as trust of health authorities, the use of safe burial practices, and the acceptance of health care workers survivors and family member of the deceased, back into their communities. Early experience in EVD outbreak of 1995 DRC. Health education played a significant role in controlling the disease by people understood the part of quarantine and contact tracing [29]. The best example was in the DRC (1995) and Uganda (2000) epidemics, because of good active case tracing and quarantine. Also, health education was believed to be productive in reducing the spread of Ebola [30]. But, it is necessary to establish and disseminate health-related information, and the information must be related to traditions of the target population without causing an adverse reaction.

Limitations and Delimitations

Limitations

The study was conducted with major financial constraints; otherwise, a prospective cohort study would be preferred. The prospective cohort study is a better study design to conduct sociological and environmental investigations, factors that may influence the emergence of EVD in Guinea. The distinctive quality of a prospective cohort study is that at the time that the researchers start enrolling subjects and collecting baseline exposure information, none of the issues have developed any of the outcomes of interest. After baseline data are collected, topics in a prospective cohort study are then followed "longitudinally," such as over a period, usually for years, to determine if and when individuals become diseased and whether their exposure status changes outcomes. In this way, researchers can eventually use the data to answer many questions about the associations between "risk factors" and disease outcomes. The hypotheses observe the relationship between Ebola outbreaks and seasonal changes. Despite voluminous anecdotal evidence implicating heavy rainfall events epidemics, only limited epidemiological research on an apparent association between heavy precipitation events and Ebola outbreaks has been published.

One of the challenges for studying this association epidemiologically has been the poor fit of traditional research designs since epidemiological studies typically evaluate outcomes at the level of the individual. Broad environmental factors like rainfall, however, are better analyzed by the outbreak and its location rather than by each affected by an Ebola outbreak due to convergence problems related to the distribution of the variables.

Measures derived from precipitation values are shown to be significant predictors of periods of elevated risk for Ebola outbreaks. Despite decades of research and progress, the understanding of Ebola's ecology remains incomplete, leaving health workers unable to anticipate greater periods of risk. Growing serologic evidence indicates some bat species may be asymptomatically infected and thereby serve as a possible reservoir. The Fruit bat movement is tied to the availability of food, which is in turn timed with the rainy season. Therefore, precipitation measurements may be highly correlated to Ebola risk if rain patterns lead to fruit availability, which in turn drives fruit bat migration and allows for the introduction of Ebola into human populations.

To increase the number of events analyzed, introductions of Ebola into humans are evaluated rather than outbreaks as some result from multiple presentations of the disease into the human population. The body of work here attempted to advance epidemiologic understanding of environmental risk factors for infectious disease not only through the specific exposure-outcome associations investigated but also through the utilization of novel applications of a retrospective, longitudinal, panel design, different case definitions, and improvements in measuring individual exposure to an environmental risk factor. However, this research employed a quantita-

tive, retrospective, longitudinal, panel design to investigate climate change and cultural, social, and economic status as independent risk factors for Ebola outbreaks was not sufficient to understand the impact of environmental risk factors associated with EVD because the design was created to investigate brief exposures that cause a temporarily increased risk of an acute-onset event.

In one study two risk factors were examined: sexual activity and coffee drinking in connection with myocardial infarction, assessing their presence in biologically relevant hazard periods [31]. In the same way, heavy precipitation is hypothesized to have a transient effect on the risk of environmental changes associated with Ebola outbreaks. Just as Maclure assessed the presence of the exposure in periods with and without the outcome for each, this study evaluated, for each outbreak location, the presence of heavy rainfall events in times of the Ebola outbreak as well as in control terms that occur at the same time.

A strength of this study design is that variables that may confound the exposure-outcome relationship were inherently matched between the case and control periods. Hypothesis 2 reviewed the sociological or cultural factors that might have contributed to the emergence of Ebola in West Africa. It is documented that the spread of outbreak into Sierra Leone was associated with infection and death of a traditional healer and the individuals who had participated in the funeral [32].

