Heatwaves-Driven Human Morbidity and Mortality over Selected Counties in Kenya

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1.0 EXECUTIVE SUMMARY

Although heat-related disasters have risen worldwide, lack of reliable and consistent climate datasets and standard detection metrics in Africa can easily downplay not only the existence of episodes of extreme heat, but also the concomitant human health impacts. This is particularly the case within the rapidly growing metropolises of sub-Saharan Africa, including those in Kenya. In parallel, there is increasing evidence that such extreme heat is affecting health.

This study sought to investigate the temporal distribution of heatwave events and its concomitant effect of human health. To do so, the study relied on both daily observed and satellite maximum temperature data for Nairobi, Tana River, and Turkana Counties from 1991 to 2020. Heatwave Magnitude Index daily (HWMId) was employed as a measure of heatwave events. For Pearson's' correlation analysis between annual records of heatwave magnitudes and duration, annual records of Chronic Obstructive Pulmonary Disease prevalence and deaths were obtained from the Institute of Health Metrics and Evaluation (IHME) from the University of Washington

The linear relationship between the independent variables (i.e., heatwave magnitude and heatwave duration) and COPD prevalence and deaths was first confirmed using non-parametric multiple analysis using a Generalized Additive Model (GAM). The fitness of the statistical models considered degrees of freedom (DF) and autocorrelation. A parametric multivariate analysis between heatwave magnitude and duration, and Chronic Obstructive Pulmonary Disease prevalence and deaths was conducted using a Generalized Linear Model (GLM) in order to determine percentage change in relative risk.

The study found out that heatwave events ranging from normal to very extreme have occurred in Kenya during the study period. The magnitude of heatwave events varied from zero (i.e., no heatwave events) to a very extreme heatwave event (i.e., 9) observed around Turkana in 2005. In the same year an extreme heatwave event (i.e., 7) was recorded in Nairobi. Nairobi also experienced a heatwave event of comparable magnitude (i.e., 6) in 2012. Generally, the three selected counties (i.e., Nairobi, Tana River and Turkana) experienced normal to moderate on average over 1991–2020 period. Over the study duration the longest periods (i.e., 4 continuous years) during which no single heatwave event was observed over the three selected counties were 1993 to 1996 and 2017 to 2020. Given that the p-value associated with Mann Kendall test statistic, it is concluded that no statistically significant trend is present in both heatwave magnitude and duration.

Heatwave duration ranged from a minimum duration of 3 days to about 9 days for each event. The longest heatwave events occurred in 2012, 1991 and 2005, and span 9 days, 6 days and 7 days over Nairobi, Tana River and Turkana Counties, respectively. Based on the starting date, most heatwave events recorded in the selected counties were observed to begin around the months of February–March with the exception of a moderate heatwave that was observed late in the month of January over Turkana.

An analysis of the kernel density plots revealed that heatwave magnitude datasets indicate right-skewed distribution. Although both datasets depict non-asymmetric bimodal distribution, it is more prominent with the deaths. The non-asymmetric bimodal distribution seems to show an outlier within the heatwave magnitude over Turkana. Given that the mean and range are more sensitive to such outliers; it would be more appropriate to use median. This implies that the mean, median, and mode are not good measures of the dataset: the median is lower than the mean, because the mean is more sensitive to the higher values and is drawn towards the tail of the density plot. Death associated with Chronic Obstructive Disease show an even more marked bimodal distribution and some asymmetry. Prevalence on other hand depict varied skewness in its distribution.

COPD prevalence and deaths are understandably significantly correlated as are the heatwave magnitude and duration. At 0.001 significance level, the correlation is above 0.8 over Nairobi County. This is also known as *collinearity* (or *multicollinearity* between two or more variables). The duration of a heatwave is statistically dependent on the magnitude of the same heatwave. On the other hand, the mortality as a result to Chronic Obstructive Pulmonary Disease is statistically related to its prevalence. Although not statistically significant, heatwave characteristics influences the prevalence and deaths due to COPD. Over Nairobi heatwave magnitude and duration is correlated with deaths due to COPD with 0.12 and 0.14 correlations coefficients.

The risk of COPD prevalence and deaths depict different degrees of linearity with the heatwave characteristics over the three Counties. The risk of COPD prevalence varies at different levels of heatwave duration over Nairobi and Tana River Counties. The ACF of the GAM model did not show a significant autocorrelation. Based on the GLM results, a statistically significant percent relative risk of COPD prevalence of 0.76 % ((-1.82 % to 3.32 %)) increase with respect to a one-day increase in the duration of heatwave events over Nairobi was observed. Based on the acceptable linearity assumption, one-day increase in the duration of heatwave events will lead to a 0.03 % ((-0.99 % to 1.04 %)) increase in the risk of COPD prevalence over Tana River. As proposed by Curriero et al. (2002), the low and/or insignificant relative risk for COPD could be attributed to acclimatization. Over Turkana County for example, adaptation of populations to their local climate is evident by the decrease in COPD risk even with prolonged heatwave duration.

On the basis of the findings presented in this report, it is recommended that, in order to establish cause effect, cause specific (e.g., emphysema, chronic bronchitis etc.) morbidity and mortality data segregated along age and gender and for specific health facilities should be incorporated. Research therefore examining whether socio-economic or demographic variables or other comorbidities could have a potential confounding or modifying effect on the mortality–temperature relationship are recommended.

Regarding humanitarian work, the observed seasonality in the occurrence of the heatwave event point to the need for accurate and timely seasonal forecast of maximum temperature and the accompanying triggers i.e., wind and humidity. With such forecasts humanitarian work can be deployed to manage extremely hot and humid days with the understanding that there is no better way to avoid a COPD flare-up than to stay indoors. In acute forecasts the populace who have pre-existing respiratory health conditions would be advised to even move to parts of the country where weather temperatures are more moderate e.g., highlands west and east of the Rift Valley and the western parts. Additionally, and given that studies have demonstrated that air pollution worsens the effect of weather on human respiratory health, the populace should protect itself from both indoor and outdoor pollutants particularly over crowded urban built areas in the ASALs. While outdoor, one ought to limit the level of physical activity.

