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# The Rise of Malaria and upper Respiratory Tract Infections during the El Nino Season Using Logistics Regression Analysis and Bayes Theorem

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**Abstract**

Malaria and URTI'S are known to be caused by different factors that range from environmental patterns to immunity of individuals. The prevalence of these two diseases usually increase from time to time due to situations such as lack of medical care, poor living standards and many other related factors. The abnormal increase of cases for such diseases can be caused by abnormal weather conditions like a rapid increase in precipitation. In this study, a scientific approach was employed in defining the epidemic of malaria and URTI'S by the use of effect size measures and probability models. This was based on the fact that there was a prediction of the El Nino condition by the meteorological department of Kenya and National Oceanic and Atmospheric Administration in America that was to affect the east African region between October 2015 to early 2016. The objective of this project was in line with the strategy of WHO/IDSR launched since 1998 and that is to provide a logistics probability model that investigates on the epidemics of URTI's and Malaria occurring during the El Niño season. The project was conducted in Maasai Mara University; Narok using secondary data from the University health unit and it encompassed the number of Malaria and URTI cases reported during the year 2015. The incorporation of Bayesian analysis was reasonable to provide a clear picture of the effects of El Nino in the health sector and the remedies available.

***Keywords:*** Bayes Theorem; Communicable Disease; El Niño; Endemic Areas; Epidemic; Pandemic Areas; Posterior probability; Prevalence; Prior probability; Prognostic Factors.

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## 1. Introduction

Malaria and respiratory disease epidemics are common in developing societies. Various factors that are hard to manage are the sources of these epidemics. Most of these factors are in existence and can hardly be traced using normal observations. In fact, these factors are *hidden variables* over which we have no control [12]. Nevertheless, seasonal trends of weather, erratic behaviors and characters of human beings can be seen to be the major causes of such problems.

Populated areas where social interactions are common, are zones for easy transfer of infections between people. In local institutions, cases of infectious disease outbreaks are reported frequently. The sources of contamination can be attributed to the changes in weather conditions that favor the habitation of disease causing micro-organisms.

Events of nature like the El Nino have resulted to epidemics. At the beginning of 2015, the Meteorological Department of Kenya published an advisory on the development of El Nino in the October-December short rain season and explained the persistence of the rains to early 2016. Although El Nino events have been occurring within October-December period, the impact of the rains has not been severe yet, apart from the one experienced in 1997/1998. Furthermore, the projected Global models have currently indicated high rainfall levels in the east African region that could affect different sectors especially the health sector where an epidemic of malaria and rainfall related diseases is likely to occur. During this period, modification of the physical environment usually takes place making it suitable for the disease causing micro-organisms to increase in number. For example, during 2001 to 2006, epidemics following heavy rainfall were reported from eastern and southern Africa. The results of this epidemics were an increased number of death cases in the affected regions.

During a heavy rainy season, there are reports of an increase in malaria, fevers and respiratory illnesses. These seasons are connected to such disease patterns thus, control and regulation must be covered in the community affected therefore using different programs, like the disaster management program that is currently operating in Kenya to cater for the effects of projected heavy rains.

Description of the condition of the affected community also is necessary to investigate the sequence of events during the period of contamination. This is achieved by use of models. Different approaches are helpful in guiding different stages of the disease through assembling available information and using it for prediction. Several models have been used in epidemiological studies. Common malaria models like the Ross model explain the relationship between the number of mosquitoes and incidence of malaria in humans [13]. Network models (graph models) having nodes (vertices) and edges (links) have long been used to investigate the impact of spatial structure on the transmission of infection.

For example, in the transmission of HIV and STI'S, there are natural well-defined network structures being exploited by the medical fraternity called sexual partnership structures [3]. It is felt that a combination of different approaches, rather than a single type of modelling, may have long term usefulness in eradication and control [13].

Along with the programs and models, measures and tools have been implemented in health offices to curb epidemics. The normal schemes used to stop epidemics are many and need continual improvements as per the standard of the current world. Apart from creating awareness and periodic checkups, it is also essential to focus such issues mathematically for better understanding. For example, in this study a logistics regression model was used to obtain the logic behind the future event of an epidemic.

Malaria and URTI cases have been rampart and effected in mortality. In 2012, more than half a million cases of Malaria were reported according to the WHO report [17]. Furthermore, studies have shown that Upper respiratory tract infections (URTI's) account for 7.5 million deaths annually in developing countries.

Generally, during the El Nino season, the affected region is in the freedom of an epidemic. In this study, the focus was on the reported cases of Malaria and URTI's. They are diseases that are prevalent in the University of Maasai Mara; an institution that accommodates not less than 4000 students in a row of semesters. By assigning probabilities, it was possible to output the magnitude of these diseases and determine the chance of their epidemics at set probability thresholds within that currently predicted rainy season.

### *1.2 Statement of the problem*

The problem in this study was based on the fact that there are many factors that can lead to the causation of malaria and URTI'S. But in this research project, the causation of the two diseases was constrained to anomalous weather conditions of increased rainfall in the east African region. Furthermore, these conditions were to be favoured by the El Nino effect that was predicted in early 2015 by the meteorological department of Kenya and the National Oceanic and Atmospheric Administration of America (NOAA), to happen during the October-December short rain periods and persist to early 2016. Recent studies on the effects of El Nino on human health have shown increased malaria and respiratory infections beyond normality which have contributed to an increased death toll. Therefore, the research project was a cross sectional study conducted in Maasai Mara university during the October-December period to investigate and certify if there was a rise in malaria and URTI cases compared to the other periods of the year. The expected outcome was that if the malaria and URTI cases were recorded above normal count over independent individuals within the University during the October-December period, then it would be a clear indication of an upcoming epidemic. This would be supported or disapproved using the measures of effect size and probabilities together with a logistics regression model. If proved that an epidemic would occur, then necessary remedies and recommendations would be given to the health fraternity.

### *1.3 Objectives of the study*

#### *1.3.1 General Objective*

The main purpose of this study was to establish the relationship between increased cases of Malaria/ URTI'S and heavy rainfall resulting from the El Nino using logistics regression model.

#### *1.3.2 Specific objectives*

- To calculate the probability of an epidemic during El Nino season.
- To measure the effect size of the epidemic using the odds ratio and the relative risk.
- To improve on the surveillance of malaria and respiratory diseases in an institution.
- To give statistical recommendations to the health fraternity and target population.

### *1.4 Justification*

There is a necessity of taking measures earlier to stop an epidemic of diseases such as Malaria and URTI'S. The series of outbreak cases reported yearly or monthly if accumulated together and compared can produce the correct program of eradication. An illustrative model that is ideal can benefit the community and any institution to quickly employ timely and appropriate responses to a predicted epidemic. This study therefore was to enable institutions to control epidemics of malaria and respiratory diseases pronto by improving surveillance of the diseases. It should have been of great assistance to student researchers in the university who would come up with modified techniques of such kind. In addition, this study was to be used for the monitoring of the status of current events of the impact of upcoming rains especially to the health sector. The World Health Organization African Regional Office (WHO/AFRO) launched the Integrated Disease Surveillance and Response (IDSR) strategy and has been providing technical and financial resources to African countries to strengthen epidemic preparedness and response (EPR) activities. Therefore, the provision of technology and disbursement of finances to the health department to stop the epidemics was to be much simpler. This means that the health unit fraternity was to be priority number one stakeholders of the study under clear notifications.

### *1.5 Scope of the study*

Pauline V. Young describes a case study as "a comprehensive study of a social unit be that of unit a person, a group, a social institution, a district or a community." [18]. This definition is succinctly tied up with the scope of this study which was a social unit in the Maasai Mara University, Narok county Kenya. The involved population consisted of Maasai Mara University students with an invariant totality of not less than 4000 students per semester.

### *1.6 Limitations of the study*

The challenge encountered in this study was during data collection. The effect of redundant records and names of patients was a constraint. It was time confronting to obtain a single case of malaria or URTI for each unique individual from the records due to repeated diagnosis of the same person over time. In this case some of the records were overlapping.The same individual who for example was found with Malaria, would reappear again the following day or later within the period, though readily counted into the Malaria dataset. This may have led to repetitions that may have declared an over count on the frequency toll.

## 2. **Review of the theoretical literature**

### *2.1 Malaria*

It is an acute febrile disease caused by protozoan parasites *Plasmodium falciparum*, *P. malariae*, *P. ovale*, and *P. vivax.* The source or carriers of the parasites are infected female mosquitoes of the genus *Anopheles*. There are several modes of transmission for malaria. These include:

i.) Bite of infective anopheles' female mosquito.
ii.) Blood transfusion from infected persons.
iii.) Congenital and parenteral transmission.