There is a need to identify more precise data on these events so that acceptable culturally specific public health practices can be established. These data also allowed stakeholders to improve attempts in epidemic dynamics. For instance, funerals are an important feature of transmission, and the nature of them can define an epidemic spread. However, the data did not include many of the public health or cultural factors that could be associated with the transmission and spread of EVD. Thus, due to unavailability of certain data, lurking factors may be present that could not be tested for in this study. In the current study, it was difficult but not impossible to assess the effect of a significant precipitation event in the hazard periods of 2 and 4 weeks before an Ebola outbreak. Regarding location as an individual may be seen as unconventional, but it is the logical unit of analysis for studying outbreaks.

It should be noted that researchers were not concerned if each cell in a body was equally exposed to carcinogens when an apparent association between cigarettes and cancers was first studied. The outcome was defined in an individual as the presence of malignancy in the body. Similar is a geographic area that has poor health infrastructure but people relying on traditional healers as a cohesive unit. Focusing on individual cases of disease is no more helpful than tallying individual cells in a body. Ebola, its nature of transmission, is mainly guided by cultural and behavioral practices that appear at the family and population levels and within a health care setting involving patient care as well as individual involvement and role, health-seeking behaviors, and responses. Subsequently, there is no one "community," and the cultural diversity that defines the area requires being measured in local disease emergence prevention as well as in the public health response. The other research obstacles were an area of data collection relating to human-mediated landscape alteration to associate with increasing contact to Ebola reservoirs.

It is relevant that increased population in the natural habitat of the potential reservoirs equals to more exposure to a host of Ebola viruses. However, it is very likely that before humans start to reside in the area, the area can be modified to make it "habitable." In realizing this, the area may no longer be considered as a suitable habitat for wildlife as well as the reservoir of Ebola viruses. The most important factor that facilitates disease transmission does not have to be the proximity of human beings and the reservoirs, but the overlapping of their habitats and the social landscape of people because humans are very movable. It is significant to determine whether Ebola spillover can occur independently of bush meat utilization and exposure.

Delimitations

Because of the complexity of the spread of Ebola in West Africa, the study concentrated on only cases of Ebola that occurred in Guinea between March 2014 and December 2015. The behavior and culture in disease transmission are very complex and contribute to significant problems in Ebola and another infectious disease transmission. Ebola transmission influenced by local and regional cultural and behavioral practices that occur in the household can affect the entire community. An apparent reassessment of our trend towards the social and cultural issues in society and the role

of traditional healers is needed. Perhaps also needed is a clear understanding of the complexity of the public health care system and proper management to resolve health care burdens in a given society. The study included cases that happened in the following regions of Guinea, the area which was explored. At the same time, an analysis is made of the most important environmental factors that sociological or cultural factors directly influence the transmission of Ebola. These factors are fundamentally grouped into climatic, cultural, social, and other environmental activities.

Based on the area under study, six regions of Guinea were included in the research proposal. Climatic stations are proposed for collecting the annual means corresponding to a period of no less than 3 years to establish the possibility of seasonal transmissions and permit the application of prediction indices. Regarding climate, an analysis must be made of all the factors available from each of the meteorological sampling stations with monthly recordings. Based on these climatic data, the different climate-diagrams corresponding to each location are elaborated and used to infer certain general climatic features of the area that may be of epidemiological interest, such as delimitation of the wet and dry seasons, the period of frost, and the mean and extreme temperatures.

Suggestions for Future Research

While the focus of research on the associations between demographic, sociological, and environmental factors which may have predisposed the emergence of Ebola in Guinea, this study has offered some understanding into the associations among the demographic, sociological, and environmental factors that may have predisposed the emergence of Ebola. Although we studied in detail the spread of EVD in Guinea and factors that contributed to the transmission of the disease, future research can further establish understanding and assess the environmental, demographic, and sociological factors relevant to other settings. The prospective cohort study would be preferred. The prospective cohort study is a better study design to conduct sociological and environmental investigations, factors that may influence the occurrences of EVD.

The characteristic feature of a prospective cohort study is that at the time that the researchers start enrolling subjects and collecting baseline exposure information, none of the issues have developed any of the outcomes of interest. After baseline data are collected, topics in a prospective cohort study are then followed "longitudinally," such as over a period, usually for years, to determine if and when individuals become diseased and whether their exposure status changes outcomes. In this way, researchers can eventually use the data to answer many questions about the associations between "risk factors" and disease outcomes. The hypotheses observe the relationship between Ebola outbreaks and seasonal changes. Despite voluminous anecdotal evidence implicating heavy rainfall events epidemics, only limited epidemiological research on an apparent association between heavy precipitation events and Ebola outbreaks has been published.