2.0 ABSTRACT

This study sought to investigate the temporal distribution of heatwave events and its concomitant effect of human health. To do so, the study relied on both daily observed and satellite maximum temperature data for Nairobi, Tana River, and Turkana Counties from 1991 to 2020. Heatwave Magnitude Index daily (HWMId) was employed as a measure of heatwave events. For Pearson's correlation analysis between annual records of heatwave magnitudes and duration, annual records of Chronic Obstructive Pulmonary Disease (COPD) prevalence and deaths were obtained from the Institute of Health Metrics and Evaluation, University of Washington

The linear relationship between heatwave magnitude and duration and COPD prevalence and deaths was first confirmed using non-parametric Generalized Additive Model (GAM). A parametric multivariate analysis was then conducted using a Generalized Linear Model (GLM) in order to determine percentage change in relative risk.

It is concluded that the observed heatwave events ranging from normal to very extreme have had a negative impact on the human respiratory health. It is recommended that, in order to establish cause effect, cause specific morbidity and mortality data segregated along age and gender and for specific health facilities should be incorporated.

***Keywords**: heatwaves, extreme heat, prevalence, morbidity, hospital admission, deaths, mortality*

3.0 PURPOSE

Global warming will lead to rapid intensification of extreme events, including heatwaves (Dosio et al., 2017). Studies have reported that the duration, frequency, and intensity of heatwaves will increase worldwide (Harrington and Otto, 2020). About 3,000 global mortalities were reported due to heatwaves in 2018 (Harrington and Otto, 2020). Although heat-related disasters have risen worldwide, lack of reliable and consistent climate datasets and standard detection metrics in Africa can easily downplay not only the existence of episodes of extreme heat, but also the concomitant human health impacts. This is particularly the case within the rapidly growing metropolises of sub-Saharan Africa, including those in Kenya. In parallel, there is increasing evidence that such extreme heat is affecting health. Such negative effects of climate change are bound to be reported in Africa, including Kenya, due to greater exposure and vulnerability of the rapidly growing populace like has been reported (Ceccherin et al., 2017). According to Amou et al. (2021) heatwaves in Africa, including Kenya, are likely to kill people "silently" because it is rarely given the adequately deserving attention.

The Kenyan Vision 2030, together with the County system of governance, endevours to deliver a climate resilient development for its citizenry. This plan reflects the desire of Kenyans for a healthy population that contributes to nation building. To do so, the Kenyan government required scientific input on such climate extremes as flood and drought. Given the existing inadequate status of knowledge on due to lack of dense network of accurate weather instrumentation and data (Donat et al., 2013, the country runs the risk of misunderstanding the concept of heatwave. This study will therefore contribute in the development of local heatwave and its impacts on human health. Such scientific understanding of the quantitative temporal distribution of heatwaves in the observed and satellite maximum temperature is essential for public awareness and decision-making on local intervention programs.

The proposed study was carried out in three counties within Kenya: Nairobi (comparatively urban), Tana River (comparatively coastal lowland) and Turkana (comparatively ASAL). Kenya is a tropical country nearly bisected by the geographic Equator. Rainfall patterns depict a bimodal distribution: long rains and short rains are received in MAM and OND seasons, respectively (Camberlin et al., 2009). Although it is generally warm throughout the year, the warmest and coldest seasons are December–February (DJF) and June–August (JJA), respectively (Omondi et al., 2014). The ITCZ has been reported as the main driver of these seasons (Camberlin et al., 2009).

4.0 LITERATURE REVIEW

Heat waves can be defined as consecutive days of extremely hot conditions which exceed thresholds of temperature and span consecutive days (Wang et al., 2020). There is however no single and universally accepted definition (Amou et al., 2021). This is because of the differing thresholds, duration and ancillary variables contributing to divergence in defining heat waves (Engdaw et al., 2022).

Africa is considered one of the most vulnerable regions to weather and climate variability (Solomon, 2007); extreme events such as heat waves have an impact on public health, water supplies and food security although there is very little information on the magnitude of the impact of heat on health in Africa in the current climate. According to Saracci (1997), human health is defined as "a state ofcomplete physical, mental and social well-being and not merely the absence of disease or infirmity".

Many regions of Africa have already experienced increases in surface temperature as reported for different subregions, analysing various data sets and temperatures are estimated to be 1–2°C higher in the recent decades than during the Medieval Climate Anomaly (Nicholson et al. 2013) therefore improving knowledge of temperature changes, the occurrence of heat waves, and the time of emergence over natural variability has vital societal importance (Harrington and Otto, 2020).

Despite Africa's vulnerability, its distribution of heat waves is still poorly understood due to the lack of accurate baseline data on current climate (UNECA, 2011). Specifically, there are still uncertainties in the state of the art of the actual understanding of temperature extreme regime; only a few studies have considered the whole of Africa (Collins, 2011).

According to Amou et al. (2021), though global temperatures continue to rise unabated and the episodes of heat-related catastrophes across the world intensifies through heatwave phenomena and its associated impacts they are mainly ignored and neglected especially in Kenya due to several reasons; unreliable and inconsistent weather datasets and heatwave detection metrics. Some of the impacts of heatwaves as stated by Coumou and Rahmstorf (2012) include increased rates of human mortality, strains on man-made infrastructure, and increased rates and intensities of wildfires, which have devastating effects on both the natural and built environment. Studies done in the past shows that the impacts of heat waves are influenced by the characteristics of individual heat waves i.e. heat waves occurring earlier, lasting longer and being more intensive had larger health impacts (Son et al., 2012).

Most studies of heat waves and morbidity have considered specific major heat waves without adjusting for temperature (Li et al., 2015). Studies take temperature into consideration since its variability is a key factor in explaining differences in temperature-related mortalities across different regions. Egondi (2012), one such study on heatwaves that considered temperature among the urban poor population in Nairobi, evaluated the effect of temperature on all-cause mortality in two informal settlements in terms of mortality risk. The study concluded that both low and high temperatures were associated with excess mortality.

A study done by Kinney et al. (2008) showed that the relationship between heat and morbidity in any specific area may be affected by local population demographics, economic well-being, underlying disease risk, the presence ofvulnerable subpopulations, weather variability, physiologic acclimatization, and locally available adaptations.

Temperature-related illness and death are likely underestimated, given the challenges in consistent reporting by clinicians. Often death certificates and hospitalization records do not explicitly state that an individual had a temperature-related response (Sarofim et al., 2016), especially when temperature is not directly identified as a contributing factor.

According to Ncongwane (2021) heat stress and human health research has progressed well and is generally now embedded within the field of climate change and human health. Interestingly, the subject matter has been growing steadily since the early 1990s, following widespread attention on the human health consequences of climate change from scholars worldwide.

Heat wave is an important aspect to understanding the overall impact of climate change on human health in terms of how it will affect mortality and morbidity in the future (Campbell et al., 2018) concluded that heat waves have a direct linkage to global climate change and is associated with increased morbidity and mortality.