Common symptoms associated with malaria are usually chills, nausea, headache and fever every 2-3 days. Studies have shown that approximately 90% of the one million deaths caused by malaria each year occur in Africa. It is also estimated that 74% of the population in the African region lives in areas highly endemic for malaria while 19% resides in epidemic-prone areas. A malaria epidemic is signaled by a sharp increase in clinical malaria in areas of moderate transmission i.e. above 100 cases per month. In fact, partial immunity is found in individuals with continuous exposure in endemic areas. Malaria epidemics frequently affect highlands and semi-arid areas where inhabitants lack immunity. They may be caused by natural variables (climatic variations, natural disasters) and manmade situations (conflict and war, agricultural projects, dams, mining, logging) that modify the physical environment and increase the capacity of mosquitoes to transmit malaria in non-immune populations. Malaria epidemics have also increased in recent times since climate change or global warming is predicted to have unexpected effects on its incidence. Both increase and fluctuation in temperature affects the vector and parasite life cycle. This can cause reduced prevalence of the disease in some areas, while it may increase in others.

A study was conducted on the trends of major disease outbreaks in the African region [10]. It was stated that climate change can affect malaria prevalence pattern by moving away from lower latitudes to regions where populations have not developed immunity to the disease. Also he stated that an estimate of about 125 million Africans residing in 20 countries are at risk of malaria epidemics. Since the epidemics occur in population with little immunity, it is estimated that 5% of the cases may progress to severe malaria, resulting in 10% case fatality.

For example, in 2003 three countries were most affected by malaria epidemics: Ethiopia (617,446 cases/2,064 deaths), Burundi (78,781 cases/0 deaths) and Kenya (2,528 cases/32 deaths). In 2004, a large outbreak was reported from Zimbabwe (672,074 cases/1,092 deaths). Effective prevention of these epidemics is challenging especially in the highlands. Furthermore, an additional challenge is the growing resistance of plasmodium, the malaria-causing agent, to antimalarial drugs.

Different methods have been used to model malaria transmission in Africa through the Malaria Risk in Africa (MARA) project where the role of temperature and rainfall from meteorological stations and community-based parasitological survey is used in the prediction of malaria risk [15]. The effect of vector abundance and population immunity on malaria incidence is joined up to predict the seasonal pattern of malaria. Researchers have also used elaborate time series analysis models to show seasonality patterns in the malaria incidence [9]. With the availability of world-wide datasets on population distribution, global circulation, environmental factors, and parasitological prevalence, epidemiologists have now increasingly been interested in global modelling perspectives. Such activities require, along with mathematical models, in depth statistical modelling techniques such as, Bayesian inference and multivariate statistical modelling techniques to generate maximum likelihood predictions for posterior probability of parasite distributions on the world map.

### *2.2 Upper respiratory tract infections (URI or URTI)*

They are illnesses caused by an acute infection which involves the upper respiratory tract including the nose, sinuses, pharynx or larynx. URTI's are often referred to as "colds". URTI's can be characterized by a group of disorders which include common cold, pharyngitis, tonsillitis, epiglottitis, sinusitis, bronchitis, rhinitis, and nasopharyngitis, which significantly occur in the upper respiratory tract.

URTIs are contagious. The transmission of organisms causing URTI's has been known to occur by aerosol, droplet, and direct hand-to-hand contact with infected secretions. In addition, subsequent passage to the nares and eyes also forms the basic procedure of acquiring infections, and hence, it has been suggested that the transmission occurs more commonly in crowded conditions [4].

URTI's have been regarded as the most frequent illnesses affecting people worldwide. Several factors contributing to the widespread occurrence of URTI's may be attributed to breathing of contaminated air, direct contact with infected people, over-crowded places, cigarette smoking and exposure to pathogens.

Various signs and symptoms of URTI's have been reported which include stuffy and runny nose, sneezing, coughing, sore throat, fever, vomiting, irritability, loss of appetite, and watery eyes [6]. However, URTI infections have been suggested to be mild and self-limiting, but they have been reported to lead to life threatening complications. URTI's have been known to be caused by either viruses and bacteria; or combination of both. Most studies have suggested the cause to be bacterial. Viruses causing most URTI's include rhinovirus, parainfluenza virus, coronavirus, adenovirus, respiratory syncytial virus, coxsackievirus, and influenza virus in most cases, whereas beta-hemolytic streptococci, *Corynebacterium diphtheriae*, *Neisseria gonorrhea, Arcanobacterium haemolyticum*, *Chlamydia pneumoniae*, *Mycoplasma pneumoniae*, *Streptococcus pneumoniae*, *Haemophilus influenzae*, *Bordetella pertussis*, and *Moraxella catarrhalis* are the most common bacteria causing URTI's [16].

URTI's can be categorized as epidemic and pandemic infections, which can be evidenced by the fact that most epidemics have been believed to spread among students. During high rainfall periods, there is a decrease in temperatures as the land cools down. Furthermore, mixture of clean water and contaminated water especially in poor drainage areas is common. This boosts the prevalence level of URTI'S. In 2004, a study was conducted to determine the risk factors of URTI's in Uganda. The results of the study confirmed generally that the source of drinking-water, personal hygiene, disposal of garbage, and absence of latrine are risk factors for URTI's [5].

### *2.3 El Nino*

El Niño is a complex weather pattern resulting from variations in ocean temperatures in the Equatorial Pacific. It refers to the large-scale ocean-atmosphere climate interaction linked to a periodic warming in sea surface temperatures across the central and east-central Equatorial Pacific. This condition of warmer than average waters in the Eastern pacific affects weather around the world. El Niño is referred to as the warm phase of the el Niño-Southern Oscillation Cycle (ENSO) as opposed to the cold phase called La Nina. The ENSO cycle describes the fluctuations in temperature between the ocean and atmosphere in the east-central Equatorial Pacific. These deviations from normal surface temperatures can have large-scale impacts not only on ocean processes, but also on global weather and climate. It was once suggested that minor El Niño events occurred about every two to three years and major ones about every eight to 11 years. Today, El Niño has a return period of four to five years. When an El Niño event occurs, it often lasts from 12 to 18 months. El Niño means the little boy or Christ child in Spanish. It was originally recognized by fishermen off the coast of South America in the 1600's, with the appearance of unusually warm water in the Pacific Ocean [7]. The name was chosen based on the time of the year (around December) during which these warm waters events tended to occur. It has been observed that during El Niño, there is a disruption in the global weather patterns in the tropics including Kenya and worldwide extremes in weather and climate such as droughts, floods, cold/hot spells and tropical cyclones, among others, are common, even in some regions that are very far away from the Pacific Ocean basin. Such severe and extreme climate episodes are often associated with far reaching socio-economic impacts including deadly epidemics. Not all El Niño events result in enhanced rainfall patterns over the country but with regards to the 1997/1998 El Niño experience the impact of it can be destructive. The evolving El Niño from the projections of the global models was to persist through the short rains season (October-December) and about 95% chance it was to extend to the early parts of 2016. Predictions indicated that there was a likelihood of enhanced rainfall over much of the country during the session. Heavy storms were likely to occur during the season, and more so, during the rainfall peak month of November. However, the rainfall intensity was not likely to reach that of 1997. The health fraternity under the disaster management sector predicted an increase in Malaria and other water-borne related diseases due to enhanced rainfall [11].

### *2.4 Summary*

The review of this study was clearly themed on gaining familiarity with the El Niño phenomenon and a deeper insight into its impact on health. The diagnosis of malaria and URTI'S for Maasai Mara university students in 2015 was to be summarized using frequencies and plotted against the probability of having the disease. The relationship between the El Nino condition as a typical factor influencing the number of malaria and URTI cases in 2015 was to be displayed using a logistics regression model. The result of the research paper was to help the whole university to improve on surveillance techniques of epidemics and create awareness on the dangers of neglecting the effects of El Nino on disease patterns. This research was to be of great service to the community too as it showed the current status of events that could have tampered with the socio-economic sector.

## 3. Methods

### *3.1 Research Design*

"A research design is the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose with economy in procedure." [1]. The diagnostic research here combined two variables; Malaria and URTI cases such that the daily frequencies in which they occur in the University of Maasai Mara was obtained from the medical library of the health unit. The data documented was separated into two to explain the observational design in the study. The implication derived was that in the first category (from January to September), the rains were happening sporadically. In the second category (from October to December), the level of precipitation increased as discussed by the intuitive prediction of the global weather forecast. The two situations created strata with two different properties as shown in the statistical model below. In this study it was possible to define the confounded relation of the two diseases and the weather condition as follows.