One of the challenges for studying this association epidemiologically has been the poor fit of traditional study designs because epidemiological studies typically evaluate outcomes at the level of the individual. Broad environmental factors like rainfall, however, are better analyzed by the outbreak and its location rather than by each affected by an Ebola outbreak due to convergence problems related to the distribution of the variables.

Conclusion

This study was written on the bases of complex and system theory; the systems theory is merely the name given to an object studied in some field; it can be an abstract or definite; basic or compound; linear or nonlinear; simple or complex. It demonstrates that natural, economic, social, cultural, political, organizational, technological, and psychological environments have a direct influence on the level of susceptibility. Complex theory relates to systems theory, and many variables interrelate to create awareness. The complex theory suggests that there is no probability to differentiate simple linear cause and effect relationships. In its place, several variables interact in complex modes to produce epidemics. Originators of the complex theory would thus recommend that susceptibility is reduced by focusing on multiple variables concurrently. Based on complex theory, the capacity to identify and prevent dissemination of infectious diseases has usually depended on knowledge acquired through mathematical modeling [33]. Therefore, the systems theory is relevant to evaluate the correlations between factors and EVD such as demographics, as well as sociological and environmental factors presented in this study. However, these different methods act together in complex ways. One example is that the site and building of a village may relate to policy enforcement

and sociocultural inclinations as well as social factors, economic status, risk awareness, urbanization, and the level of education of the population.

All research questions have been answered. The reemergence of Ebola Virus Disease (EVD) in Guinea in 2014 suggests a connection to the climate changes afflicting the region in recent years. This study observed the significant social, ecological, and demographic activities that can manifest in spreading EVD to some communities. Before Guinea EVD outbreaks in 2014, over 30 epidemics occurred since the first Ebola outbreak in DRC and Sudan. The outbreak in Guinea caused the massive outbreak to spread to other West African countries. Previous Ebola outbreaks in Equatorial Africa have been related to hunting or eating bush meat, and they occurred in remote a7reas. However, the outbreak patterns in Guinea and other West African countries are characteristically different from those in other parts of Africa, for it is clear no evidence of animal to human transmission was confirmed. Also, most cases of EVD occurred in highly populated areas compared to Equatorial Africa where the disease occurred in remote regions. The results of this research support the idea that associations among demographic, sociological, and environmental factors may have predisposed the emergence of Ebola in Guinea between 2014 and 2015. Also, this study could increase understanding of the mechanisms by which the Ebola virus does spread. Besides, the study can provide valuable information and results towards suggesting planning and further research or improving the approach to the process of controlling the disease as the greater demand for control of EVD might be accomplished by uncovering the critical areas that allow the Ebola host to be in contact with humans.

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Conflict of interest

No conflicts of interest present.

Appendix A: West African Countries Affected by Ebola 2014-2015.

Source: Centers for Disease Control and Prevention (CDC).

Appendix B: Guinea Ebola Outbreak Timeline 2014-2015.

Ebola Virus Disease Timeline in Guinea between 2014-2015

Season	Time	Events	Response
	December 26, 2013	The initial patients(index case) reported in December 2013. A 2 years old boy from a small village in Guinea is believed to have been infected by bats.	
Season 1		Several immediate families of the first case of Ebola contacted similar illness and died.	An official medical alert was issued
	February 1, 2014	The Ebola virus was carried into the capital, Conakry, by an infected member of the first patient extended family.	Nobody suspected Ebola. No protective measures are taken to protect staff and other patients. As the month progressed, cases spread to other areas of Macenta, Baladou, N'Zerekore, and Farako also several communities along the way to Conakry.
	March 13, 2014.	More cases of mysterious illness and death.	The Guinea Ministry of Health(MOH) issued its first alert to the mysterious disease. WHO's Regional Office for Africa (AFRO) formally opened an Emergency Management System event for a disease suspected to be Lassa fever.
	March 13-25,2014	site visits to Kissidougou, Macenta, Gueckedou City and N'Zerekore. That investigation found epidemiological links among outbreaks previously not known to be connected and identified Guéckédou City as the epicenter for transmission of unknown diseases.	A major investigation, involving staff from the Ministry of Health, WHO AFRO, and MSF,
	March 21, 2014	Preliminary laboratory result of the specimen from Pasteur Institute in France	Laboratory confirmed the presence of filovirus, narrowing the diagnosis down to either Ebola virus disease or Marburg fever.
	March 23, 2014	Pasteur Institute in France confirmed the illness as EVD caused by Zaire ebolavirus.	WHO officially declared an outbreak of EVD
Season 2	April 2014	*An Ebola treatment center in Guinea was attacked by an angry civilian. Increased hostility toward healthcare workers from fearful, suspicious people. *The funeral of venerated healer Mendinor, gathered a large number of mourners, caused a spread of Ebola virus to Sierra Leone and Liberia.	*Doctors without Borders (MSF) warned Ebola's spread was "unprecedented." *A WHO spokesperson called it "relatively small still."