Some of the research done in the past showed that short-term increase in mortality and morbidity occur during periods of high heat (Sarofim et al. 2016).

Epidemiological research showed that heat-related mortality is dependent on the severity of the heat event and the health status of the affected population (Sarofim et al. 2016). Heat stress could rapidly become life threatening (Mastrangelo et al. 2006) especially among those with limited access to immediate medical attention such as people with severe heat stroke symptoms who have little time to seek treatment in emergency departments (EDs) or hospitals (Kovats and Ebi 2006). According to Thiaw (2018), extreme weather events such as heat waves associated with extremely elevated air temperature and relative humidity could cause cardiovascular illnesses. This was also discovered by Owusu (2020) who stated that the more direct impacts on health included those due to changes in exposure to weather extremes such as heat waves and winter cold. From his study, heat waves were therefore categorised among weather extremes that had more direct impacts on health.

Some of the previous studies showed that heat waves are thought to be caused by climate change and its effect to human health are not well understood (Petkova et al., 2014) despite its vulnerability and distribution in Africa due to the lack of accurate baseline data on current climate (UNECA, 2011). According to the World Meteorological Organization (WMO) findings, it indicated that the years 2011–2015 had constituted the warmest 5-year period on record (WMO, 2015) and heat waves of maximum temperature had increased both in severity and number accordingly.

Heat waves are considered as one of the deadliest natural disasters since an increase in intensity and frequency of heat wave events can contribute to loss of human lives and crop damages (Engdaw et al., 2022). Mbeche et al. (2015)

established that the rise in temperatures increase incidences of diseases such as malaria in areas that were originally malaria free and other communicable diseases.

Mostly elderly people are always vulnerable thus they are at a higher risk to the impacts of extreme temperatures (Kenney et al., 2014). This is because, older adults often have pre-existing conditions such as cardiovascular, respiratory, renal, and neurological diseases that caninterfere with their body’s ability to respond to heat stress (Kenney et al., 2014). Kenney et al. (2014) proved that there is increase in mortality due to cardiovascular illness which is a result of heat waves, especially among the elderly. In percent proportions, Kovatsand Ebi (2006) reported that increased mortality during heat waves has been attributed mainly to cardiovascular illness (13 % – 90 %) and diseases of the cerebrovascular (6 % – 52 %) and respiratory systems (up to 14 %).

Previous studies have reported different patterns of morbidity in contrast to mortality pattern during heat waves. Hospital admissions during heat waves have been reported to increase among both older and younger adults, especially among adults living in institutions or engaging in outdoor activities involving exertion (Johnson et al. 2005; Kovats and Ebi 2006). Most admissions were for heat-related conditions, including heat exhaustion and heat stroke, dehydration and electrolyte disorders, and acute renal failure (Kovats and Ebi 2006; Mastrangelo et al. 2006). Some increases in admissionsfor neurologic conditions and mental illnesses and ambulance transport for violence-related causes have been reported. (Kovats and Ebi 2006)

Better understanding of the patterns of morbidity during heat waves is an important tool for public health practitioners, because more intense, more frequent, and longer duration heat waves are projected for the coming decades (Meehl and Tebaldi, 2004). The health impacts of climate change are gaining considerable attention (Frumkin et al., 2008), with increases in heat wave–related illness and death among the most likely related challenges to public health (Kovats and Hajat, 2008).

Apart from heat health-related risk threats, high temperature- induced heat stress is increasingly becoming an impediment to socio-economic activities. Workers engaged in strenuous labour, mainly in humid and poorly ventilated environments, including those regularly exposed to hot working conditions, such as those inconstruction or the agricultural sector including the fisheries and forestry (Acharya et al., 2018). According to Acharya et al. (2018) exposure to extreme and prolonged heat has led to reduced worker enthusiasm and performance at their work; at the same time, a natural reaction of self-pacing working activities to maintain inner core body temperature will reduce working capacity and lower workers’ productivity. McMaughan et al. (2020) shows that the increased heat susceptibility due to disadvantaged socioeconomic status may be related to poor baseline health status, limited access to health care and high prevalence of health problems. They showed that men are assumed to be more stressed by heat than women, as men are exceedingly exposed to heat in physically demanding outdoor activities (e.g., farming, mining and construction work). Other studies have reported that men and women have slightly different physiology, endocrinal physiology and body characteristics, specifically that women have a larger surface to mass ratio, which implies that women are more prone to heat loss (McMaughan et al., 2020). Experimental evidence also showed that females were more heat intolerant than males due to potential gender-related physiological and thermoregulatory differences

5.0 RESEARCH METHODOLOGY

5.1 Heatwave Magnitude Index Calculation

With the daily observed and satellite maximum temperature data for Nairobi (comparatively urban), Tana River (comparatively coastal lowland) and Turkana (comparatively ASAL) Counties, the magnitude and duration of heatwave events during the past three decades (i.e., period from 1991 to 2020) was obtained using Heatwave Magnitude Index daily, HWMId (Russo et al., 2015). According to Amou et al. (2021), HWMId has been recently developed to remedy the limitations of Heatwave Magnitude Index, HWMI (Russo et al., 2014). Amou et al. (2021) defines HWMId as the maximum magnitude of the heatwaves in a year. Heatwave, on the other hand, operationally refers to a duration of at least three consecutive days with maximum temperature above 90th percentile threshold of the reference period (Funk et al., 2019), which in this study is the 30-year period from 1989 to 2018. This definition permits the comparison of heatwaves of different lengths and peak magnitudes that have occurred in the three Counties in different years. The definition sums excess temperatures beyond a certain threshold and merges durations and temperature anomalies of intense heatwave events into a single numeric indicator (Amou et al., 2021). Russo et al. (2015) defined the 90th percentile centered on 31 days' time step as is shown in *Equation 1*:

$$A_d = U_{y=1989}^{2018} \, U_{i=d-15}^{d+15} \, T_{y,i} \text{ .... Equation 1}$$

Where;

- $T_{y,i}$ is the daily maximum temperature on the ith day of the year y
- U is the union of sets
- A_d is the set of data
- d is a particular day

The three-stage procedure of obtaining HWMId index has been described comprehensively by Dobricic et al. (2020). In this study, this index was determined annually using the {*extRemes*} package, and specifically the {*hwmid*} function within the R programing language environment. With the baseline/analysis and reference data from 1991-2020 and 1989-2018 (1990 - 2021), respectively, 2019 and 2020 was used for both change detection and human health impact analysis. Probability density function was employed to display the temporal distributions. Additionally, Mann–Kendal (M-K) test was used to examine the statistical significance of the trend. The classification of heatwave severity was based on Amou et al. (2021) as shown in *Table 1*.