Sporadic rain period

Probability of an epidemic=Malaria cases / URTI cases

Increased rainfall (El Niño)

Since we had the response variable (Y) as the probability of an epidemic and also the diagnosed cases of the two diseases in the two periods, a logistic regression model was fitted as shown, the $x_i$'s being prognostic factors which influenced the success probability of Y thus;

$$Y = B_0 + B_i X_i + e_{ij} \text{ ......................................} (1)$$

OR

$$Log\frac{pr(Y=1)}{pr(Y=0)} = \beta_0 + \beta_i X_i \text{.....................................} (2)$$

$$\hat{\rho}(x) = \frac{e^{\beta_0+\beta_i x}}{1+e^{\beta_0+\beta_i x}} \text{...................................................................} (3)$$

Where,

$i = 1 \ to \ 3$

$Y$- The probability epidemic.

$B_0, B_1, B_2$- Regression parameters.

$X_1$- Malaria diagnosed cases.

$X_2$-URTI diagnosed cases.

***3.2 Target Population***

The population of interest in this research was centered on students in any institution. Emphatically, the target population that was to be the center-piece of the research problem was the recorded population from the health unit in Maasai Mara University that covered the reportage of students affected by Malaria or URTI's. The Health Unit journals were to provide sufficient data for the global scenario of students in any institution during rainy seasons.

### *3.3 Population and Sampling*

In this study, Maasai Mara University students served as a representative of the whole population of students in any other institution that were vulnerable to epidemics resulting from Malaria or URTI'S. The Malaria or URTI cases tabulated in the health unit of MMU resonated with the ones in any other institutional health office around the country due to the fact that the chief variable of this study was the El Nino rains condition that with certainty affected both Kenya and the surrounding East African countries. Therefore, MMU was taken to represent the interest of the rest of the institutions.

### *3.4 Data collection Method and Procedures*

Collection of data was from secondary sources. Service statistics from health fraternities are usually reliable, suitable and indeed adequate. The names of those suffering from the diseases of interest was kept confidential. Nevertheless, the daily toll of inclusive cases was accumulatively handed over by the nurse in charge as directed. The consideration to use secondary data as the collection procedure was satisfactory and efficient since the same data was to be used by the health clinic to produce a report at the end of the semester.

### *3.5 Data Analysis Method*

The data obtained from the health unit was to undergo the following analysis methods.

a. Time Series- Linear Trend Description- The long term upward or downward movement of the trend was also traced to explain the prevalence of the diseases within the months.

b. Test for Normality- Shapiro Wilks Test– The data was approximated if it assumed normality.

$H_0$: The respective distribution is Normal.

$H_1$: The respective distribution is not Normal.

c. T-test comparison of Means between the Rains and No Rains periods - The T-test for the difference in means was checked to affirm the significance of the study. The Behrens-Fishers problem was used as a platform for testing equality of means of two normal distributions that do not have the same variance as shown in equation 4.

$H_0$: There is no significant difference between the El Niño session and sporadic rain period with respect to reported cases.

$H_1$: There is a significant difference between the El Niño session and sporadic rain period with respect to reported cases.

$$t = \frac{\left(\overline{X}_1 - \overline{X}_2\right)}{\sqrt{\left(\frac{s_1^{\ 2}}{n_1} + \frac{s_2^{\ 2}}{n_2}\right)}} \qquad \text{(4)}$$

The approximate degrees of freedom were given as:

d. Using STATA11 it was possible to obtain the odds ratio, relative risk, risk difference and the resulting chi-square value from the cross- tabulation shown.

| | **RAIN** | **NO RAIN** |
|---|---|---|
| **Affected** | 2nd period cases | First period cases |
| **Not Affected** | 4300-2nd period cases | 4250-first period cases |

**Figure 1:** Cross Tabulation

The *risk difference* (attributable) risk provided a measure of the public health impact of an exposure (assuming causality). The hypothesis of equal proportions was given by;

$H_0$: $p_1 - p_2 = 0$ $\qquad$ $H_1$: $p_1 - p_2 \neq 0$

The *relative risk* provided a measure of the magnitude of the disease-exposure association for an individual.

The hypothesis of equal proportions was given by;

$H_0$: $\frac{p1}{p2} = 1$ $\qquad$ $H_A$: $\frac{p1}{p2} \neq 1$

The Relative risk in this case is the risk ratio = ratio of proportions i.e.

$$R\hat{R} = \frac{\hat{p}1}{\hat{p}2}$$

*Odds Ratio.*

The hypothesis of equal proportions for the odds ratio is

$H_0$: OR=1

$H_A$: OR≠1

The odds ratio is a function of risk (prevalence). Odds is the ratio of the risk of having an outcome to the risk of not having an outcome. P being the risk of an outcome,

Odds=$\frac{p}{1-p}$.

*Inference for the slope.*

The significance of the slope $\hat{\beta}1$ was tested using the z-test for the following hypothesis

*H*0: $\hat{\beta}1$ =0 versus *Ha*:$\hat{\beta}1 \neq 0$;

Z=$\frac{\hat{\beta}_1}{SE(\hat{\beta}1)}$;

e. Bayes Theorem and the Probability Tree- Prior and Posterior probabilities were used to show the inter-relation between the two parameters in the study.

$$P(E|R) = \frac{P(R|E)P(E)}{[P(E).P(R|E)]+[P(\bar{E}).P(R|\bar{E})]} \quad \text{………………………………………… (5)}$$

| Event | Description |
|---|---|

E=" An epidemic of malaria or URTI happens" i.e. $E_m$ and $E_u$.

$\bar{E}$=" No epidemic of malaria or URTI happens" i.e. $\bar{E}_m$ and $\bar{E}_u$.

R=" It rains during October-December short rain period"

$\bar{R}$=" It does not rain during October-December short rain period"

P(E)= $[P(E).P(R|E)] + [P(\bar{E}).P(R|\bar{E})]$ is called the prior predictive distribution which was calculated using the law of total probability stated as;

If events R1, R2, ……., Rk constitute a partition of the sample space S and P (Ri) ≠ 0 for i = 1,2, ……., k, then for any event E in S, p(E) =$\sum_{i=1}^{k} P(E|R_i)$ P($R_i$). The following software for processing the data were to be used MS EXCEL, R(Epicalc) and STATA11.

**4. Results and Discussions**

***4.1 Background information***

The number of monthly cases for Malaria and URTI that were reported in the MMU health unit for the year 2015 are shown in Table 1.

**Table 1:** Number of Monthly Diagnosed Cases for Malaria and URTI'S

| | Diagnosed Cases | |
|---|---|---|
| | Malaria | URTI |
| January | 20 | 25 |
| February | 35 | 53 |
| March | 133 | 153 |
| April | 130 | 118 |
| May | 54 | 58 |
| June | 273 | 334 |
| July | 284 | 269 |
| August | 382 | 270 |
| September | 310 | 260 |
| October | 676 | 501 |
| November | 703 | 400 |
| December | 200 | 170 |
| Total | 3200 | 2711 |

### *4.1.1 Linear Trend Description*

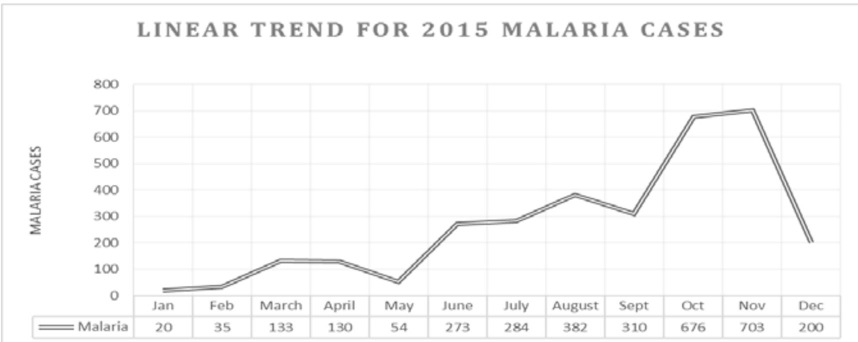


**Figure 2:** The Yearly trend for URTI Cases.

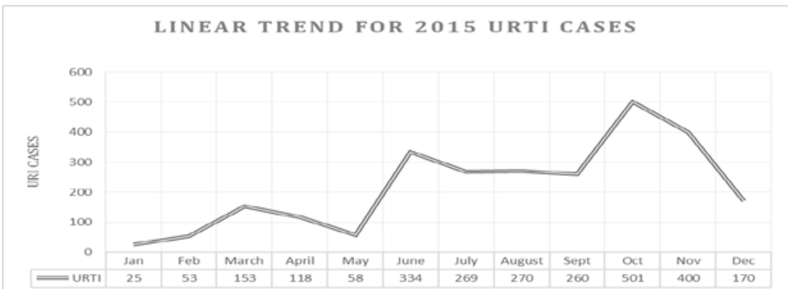


**Figure 3:** The Yearly trend for Malaria Cases.

From the graphs above (Figure 2 & 3), the number of cases for both diseases between September and November were much higher than the number of cases during the other months. This situation can be equated to the fact that there was an increase in precipitation within this short rain period that was predicted to persist to early 2016. This also was clear indication of an impact to the health sector as a result of the sharp increase in Malaria and URTI cases.