	May 24, 2014	A large number of Ebola confirmed in Sierra Leone.	
	June 2014	Liberia reported Ebola cases in its capital, Monrovia.	
Season 3	July 2014	*The Ebola spread to Nigeria, as a Liberian-American arrived by plane in Lagos and died in quarantine. * Dr. Sheik Umar Khan, who led Sierra Leone's fight against the epidemic, died from Ebola.	MSF declared Ebola "out of control." Liberia closed its schools and shut some border crossing points, using troops for enforcement.
	August 2, 2014	First United States missionary, was infected with Ebola in Liberia, was flown to Atlanta for treatment.	
	August 5, 2014	A second US missionary infected with Ebola was flown from Liberia to Atlanta for treatment	
	August 8th, 2014		The WHO declared the Ebola epidemic a "public health emergency of international concern".
	September 2014	A beginning of the fight back to control the EVD in West Africa. But with slow of international response.	Available data of Ebola MOH guinea and WHO situation.
Season 4	October -December 2014	The steady rising of cases	
Season 5	January 2015	The decline in a new number of Ebola in all three countries – Guinea, Sierra Leone, and Liberia.	WHO announces a 'turning' point in the Ebola crisis
	February 2015	The rise of EVD cases where recorded in Guinea.	*The Health officials thought that because they "were only now gaining access to faraway villages," where violence had previously prevented them from entering. *Higher hostility and Resistance to health officials by a group of Guinean population then Sierra Leone and Liberia.Increased concerns of caring and identifying new cases.Also fear of life for healthcare workers.
Season 6	May 2015	Rise in case	Believed to be funeral transmission
	June 2015	WHO reported that "weekly case incidence has stalled at between 20 and 27 cases	reported that violent protests in a north Guinean town at the border with Guinea-Bissau had caused the Red Cross to withdraw its workers
Season 7	July 2015	a sharp decline in cases was reported,	
	August 2015	The number of cases eventually plateaued at 1 or 2 cases per week	
Season 8	November 2015	No new cases of Ebola Reported	The 42-day countdown toward the country being declared Ebola-free started on 17 November, the day after the patient yielded a second consecutive negative blood test
	December 29, 2015		WHO declared Guinea Ebola-free