Table 1: Classification of Heatwave Magnitude Index daily (HWMId)

Category	Range
Normal	1≤HWMId<2
Moderate	2≤HWMId<3
Severe	3≤HWMId<4
Extreme	4≤HWMId<8
Very Extreme	8≤HWMId<16
Super Extreme	16≤HWMId<32
Ultra Extreme	HWMId≥32

Source: Amou et al. (2021)

5.2 Climate and Health Regression Analysis

So as to enable correlation between annual records of heatwave magnitude and duration, annual Chronic Obstructive Pulmonary Disease prevalence and deaths were obtained from the 2019 Global Burden of Diseases (GBD) at the Institute of Health Metrics and Evaluation (IHME) from the University of Washington. This dataset includes all COPD causes, annual measure of prevalence and mortality for all age groups and all sexes for the three selected Counties in Kenya. According to Marmo et al. (2006), COPD is a group of lung diseases, commonly emphysema and chronic bronchitis, that block airflow and make it difficult to breathe with the following accompanying symptoms: shortness of breath, wheezing or a chronic cough.

The temporal evolution and spatial comparison was made using the daily and monthly morbidity and mortality records collected from the representative health facility within the three Counties for at least two recent study period/years.

After performing univariate analys using Spearman ‘s correlation coefficients, a regression model was developed. Multiple regression analysis technique is as shown in *Equation (2).*

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + \ldots b_nx_n \text{------------------} \quad (2)$$

Where $\hat{y}$ is the predicted or expected value of the dependent variable (health outcome), x_1 through x_n are n distinct independent or predictor variables (maximum temperature), b_0 is the value of y when all of the independent variables (i.e., x_1 through x_n) are equal to zero, and b_1 through b_n are the estimated regression coefficients.

In order to control for day of week, a 7-day moving average smoothing approach was performed. For unusual events such as public holidays and medical strikes, no adjustment was made.

The linear relationship between the independent variables (i.e., heatwave magnitude and heatwave duration) and COPD prevalence and deaths was first confirmed using non-parametric multiple analysis using a Generalized Additive Model (GAM).

The fitness of the statistical models considered degrees of freedom (DF) and autocorrelation. In order to check the linearity of heatwave characteristics, a sensitivity analysis was conducted by comparing the results while adjusting the degrees of freedom (i.e., *k*). Given that the sample size was less than 10,000, the *gam ()* functionality was used as opposed to the *bam ()*. In addition the *te()* smooth function, as opposed to *s()*, was used given that the heatwave characteristics are not isotropic (i.e., have different units of measure. Given the length of the study dataset, the default value of *k =5* for *te()* could not be used; *k = 4* was used for Nairobi and Turkana and *k = 3* for Tana River. The form of the model used is as shown in Equation (3).

gam<-gam(data[1:30,2]~te(data[1:30,4],k=4)+te(data[1:30,5],k=4),family=poisson()) …………………. (3)

Due to skewness in the Chronic Obstructive Pulmonary Disease prevalence and deaths, the relative risk was then transformed to a logarithmic scale in order to achieve a normal distribution just as is the case in epidemiological studies (e.g., BMJ, 2012).

A parametric multivariate analysis between HWMId, heatwave duration and intensity, and human health morbidity and mortality was then conducted using a Generalized Linear Model (GLM). *Equation 4* shows the general form of the *glm( )* function used to fit GLMs.

glm(formula, family=familytype(link=linkfunction), data=) .... (4)

Since health data are commonly assumed to follow a Poisson process (Ahlbom, 2017), a Poisson regression was applied in this study i.e., *poisson* {family} and *logit* {link} functions. *Equation 5* shows the form of the *glm( )* function that was used to fit GLMs in this study.

glm<-glm(data[1:30,2]~(data[1:30,4])+(data[1:30,5]),family=poisson()) .... (5)

Using output from the GLM, percentage change in relative risk for Chronic Obstructive Pulmonary Disease was then determined.

6. FINDINGS AND CONCLUSION

6.1 Heatwave Analysis

6.1.1 Heatwave Magnitude Index Daily (HWMId)

Figure 1 shows the temporal evolution of annual records of Heatwave Magnitude Index Daily (HWMId) between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya. Based on the heatwave classification in Table 1, heatwave events ranging from normal to very extreme have occurred in Kenya during the study period. The magnitude of heatwave events varied from zero (i.e., no heatwave events) to a very extreme heatwave event (i.e., 9) observed around Turkana in 2005. In the same year an extreme heatwave event (i.e., 7) was recorded in Nairobi. Nairobi also experienced a heatwave event of comparable magnitude (i.e., 6) in 2012. Generally, and as is shown in Figure 1, the three selected counties (i.e., Nairobi, Tana River and Turkana) experienced normal to moderate on average over 1991–2020 period. These results are in agreement with those of Amou et al. (2021) over Garissa, Tana River, Turkana, and West Pokot counties. In contrast, Amou et al. (2021) report moderate to severe on heatwave events on average over most other parts of the country including Nairobi. It is worth noting that Amou et al. (2020) relied on CHIRTS data for the period 1987–2016. Over the study duration the longest periods (i.e., 4 continuous years) during which no single heatwave event was observed over the three selected counties were 1993 to 1996 and 2017 to 2020. Given that the p-value associated with Mann Kendall test statistic, it is concluded that no statistically significant trend is present in both heatwave magnitude and duration.