#### *4.1.2 Test for Normality*

Using the Shapiro-Wilks test, the Malaria and URTI weekly cases were approximated for normality in R and the result was as follows:

Shapiro-Wilk normality test

data: Malaria

W = 0.8839, p-value = 0.0001983

Shapiro-Wilk normality test

data: URTI

W = 0.9454, p-value = 0.02621

The test for normality was significant hence the t-test for comparison of means was used to find out if there was a significant difference in the El Nino period and sporadic rain session.

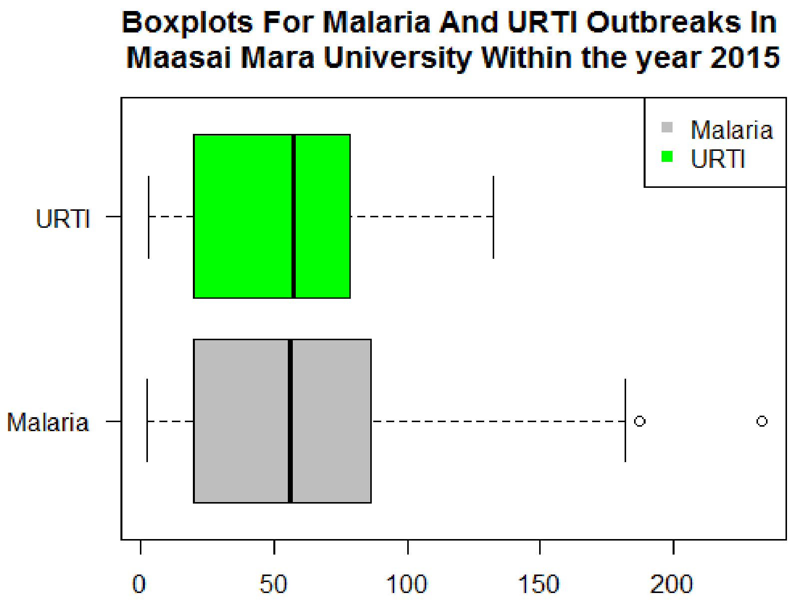


**Figure 4:** Boxplots for the Year 2015

The boxplots were not grossly asymmetrical and their size was not similar. The conclusion was that there was no evidence of non-normality and the variances were clearly unequal. Therefore; the t-test for comparison of means was likely applicable.

#### *4.1.3 T-test Comparison of Means*

```
. ttest cases1 == cases2, unpaired unequal welch

Two-sample t test with unequal variances
```

| Variable | Obs | Mean | Std. Err. | Std. Dev. | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| cases1 | 7 | 277 | 84.90443 | 224.636 | 69.24635 | 484.7537 |
| cases2 | 5 | 774.4 | 156.5831 | 350.1304 | 339.6557 | 1209.144 |
| combined | 12 | 484.25 | 107.1227 | 371.0839 | 248.4745 | 720.0255 |
| diff | | -497.4 | 178.1208 | | -913.6429 | -81.15714 |

```
    diff = mean(cases1) - mean(cases2)                         t =  -2.7925
Ho: diff = 0                          Welch's degrees of freedom =  7.43515

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0126         Pr(|T| > |t|) = 0.0252          Pr(T > t) = 0.9874
```

**Figure 5:** T-test Comparison of Means

The Welch's test specified that the approximate degrees of freedom for unequal variances was at 7.43515. It was found that the means were statistically different from each other at any level greater than 2.52% with a 95% confidence interval. This was a clear indication that the number of cases reported from January to July (cases1) were different from the cases reported within August and December (cases2). (4) .

Therefore, t-statistic was obtained as shown: $t = \dfrac{277-774.4}{\sqrt{\dfrac{224.636^2}{7}+\dfrac{350.1304^2}{5}}} = -2.7925.$

#### *4.2 The STATA Cross Tabulation*

```
. csi 4141 1939 159 2311,or
```

| | Exposed | Unexposed | Total | |
|---|---|---|---|---|
| Cases | 4141 | 1939 | 6080 | |
| Noncases | 159 | 2311 | 2470 | |
| Total | 4300 | 4250 | 8550 | |
| Risk | .9630233 | .4562353 | .7111111 | |

| | Point estimate | [95% Conf. | Interval] | |
|---|---|---|---|---|
| Risk difference | .506788 | .4907864 | .5227895 | |
| Risk ratio | 2.110804 | 2.041589 | 2.182365 | |
| Attr. frac. ex. | .5262469 | .5101855 | .5417816 | |
| Attr. frac. pop | .3584191 | | | |
| Odds ratio | 31.04061 | 26.20549 | 36.76768 | (Cornfield) |

```
                 chi2(1) =  2672.24  Pr>chi2 = 0.0000
```

**Figure 6:** Epidemiological test

a) Risk difference

The *risk difference* (attributable) provided a measure of the public health impact of an exposure (assuming causality).

The hypothesis of equal proportions was given by;

$H_0$: $p_1 - p_2 = 0$ $\quad\quad\quad\quad$ $H_1$: $p_1 - p_2 \neq 0$

The risk difference in this case was;

Risk difference (attributable risk) = difference in proportions i.e.

$\hat{p}_1 - \hat{p}_2$

Therefore; 0.963-0.456=0.507.

Decision: We reject the null hypothesis at 95% confidence level.

Conclusion: This means that if 1000 students in the university/institution were exposed to the short rain period of El Nino, it would have increased the number of cases by 507 relative to the number of cases of 1000 students not exposed to the short rains period.

Study results suggest that the increase in cases from 1000 students during the short rain session could range from 490 to 522 more than the number occurring if the 1000 students were not exposed to the short rains.

b) Relative Risk

The *relative risk* provided a measure of the magnitude of the disease-exposure association for an individual.

The hypothesis of equal proportions was given by;

$H_0$: $\frac{p1}{p2} = 1$ $\quad\quad\quad\quad$ $H_A$: $\frac{p1}{p2} \neq 1$

The Relative risk in this case was;

Relative risk (risk ratio) = ratio of proportions i.e.

$$R\hat{R} = \frac{\hat{p}1}{\hat{p}2}$$

Therefore; the risk of having an epidemic during the El Nino session relative to the period without the rains was

$$\frac{0.963}{0.456} = 2.1118$$

Decision: We reject the null hypothesis at 95% confidence level.

Conclusion: The risk of an epidemic within the El Nino period was slightly more than twice the risk of an epidemic during the normal period.

The El Nino period increased the risk of an epidemic by nearly 2.11 times if the students were exposed to it. Study results suggest that this increase could be as small as 2.04 times and as large as 2.18 times.

c) Odds Ratio

The hypothesis of equal proportions for the odds ratio was

$H_0$: OR=1

$H_A$: OR≠1

Odds=$\frac{p}{1-p}$. For this case, the estimated risk of having an epidemic among students exposed to the El Nino period was $\hat{p}1$ =0.963. The corresponding odds estimate was

$$\widehat{Odds}=\frac{\hat{p}1}{1-\hat{p}1} = \frac{0.963}{1-0.963} \approx 26.027$$

Furthermore, the estimated risk of having an epidemic among students not exposed to the El Nino phenomenon was $\hat{p}_2$=0.456. The corresponding odds estimate was

$$\widehat{Odds}=\frac{\hat{p}2}{1-\hat{p}2} = \frac{0.456}{1-0.456} \approx 0.838$$

The estimated odds ratio of an epidemic during El Nino period with respect to the other weather periods of the year was

$$\hat{O}R=\frac{\frac{\hat{p}1}{1-\hat{p}1}}{\frac{\hat{p}2}{1-\hat{p}2}} = \frac{26.027}{0.838} \approx 31.06$$

The odds of an epidemic within the El Nino period was 31 times the odds of an epidemic in the other weather periods.

The El Nino season was associated with an estimated 69% increase in odds of having an epidemic among the students exposed to the El Nino. The results suggested that this increase in odds could be as small as 64% and as large as 74% at 95% Confidence interval.

Decision: We reject the null hypothesis at 95% CI.

Conclusion: The p-value obtained from the Chi-square test for homogeneity in proportions was 0.0000 at a Chi-square value of 2672.24. This signifies inequality of the proportions within the study.

In addition to this, being exposed to the El Nino period accounted for 52.62% of the general cases of Malaria and URTI'S in the population of MMU. 35.84% of the affected MMU population could have been prevented from the diseases if there was no El Nino.

The population proportion of the 2015 rains period was 2.89% lower for the months with cases of both diseases.

### *4.3 Logistics Regression Model*

#### *4.3.1 Malaria Epidemic Regression Model*

The Malaria data was transformed to logarithmic form so as to obtain a parsimonious logit model. The R output below was the model that described the relation between Malaria cases and the Malaria epidemic.