Bibliography

1. Pigott DM., *et al*. "Mapping the Zoonotic Niche of Marburg Virus Disease in Africa". *Transactions of the Royal Society of Tropical Medicine and Hygiene* 109 (2015): 366-378.
2. WHO, n.d. fill in.
3. Feldmann H and TW Geisbert. "Ebola hemorrhagic fever". *Lancet* 377 (2011): 849-862.
4. "Ebola Virus Disease. Fact Sheet No. 103". World Health Organization. World Health Organization, (2014).
5. Bagcchi S. "Ebola Hemorrhagic Fever in West Africa". *Lancet Infectious Disease* 14 (2014): 375.
6. Omidan, P., *et al*. "Medical Anthropology Study of the Ebola Virus Disease (EVD)". Outbreak in Liberia/West Africa.
7. Baize S., *et al*. "The Emergence of Zaire Ebola Virus Disease in Guinea: Preliminary Report". *New England Journal of Medicine* 371 (2014): 1418-1425.
8. "Ebola Data and Statistics". World Health Organization. World Health Organization (2015).
9. Bray M and DS Chertow. "Epidemiology and Pathogenesis of Ebola Virus Disease" (2014).
10. Desai R. "Ebola Education Blog" (2014).
11. Rajewski G. "What Drives Ebola" (2014).
12. Wooldridge J. Econometric Analysis of Cross Section and Panel Data, Cambridge, MA: MIT Press, 2002.
13. Santos LA and EB Barrios. "Small Sample Estimation in Dynamic Panel Data Models: A Simulation Study". *Open Journal of Statistics* 1 (2011): 58.
14. Gujarati DN. Basic Econometrics. New York: McGraw Hill Book Co., (2003).
15. Kekulé Alexander S and Jens Kuhn. "Learning from Ebola virus: How to Prevent Future Epidemics". *Viruses* 9 (2015): 3789-3797.
16. Pallant, J. SPSS survival manual: A step by step guide to data analysis using IBM SPSS (5th ed.). Sydney, Melbourne, Auckland, London: Allen and Unwin (2013).
17. Boke A., *et al*. "Quantitative Determination of the Heavy Metal Levels in the Wild Edible Plant Parts and Their Corresponding Soils of the Central and Western Regions of the Oromia State, Ethiopia". *Journal of Environmental Analysis Toxicology* 5 (2015): 299.
18. Pinzon JE., *et al*. "Trigger events: Enviroclimatic Coupling of Ebola Hemorrhagic Fever Outbreaks". *American Journal of Tropical Medical Hygiene* 71 (2004): 664-674.
19. Evans DK., *et al*. "Health-Care Worker Mortality and the Legacy of the Ebola Epidemic". *The Lancet Global Health* 3.8 (2015): e439-e440.
20. UNDP. "Confronting the gender impact of Ebola virus disease in Guinea, Liberia, and Sierra Leone". *UNDP Africa Policy Note* 2.1 (2015).
21. Fischer WA and DA Wohl. "Confronting Ebola as a Sexually Transmitted Infection". *Clinical Infectious Diseases* 62 (2016): 1272-1276.
22. Deen GF., *et al*. "Ebola RNA persistence in Semen of Ebola Virus Disease Survivors: Preliminary Report". *New England Journal of Medicine* 377 (2016): 1428-1437.
23. Gatherer D. "The Unprecedented Scale of the West African Ebola Virus Disease Outbreak is Due to Environmental and Sociological Factors, Not Special Attributes of the Currently Circulating Strain of the Virus". *Evidence-Based Medicine* 20.1 (2015): 28-28.
24. Krewski D., *et al*. "An Integrated Framework for Risk Management and Population Health". *Human Ecological Risk Assessment: An International Journal* 13.6 (2007): 1288-1312.
25. Alexander KA., *et al*. "What Factors Might Have Led to the Emergence of Ebola in West Africa?" *PLoS Neglected Tropical Diseases* 9.6 (2014): e0003652.
26. Bayer R. "Stigma and the Ethics of Public Health: Not Can We But Should We". *Social Science and Medicine* 67 (2008): 463-472.
27. Guimard Y., *et al*. "Organization of Patient Care During the Ebola Hemorrhagic Fever Epidemic in Kikwit, Democratic Republic of the Congo, 1995". *Journal of Infectious Diseases* 179 (1999): S268-S273.
28. Davtyan M., *et al*. "Addressing Ebola-Related Stigma: Lessons Learned from HIV/AIDS". *Global Health Action* 7 (2014): 26058.

29. Khan AS., *et al*. "The Reemergence of Ebola Hemorrhagic Fever, Democratic Republic of the Congo, 1995". *Journal of Infectious Diseases* 179 (1999): S76-S86.

30. Chowell G., *et al*. "The Basic Reproductive Number of Ebola and the Effects of Public Health Measures: The Cases of Congo and Uganda". *Journal of Theoretical Biology* 229.1 (2004): 119-126.

31. Maclure M. "The Case-Crossover Design: A Method for Studying Transient Effects on the Risk of Acute Events". *American Journal of Epidemiology* 133 (1991): 144-153.

32. Gire SK., *et al*. "Genomic Surveillance Elucidates Ebola Virus Origin and Transmission During the 2014 Outbreak". *Science* 345 (2014): 1369-1372.

33. Anderson R and R. May, Infectious Diseases of Humans: Dynamics and Control. London, UK: Oxford University Press (1991).

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