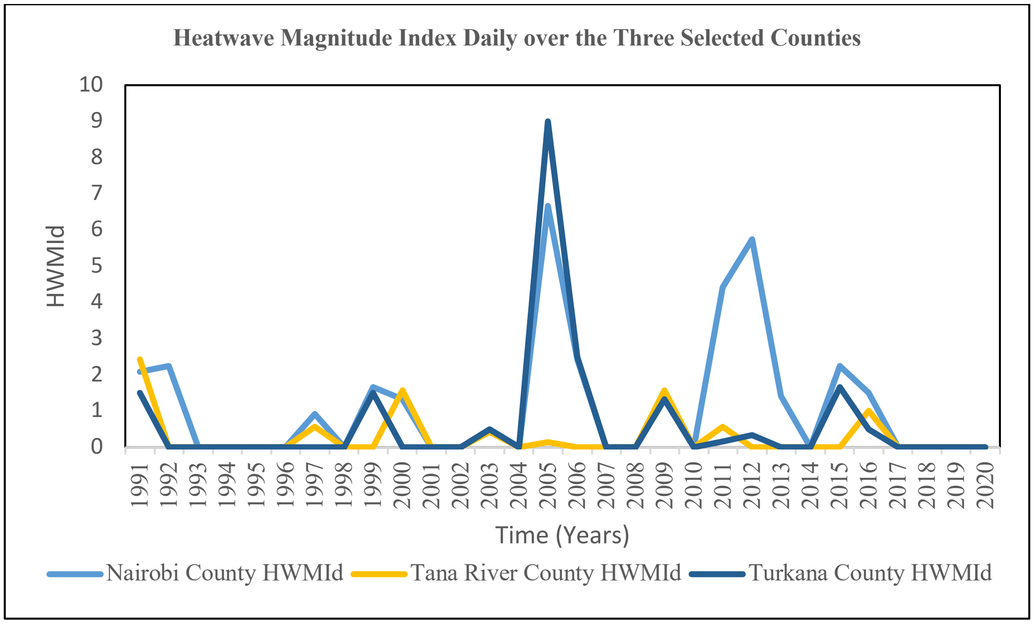

Figure 1: Heatwave Magnitude Index Daily between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya

6.1.2 Heatwave Starting Day and Duration

Figure 2, *Figure 3* and *Figure 4* show starting date and duration (in days) associated with the heatwave events observed between 1991 and 2020 over Nairobi, Tana River and Turkana Counties, respectively. As is evident, heatwave duration ranged from a minimum duration of 3 days to about 9 days for each event. The longest heatwave events occurred in 2012, 1991 and 2005, and span 9 days, 6 days and 7 days over Nairobi, Tana River and Turkana Counties, respectively. It is worth noting that the longest heatwave event over Turkana was very extreme whereas that over Tana River was moderate. Based on the starting date, most heatwave events recorded in the selected counties were observed to begin around the months of February–March with the exception of a moderate heatwave that was observed late in the month of January over Turkana. Given the country's latitudinal location, this start dates may be linked to the equatorward approach of the overhead sun in tandem with its apparent south to north movement. The cloudiness associated with the March-April-May long rains appear to moderate the daily temperature range thereby limiting the occurrence of the heatwave events.

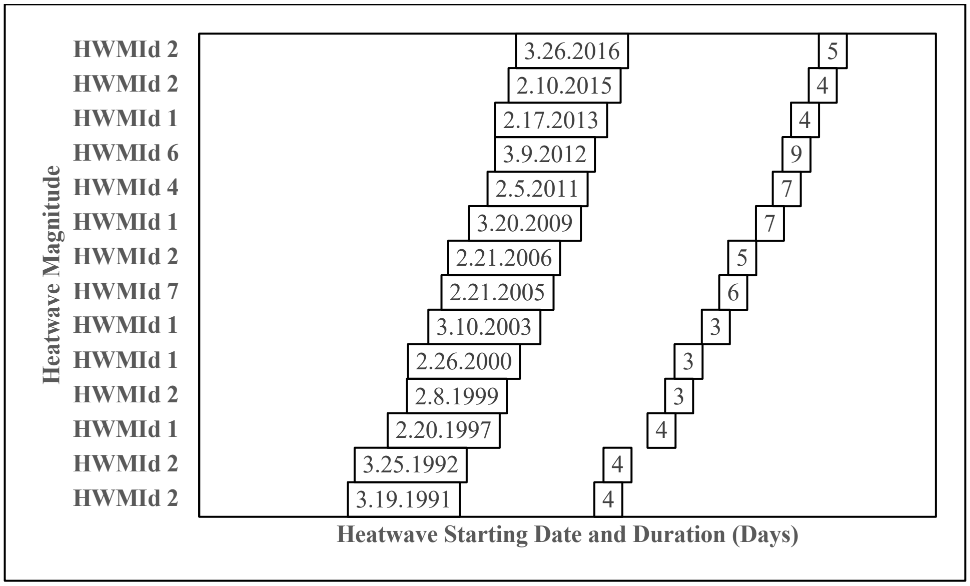

Figure 2: Heatwave Magnitude, Starting Date and Duration (Days) between 1991 and 2020 over Nairobi County

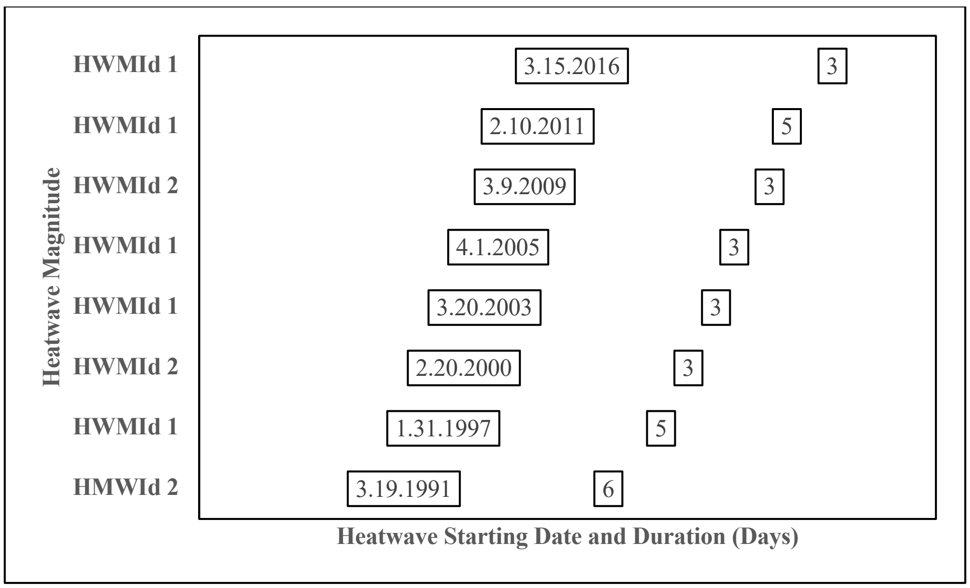

Figure 3: Heatwave Magnitude, Starting Date and Duration (Days) between 1991 and 2020 over Tana River County