Call: For Malaria

Generalized linear model

(formula = Malaria. Epi ~ log10.Mal, family = binomial, data = Malaria data)

Deviance Residuals:

| Min | 1st Quartile | Median | 3rd Quartile | Max |
|---|---|---|---|---|
| -1.9519 | -0.4939 | 0.3110 | 0.4696 | 2.2170 |

Coefficients:

| | Estimate | Std. Error | z value | Pr. (>\|z\|) |
|---|---|---|---|---|
| (Intercept) | -5.242 | 1.696 | -3.092 | 0.001991 ** |
| log10.Mal | 4.112 | 1.140 | 3.606 | 0.000311 *** |

---

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 57.949 on 47 degrees of freedom

Residual deviance: 34.158 on 46 degrees of freedom

AIC: 38.158

Number of Fisher Scoring iterations: 5

From the output, the maximum likelihood estimates for the intercept and slope were $\hat{\beta}0$ = -5.242 and $\hat{\beta}1$ =4.112; which yielded the following estimated logistic regression model:

$$\hat{p}(x)=\frac{e^{-5.242+4.112x}}{1+e^{-5.242+4.112x}} \qquad (3)$$

Plugging in a value for *x*, the number of malaria cases, yielded the estimated probability of having an epidemic of malaria. A plot of the sample proportions and the estimated logistic regression curve was plotted below in Figure 7.

<u>Inference for the Slope</u>

The significance of the slope $\hat{\beta}1$ was tested using the z-test for the following hypothesis

$H0$: $\hat{\beta}1$ =0 versus $Ha$:$\hat{\beta}1 \neq 0$;

$Z=\frac{\hat{\beta}1}{SE(\hat{\beta}1)}$; The *z* test statistic then was

$Z=\frac{4.112}{1.140}$=3.6; which was highly significant ($p < 0.00$).

The Wald test and Likelihood ratio test which use the Standard error at Maximum likelihood estimates depicted the same significance of $\hat{\beta}1$ as shown at 95% confidence interval;

| | OR | (95%CI) | P (Wald's test) | P(LR-test) |
|---|---|---|---|---|
| log10.Mal (cont. var.) | 61.06 | (6.53,570.67) | < 0.001 | < 0.001 |

Log-likelihood = -17.0791

No. of observations = 48

AIC value = 38.1581

By definition; the variable X representing malaria cases which was transformed to log base 10 lied between 0 and 1 i.e.0≤X≤1.

And which is the probability of a malaria epidemic lied also between 0 and 1 i.e.

$$Y = \begin{cases} 0; \text{ for no malaria epidemic} \\ 1; \text{ for malaria epidemic} \end{cases}$$

$\hat{p}(1) = \frac{e^{-5.242+4.112}}{1+e^{-5.242+4.112}}$=0.244 for highest number of malaria cases.

$\hat{p}(0) = \frac{e^{-5.242}}{1+e^{-5.242}}$=0.00526 for least number of malaria cases.

The odds when x=1 is $\frac{\hat{p}(1)}{1-\hat{p}(1)} = \frac{0.244}{1-0.244}$=0.322.

The odds when x=0 is $\frac{\hat{p}(0)}{1-\hat{p}(0)} = \frac{0.00526}{1-0.00526}$=0.005287

The odds ratio is given by $\frac{\frac{\hat{p}(1)}{1-\hat{p}(1)}}{\frac{\hat{p}(0)}{1-\hat{p}(0)}}$ or $e^{\hat{\beta}1} \approx 61$

The interpretation of the odds ratio in this case was that the odds of a malaria epidemic was 61 times greater for the El Nino season compared to the other periods.

The probability of a malaria epidemic given a number of cases was obtained from Figure 7 above. For example, when 100 cases were reported, the probability of an epidemic was given by;

$\hat{p}(x) = \frac{e^{-5.242+4.112(\log 100)}}{1+e^{-5.242+4.112(\log 100)}}$=0.9517

For 1000 cases reported, the probability of a malaria epidemic was,

$\hat{p}(x) = \frac{e^{-5.242+4.112(\log 1000)}}{1+e^{-5.242+4.112(\log 1000)}}$=0.99917

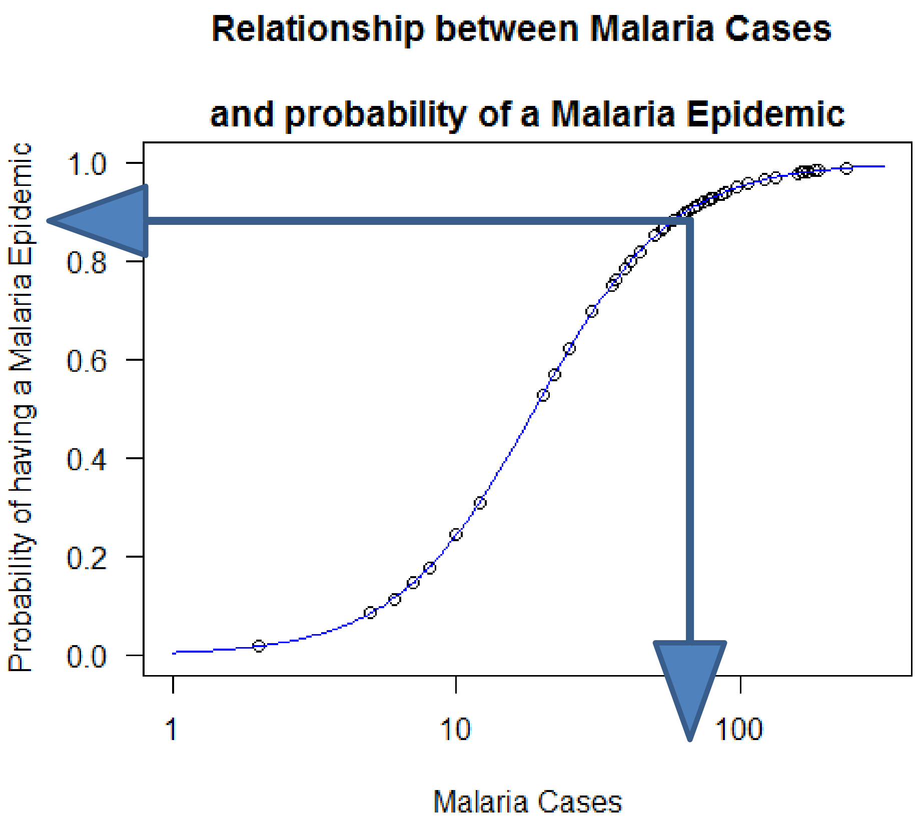


**Figure 7:** Relationship Between Malaria Cases and Probability of a Malaria Epidemic

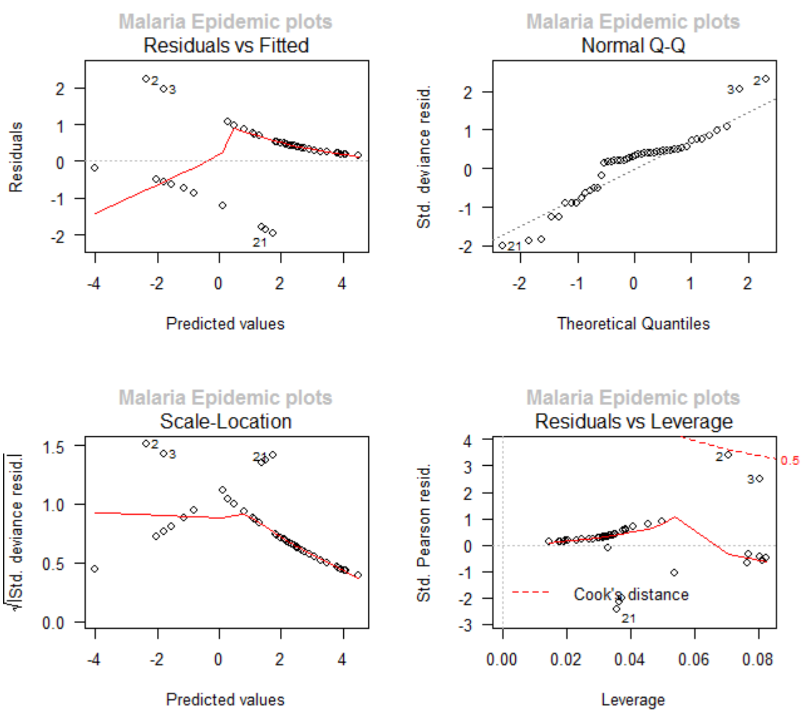


**Figure 8:** The Malaria Epidemic plots

Data points with large residuals (outliers) and/or high leverage may distort the outcome and accuracy of a regression. The scale-location plot, Leverage and Cook's distance in the charts above clearly showed that the dataset consisting of Malaria cases was fine and produced accurate results.

#### *4.3.2 URTI Epidemic Regression Model*

The URTI data was also transformed to logarithmic form so as to obtain a parsimonious logit model. The R output below was a model that described the relation between URTI cases and the URTI epidemic.

Call: For URTI

Generalized linear Models

(formula = URTI. Epi ~ log10.URTI, family = binomial, data = da)

Deviance Residuals:

| Min | 1Q | Median | 3Q | Max |
|---|---|---|---|---|
| -1.5709 | -1.0385 | -0.3202 | 0.9632 | 1.8550 |

Coefficients:

| | Estimate | Std. Error | z value | Pr.(>\|z\|) |
|---|---|---|---|---|
| (Intercept) | -4.3787 | 1.6609 | -2.636 | 0.00838 ** |
| log10.URTI | 2.6458 | 0.9791 | 2.702 | 0.00688 ** |

---

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 66.459 on 47 degrees of freedom

Residual deviance: 56.572 on 46 degrees of freedom

AIC: 60.572

Number of Fisher Scoring iterations: 4

From the output we see that the maximum likelihood estimates for the intercept and slope were $\hat{\beta}0$ = -4.3787 and $\hat{\beta}1$ =2.6458*;* which yielded the following estimated logistic regression model:

$$\hat{p}(x)=\frac{e^{-4.3787+2.6458x}}{1+e^{-4.3787+2.6458x}} \qquad (3)$$

Putting in a value for *x*, the number of URTI cases, yielded the estimated probability of having an epidemic of URTI. A plot of the sample proportions and the estimated logistic regression curve was plotted in Figure 9.

Inference for the Slope

The significance of the slope $\hat{\beta}1$ was tested using the z-test for the following hypothesis

$H0$: $\hat{\beta}1$ =0 versus $Ha$:$\hat{\beta}1 \neq 0$*;*

$Z=\frac{\hat{\beta}_1}{SE(\hat{\beta}1)}$; The *z* test statistic then was

$Z=\frac{2.6458}{0.9791}$=2.7022; which was highly significant ($p$ < 0.00).

The Wald test and Likelihood ratio test which use the Standard error at Maximum likelihood estimates depicted the same significance of $\hat{\beta}1$ as shown at 95% confidence interval;

| | OR | (95%CI) | P (Wald's test) | P(LR-test) |
|---|---|---|---|---|
| log10.urti (cont. var.) | 14.1 | (2.07,96.04) | 0.007 | 0.002 |

Log-likelihood = -28.2858

No. of observations = 48

AIC value = 60.5715

By definition; the variable X representing URTI cases which was transformed to log base 10 lied between 0 and 1 i.e. $0 \leq X \leq 1$.

And Y which is the probability of a URTI epidemic lied also between 0 and 1 i.e.

0; for no URTI epidemic

1; for URTI epidemic

Y=

$\hat{p}(1) = \frac{e^{-4.3787+2.6458}}{1+e^{-4.3787+2.6458}}$=0.1502 for highest number of URTI cases.

$\hat{p}(0) = \frac{e^{-4.3787}}{1+e^{-4.3787}}$=0.01238 for least number of URTI cases.

The odds when x=1 is $\frac{\hat{p}(1)}{1-\hat{p}(1)}=\frac{0.1502}{1-0.1502}$=0.1767.

The odds when x=0 is $\frac{\hat{p}(0)}{1-\hat{p}(0)}=\frac{0.01238}{1-0.01238}$=0.0125

The odds ratio was given by $\frac{\frac{\hat{p}(1)}{1-\hat{p}(1)}}{\frac{\hat{p}(0)}{1-\hat{p}(0)}}$ or $e^{\hat{\beta}_1}\approx$14.0947

The interpretation of the odds ratio in this case was that the odds of URTI epidemic was 14.1 times greater for the El Nino season compared to the other periods.

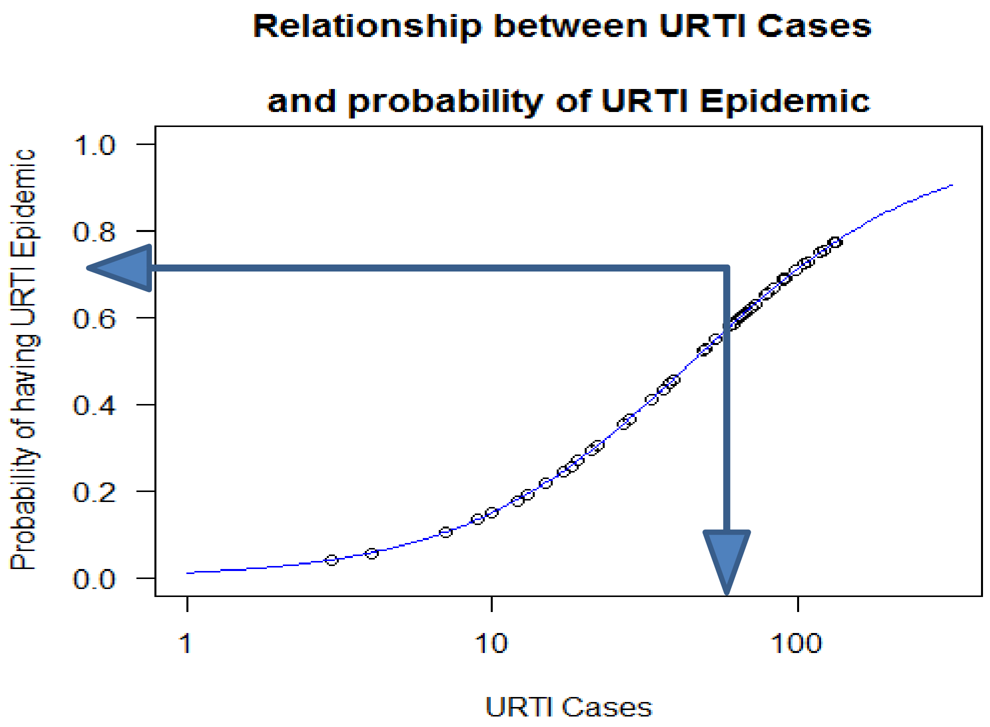


**Figure 9:** Relationship Between URTI Cases and Probability of URTI Epidemic

The probability of URTI epidemic given a number of cases was obtained from Figure 9 above. For example, when 100 cases were reported the probability of an epidemic was given by;

$\hat{p}(x)=\frac{e^{-4.3787+2.6458(\log 100)}}{1+e^{-4.3787+2.6458(\log 100)}}$=0.7135

For 1000 cases reported, the probability of URTI epidemic was

$$\hat{\rho}(x)=\frac{e^{-4.3787+2.6458(log1000)}}{1+e^{-4.3787+2.6458(log1000)}}=0.9723$$