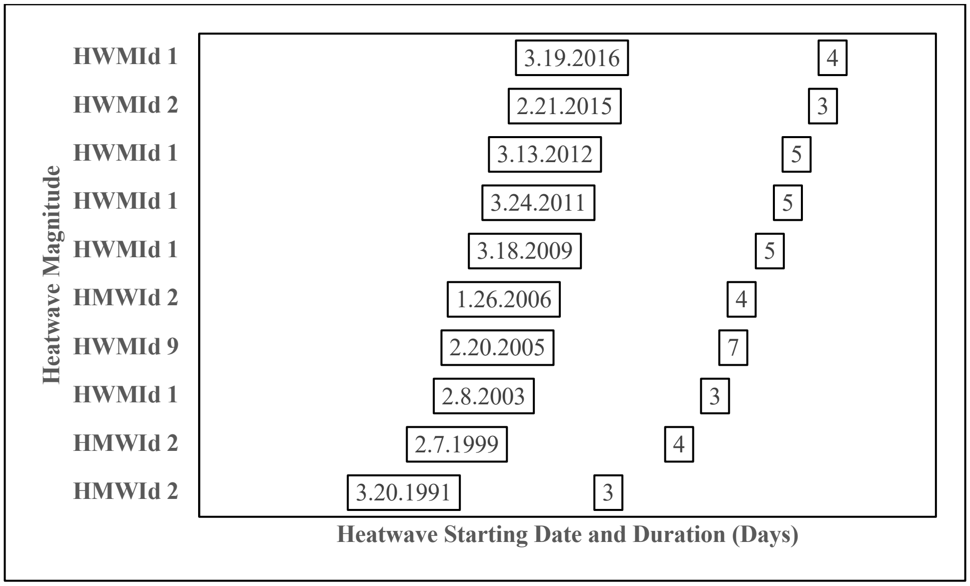

Figure 4: Heatwave Magnitude, Starting Date and Duration (Days) between 1991 and 2020 over Turkana County

6.2 Density Plot Analysis

Figure 5 and *Figure 6* depict that kernel density plots of Heatwave Magnitude Index Daily (i.e., independent variable) and Chronic Obstructive Pulmonary Disease prevalence and deaths (dependent variables) between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya, respectively. The smaller the bandwidth, the more the components of the mixture of distributions e.g., normal, uniform etc. Evaluation of the shape of the heatwave magnitude datasets indicate right-skewed distribution. Although both datasets depict non-asymmetric bimodal distribution, it is more prominent with the deaths. The non-asymmetric bimodal distribution seems to show an outlier within the heatwave magnitude over Turkana. Given that the mean and range are more sensitive to such outliers; it would be more appropriate to use median. This implies that the mean, median, and mode are not good measures of the dataset: the median is lower than the mean, because the mean is more sensitive to the higher values and is drawn towards the tail of the density plot. As is shown in *Figure 6*, deaths associated with Chronic Obstructive Disease show an even more marked bimodal distribution and some asymmetry. Prevalence on other hand depict varied skewness in its distribution

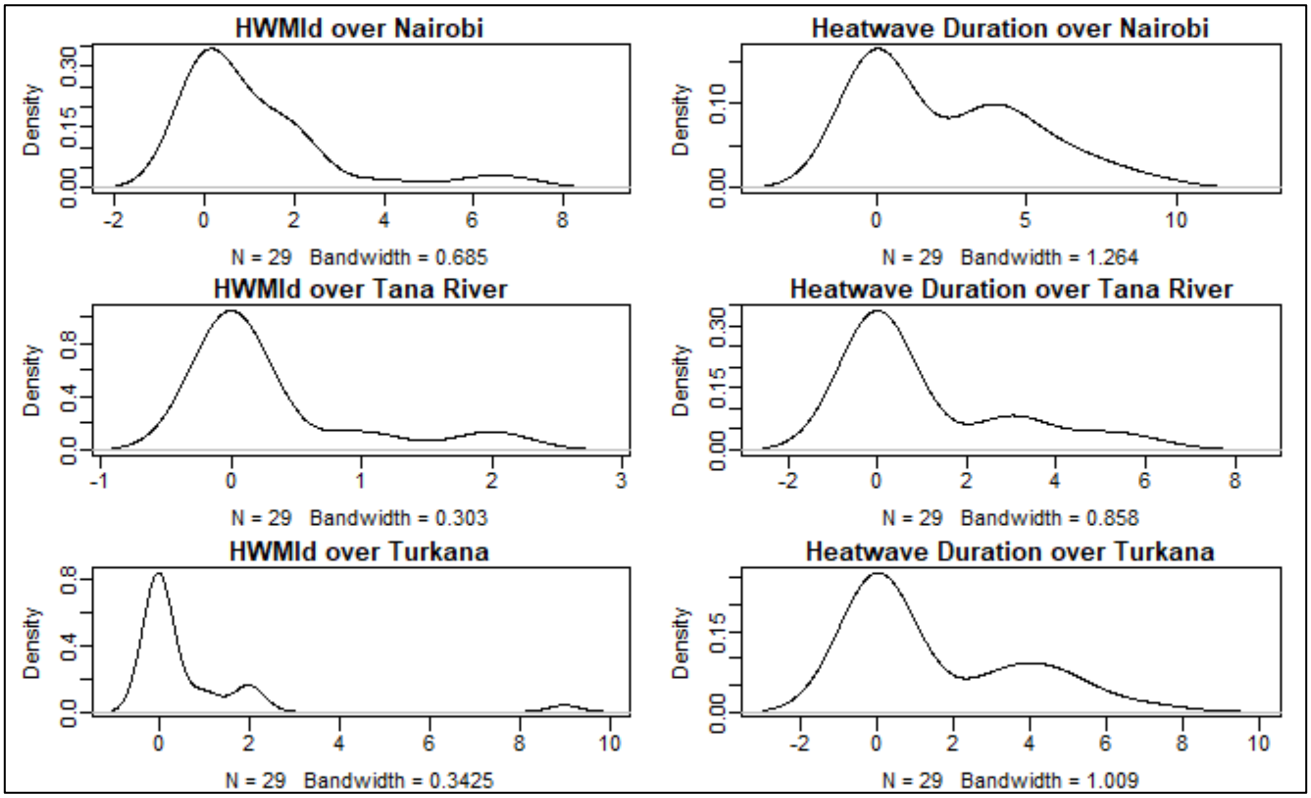

Figure 5: Kernel Density Plots of Heatwave Magnitude Index Daily between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya

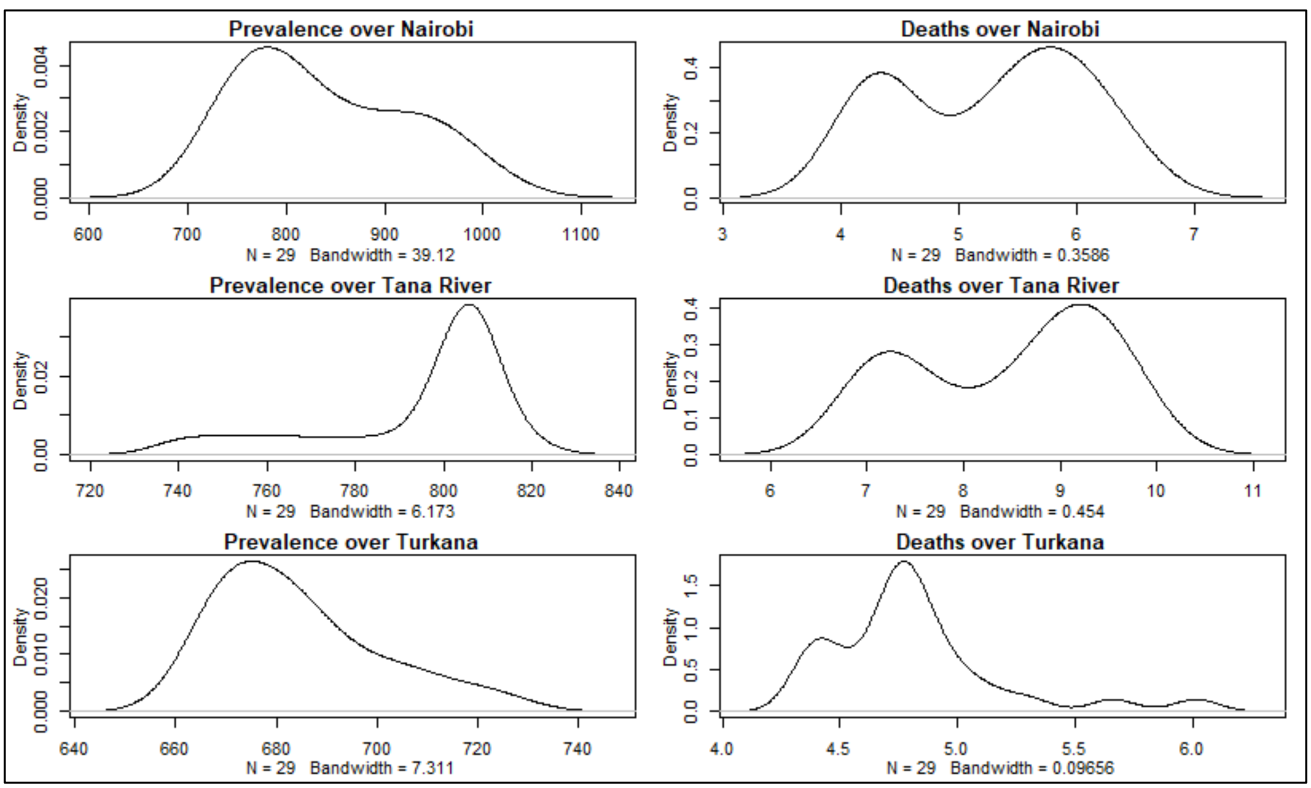

Figure 6: Kernel Density Plots of Chronic Obstructive Pulmonary Disease Prevalence and Deaths between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya

6.3 Pearson's Correlation Analysis

Figure 7, *Figure 8* and *Figure 9* gives a correlation matrix of Chronic Obstructive Pulmonary Disease prevalence and deaths and heatwave index and duration over Nairobi, Tana River and Turkana Counties, respectively. It is evident that COPD prevalence and deaths are understandably significantly correlated as are the heatwave magnitude and duration. At 0.001 significance level, the correlation is above 0.8 over Nairobi County. This is also known as *collinearity* (or *multicollinearity* between two or more variables). The duration of a heatwave is statistically dependent on the magnitude of the same heatwave. On the other hand, the mortality as a result to Chronic Obstructive Pulmonary Disease is statistically related to its prevalence. Although not statistically significant, heatwave characteristics influences the prevalence and deaths due to COPD. Over Nairobi heatwave magnitude and duration is correlated with deaths due to COPD with 0.12 and 0.14 correlations coefficients. This is in agreement with results of Kovats and Ebi (2006) on cardiovascular diseases, and Coumou and Rahmstorf (2012) and Sarofim et al. (2016) on increased rates of overall human mortality. According to Marmo et al. (2006), temperature, and other weather variables e.g., wind and humidity, can cause COPD symptoms to worsen. The dry air typical of January-February months over Kenya, coupled with other local factors and pre-existing medical conditions, can trigger a COPD flare-up.