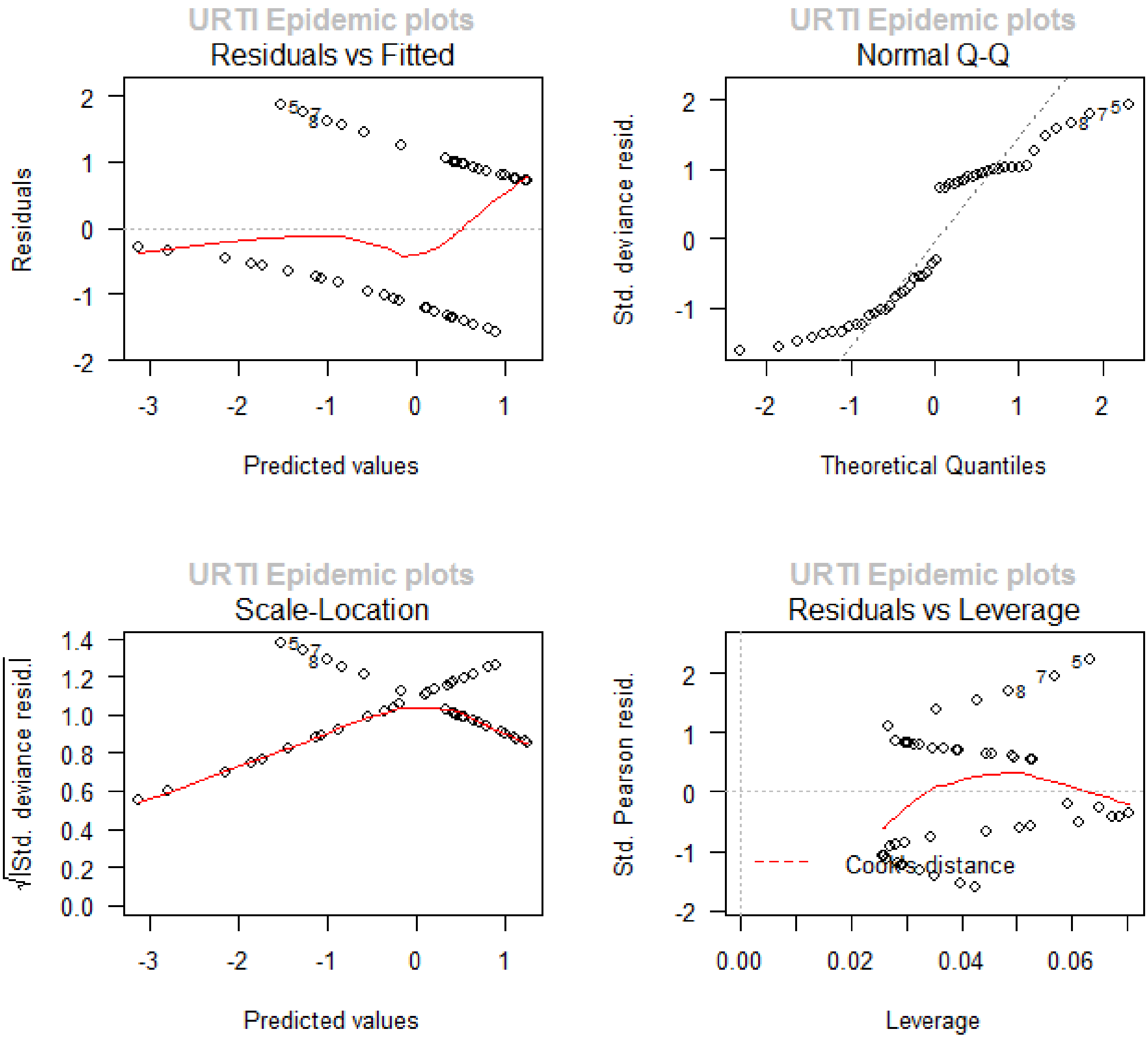


**Figure 10:** The URTI Epidemic plots

Leverages and Cook's Distance (Cook's D) statistics are ways of identifying points that do not fit with the regression model. Large values for Cook's Distance signify unusual observations. The scale-location plot, Leverage and Cook's distance in the charts above clearly showed that the dataset consisting of URTI cases was fine and produced accurate results. There is no linear effect in the relationship.

### *4.4 Bayes Theorem*

The Bayes theorem calculated the probability of an epidemic during El Nino season. The R-output below showed the measures of central tendency and dispersion of variables in the study. The prevalence which is the mean of diseased values among the study sample for the nominal variables was taken as the probability of the event happening.

No. of observations = 48

| Variable name | mean | median | stand dev | min. | max. |
|---|---|---|---|---|---|
| 1 Malaria | 66.67 | 56 | 57.72 | 2 | 233 |
| 2 Malaria Cases | 0.71 | 1 | 0.46 | 0 | 1 |
| 3 URTI | 54.4 | 57 | 36.54 | 3 | 132 |
| 4 URTI Cases | 0.48 | 0 | 0.5 | 0 | 1 |
| 5 Rain | 0.42 | 0 | 0.5 | 0 | 1 |

$$P(E|R) = \frac{P(R|E)P(E)}{[P(E).P(R|E)]+[P(\bar{E}).P(R|\bar{E})]} \qquad (5)$$

| Event | Description |
|---|---|

E=" An epidemic of malaria or URTI happens" i.e. $E_m$ and $E_u$.

$\bar{E}$=" No epidemic of malaria or URTI happens" i.e. $\bar{E}_m$ and $\bar{E}_u$.

R=" It rains during October-December short rain period"

$\bar{R}$=" It does not rain during October-December short rain period"

From the previous output, it was given that $P(E_m)=0.244$ and $P(\bar{E}_m)=0.00526$. Furthermore,

$P(E_u)=0.1502$ and $P(\bar{E}_u) = 0.01238$.

$P(R)=0.42$ and $P(\bar{R})=0.58$.

All of these probabilities were displayed in an elaborate manner using a probability tree showing the prior and posterior probabilities.

<u>For Malaria</u>

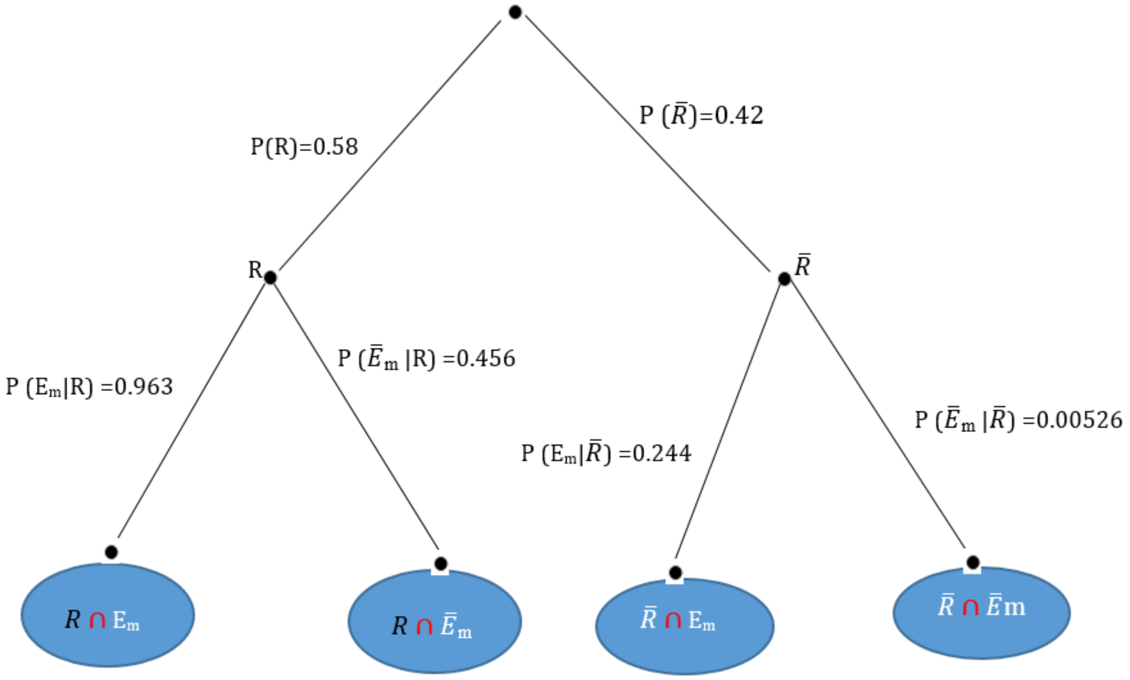


**Figure 11:** Tree Diagram for Malaria

The tree was interpreted as follows. Each dot is called a node. The tree is organized by levels. The top node (root node) is at level 0. The next layer down is level 1 and the next is level 2. Each level showed the outcomes at one stage of the events defined. Level 1 showed the possible outcomes of raining during the El Nino season. Level 2 showed the possible outcomes of an epidemic of either Malaria or URTI starting from each node in level 1.

P(E)= $[P(E).P(R|E)] + [P(\bar{E}).P(R|\bar{E})]$ the prior predictive distribution was calculated using the law of total probability;

Therefore, P(E)=0.58×0.963+0.42×0.244=0.66102

Thus,

P(E|R)=$\frac{0.963\times0.58}{0.66102}$=0.8449

<u>Conclusion</u>: The probability of having a Malaria Epidemic during the October-December 2015 short rain period was 0.8449. The high probability value was attributed to the fact that the El Nino predicted during that period had a profound impact on the health of university students.

<u>For URTI.</u>

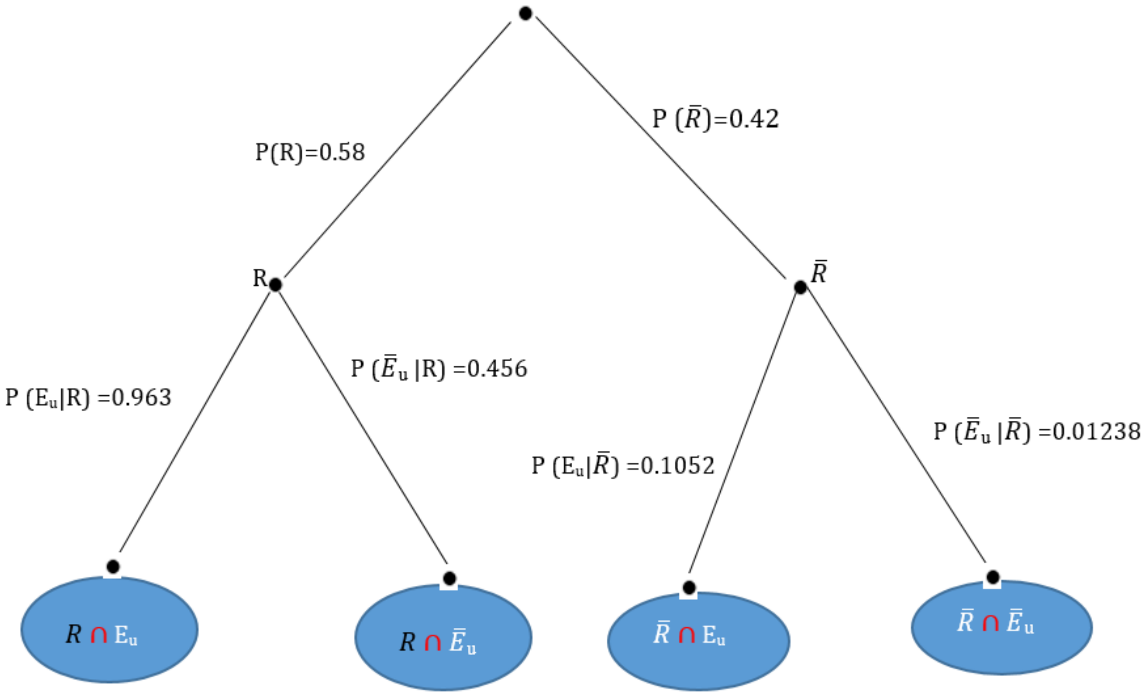


**Figure 12:** Tree Diagram for URTI

For this case, P(E)=0.58×0.963+0.42×0.1052=0.6072

Thus,

$$P(E|R)=\frac{0.963\times 0.58}{0.6072}=0.92.$$

Conclusion: The probability of having a URTI epidemic during the October-December 2015 short rain period was 0.92. The high probability value was linked to the fact that the El Nino predicted during that period had a severe effect on the respiratory health of university students.

## 5. Conclusion

This chapter consists of a summary of the research project findings, conclusions and recommendations of the study conducted at MMU. The conclusions from the summary bring up the recommendations aimed at improving the surveillance techniques for epidemics in Maasai Mara University.

### *5.1 Summary*

The research project was carried out in Maasai Mara University health unit where the reports of disease cases affecting students and staff are made. The main purpose of this study was to establish the relationship between increased cases of Malaria/ URTI'S and heavy rainfall resulting from the El Nino using a logistics regression model and Bayes formula.

The specific objectives that guided were: To calculate the probability of an epidemic during El Nino season; To measure the effect size of the epidemic using the odds ratio and the relative risk; To improve on the surveillance of malaria and respiratory diseases in an institution; To give statistical recommendations to the health fraternity and target population.

The scope of the research project covered the Maasai Mara University fraternity with the target population consisting of Maasai Mara University students with an invariant totality of not less than 4000 students per semester.

The data was obtained from secondary sources i.e. health journals and records of students infected by Malaria or URTI'S.

The method of data analysis was based on logistics regression and Bayes formula in which the following were obtained; Odds ratio, relative risk, risk difference, prior and posterior probabilities. The data was also presented by the use of tables and graphs, followed by discussions of the trend observed. From the presentation, the research project established that, the predicted El Nino had a severe positive effect on the number of Malaria and URTI infection cases.

### *5.2 Conclusion*

From the logistics regression analysis and Bayes formula, it is evident that there was a significant influence on the amount of cases of Malaria and URTI on the chance of an epidemic. The analysis indicates that the increased number of disease cases reported at the universities health center had a positive relationship with their epidemics, the El Nino season being the confounding variable. The El Nino period, where it was suggested that the amount of precipitation was large compared to other times in 2015, indeed contributed to the escalated amount of reported cases of Malaria and URTI.

The El Nino period is taken as an important factor of health discrepancies. There is good epidemiological evidence from this study that El Niño is associated with an increased risk of certain diseases in specific geographical areas where unusual climatic conditions are linked with the ENSO cycle.

The ENSO phenomenon provides good opportunities to study effects of climate variability on human health and importantly, to show complex disease dynamics. The university population vulnerability to climate variability is affected by factors such as socio-economic deprivation especially for diseases such as malaria and URTI'S. Furthermore, the public health infrastructure could be unconducive such that epidemic inhibiting programs are not considered or are ignored. Greater understanding of the impacts of climate on health through this surveillance model in this study will help reduce vulnerability to the potential health impacts of global climate change.

Reports that link disease outbreaks to a single El Niño event are difficult to interpret because there are a number of potential confounding factors that may be responsible for the observation. Nevertheless, in our study the months that were not accounted to be El Nino periods were segregated. Holding other prognostic factors constant, the findings were such that the number of cases accumulated during El Nino was more than double.

The development of health early warning systems is an area where the meteorological and health sectors can improve disaster and epidemic preparedness together. Surveillance systems should be part of a program to strengthen the capacity of the community to identify ways in which they are vulnerable to extreme weather and to prepare early to reduce impacts. There is an urgent need for the co-ordination of early warning and preparedness activities at the level of national governments.

The impacts of El Nino have shown the need of the social implications and ecological basis for malaria and URTI'S, and underlines the need of understanding how institutional populations respond to climate influences.

### *5.3 Recommendations*

From the study, it was found that the El Nino period has a large health impact specifically for the diseases of interest; Malaria and URTI's. I would thus recommend that the university of Maasai Mara and other institutions under the brink of an El Nino season to use statistical techniques and models to employ the surveillance of rainfall related diseases. For Example, the probability techniques used in this study are reliable and provide valid outputs. Malaria and URTI monitoring programs based on probability theorems should be embraced so as to educate students or any other community. The early notifications of the vulnerability of an increase in these diseases would initiate a proper control program at an early stage. E.g. donation of mosquito nets, water disinfection and environmental clean-up.

Finally, the university students should engage in further research so as to find out simpler and sufficient mathematical and statistical means of addressing epidemiology. When they do this, the institutions are bound to minimize fatality cases resulting from epidemics.

### *5.4 Areas for further research*

The application of logistic models and Bayes formula for modeling of epidemiological data has not been fully explored and hence a need for further research on issues that could improve the process. One of the areas where the researcher recommends for further study is the use of Bayesian inference in factor analysis and Markov chain Monte Carlo (MCMC) for generating samples from posterior distributions.

## References

[1] Ackoff, Russell L, (1961): The Design of Social Research. Chicago: University of Chicago Press, 1961.

[2] Anderson R & May M .Infectious Diseases of Humans: Dynamics and Control. Oxford University Press, Oxford, 1991.

[3] Alunn L & Steve V, (2005). Network Models in Epidemiology: An Overview. 18:38, September 11, 2005.

[4] Ankur R, Vineet S, Sonu K, (2013): Upper Respiratory Tract Infections: An Overview, International Journal of Current Pharmaceutical Research-5(3), 16 June 2013.

[5] Anthony K. Mbonye, (2004): Risk Factors for Diarrhea and Upper Respiratory Tract Infections among Children in a Rural Area of Uganda Centre for Health and Population Research -22(1):52-58, 28 March 2004.

[6] Cooper R, Hoffman J & Bartlett J, (2001): Principles of appropriate antibiotic use for acute pharyngitis in adults: Background. Ann Intern Med 2001; 134: 509-517.

[7] Glantz M (1996a) Currents of Change: El Niño's Impact on Climate and Society. Cambridge, Cambridge University Press.

[8] Hartmann M (2009). Demographic Methods for the Statistical Office. Methodology reports 2009:2, Statistics Sweden, Research and Development Department.

[9] Hay S, Snow R, and Rogers D, (1998): From predicting mosquito habitat to malaria seasons using remotely sensed data - practice, problems and perspectives. Parasitol Today 1998, 14:306-313.

[10] Kebede S, Duale S, Yokouide A & Alemu W, (2010). Trends of major disease outbreaks in the African region, 2003-2007. Public Health Journal [Online Serial], 7(1) 1st March 2010.

[11] Kongoti G, Advisory on Development of El-Nino-2(2), 22 September 2015.

[12] Kothari C (ed.), (2004): Research Methodology methods and techniques. Jaipur, India: New Age International Publishers.

[13] Mandal S, Sarkar R and Sinha S, (2011). Mathematical Models of Malaria: A Review. Malaria Journal, 10:202, 10th January 2012.

[14] Morbidity and Mortality Weekly Report (MMWR)-Acute Communicable Disease Control Manual (B-73) REVISION—FEBRUARY 2012.

[15] Parham P & Michael E, (2011): Outbreak properties of epidemic models: The roles of temporal forcing and stochasticity on pathogen invasion dynamics. J Theor Biol 2011, 271:1-9.

[16] Poole M & Portugal L, (2005). Treatment of rhino sinusitis in the outpatient setting. Am J Med 2005, 118: 45S-50S.

[17] The World Health Organization (WHO) report 2014.

[18] Young V, (1960). Scientific Social Surveys and Research, 3rd ed., New York: Prentice-Hall, 1960.