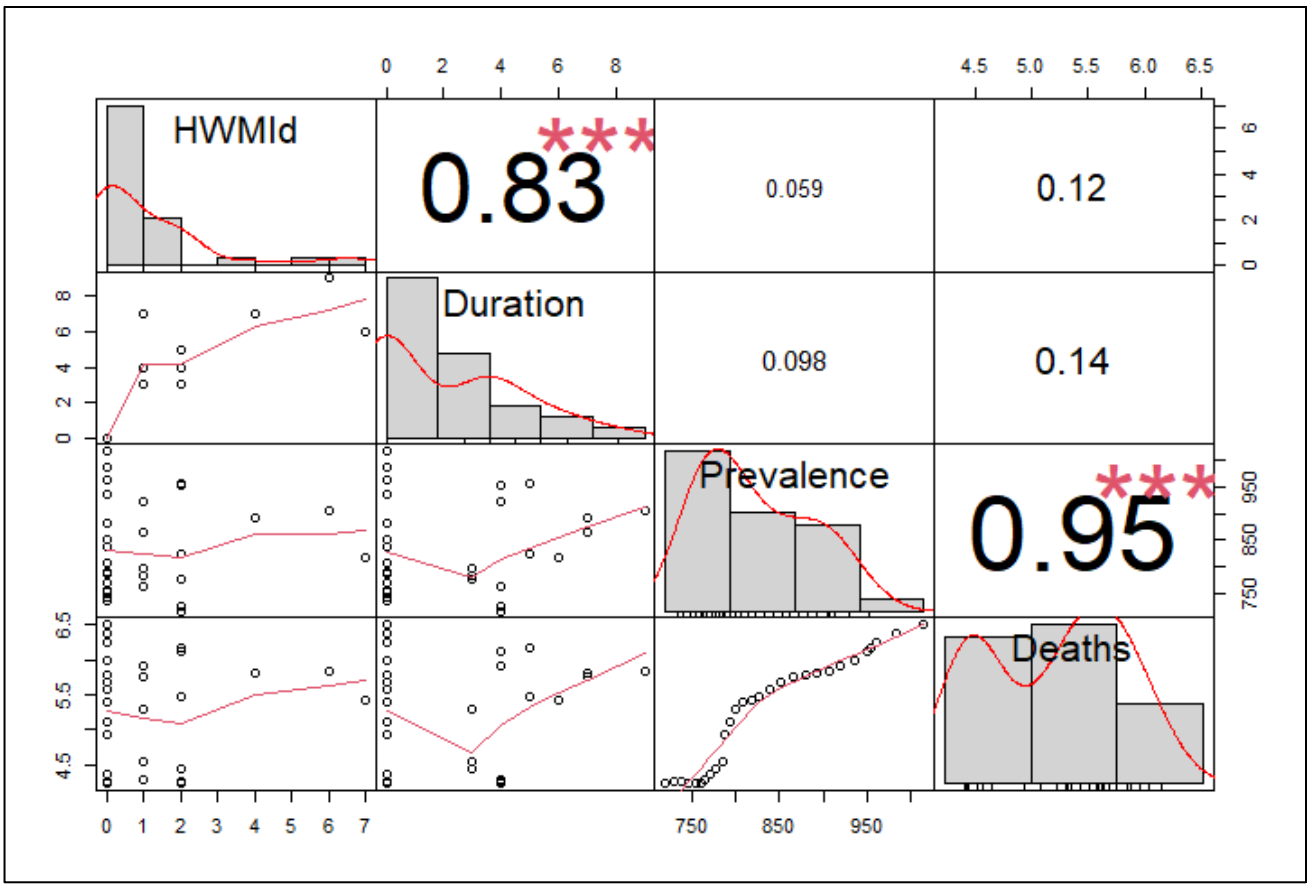

Figure 7: Correlation matrix of Chronic Obstructive Pulmonary Disease prevalence and deaths and heatwave index and duration over Nairobi County showing correlation coefficients (top of the diagonal) with red asterisks depicting statistical significance levels (i.e., *, **, and *** show 0.05, 0.01 and 0.001, respectively), bivariate scatterplots (bottom of the diagonal) with a fitted red line, and histograms (diagonal) with red kernel density overlays

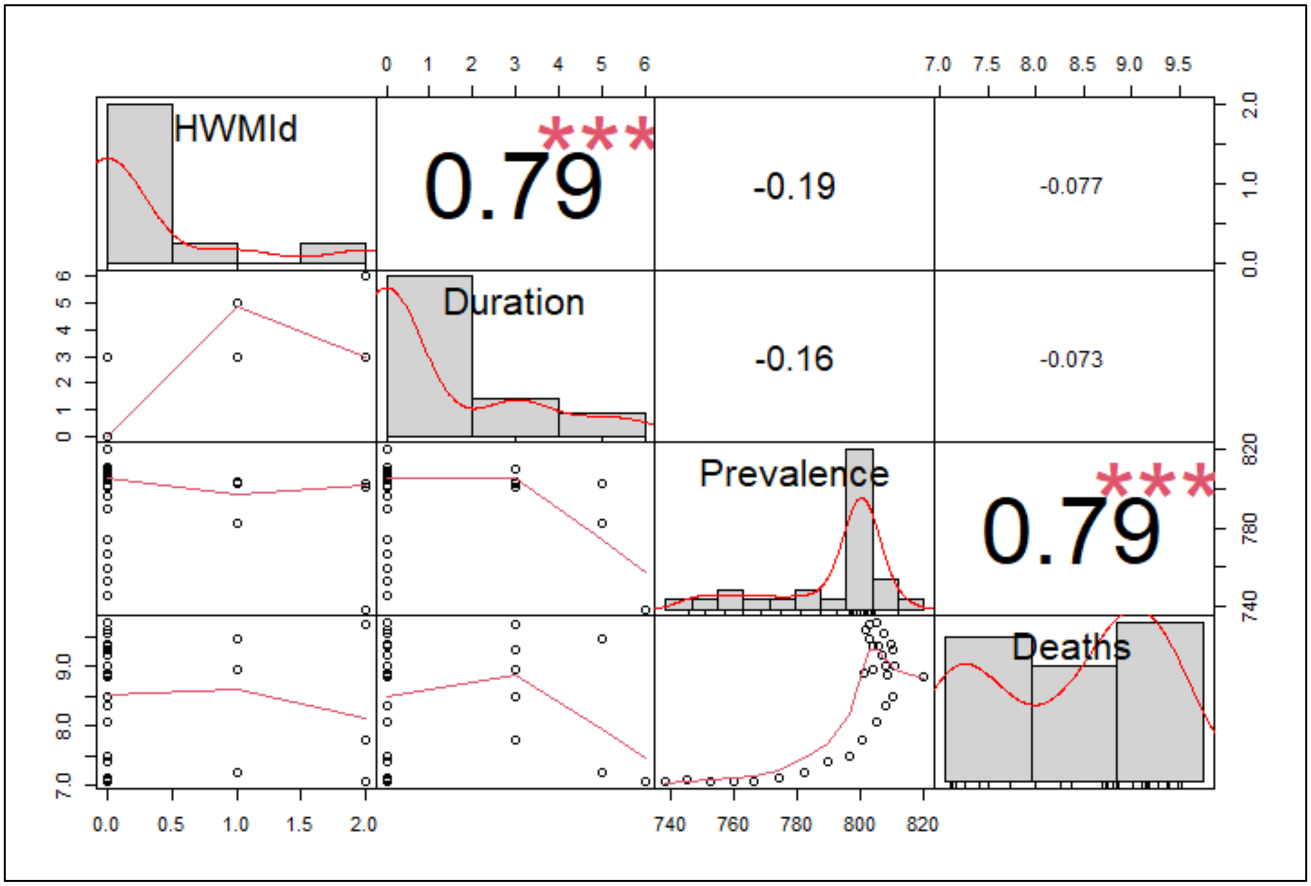

Figure 8: Correlation matrix of Chronic Obstructive Pulmonary Disease prevalence and deaths and heatwave index and duration over Tana River County showing correlation coefficients (top of the diagonal) with red asterisks depicting statistical significance levels (i.e., *, **, and *** show 0.05, 0.01 and 0.001, respectively), bivariate scatterplots (bottom of the diagonal) with a fitted red line, and histograms (diagonal) with red kernel density overlays

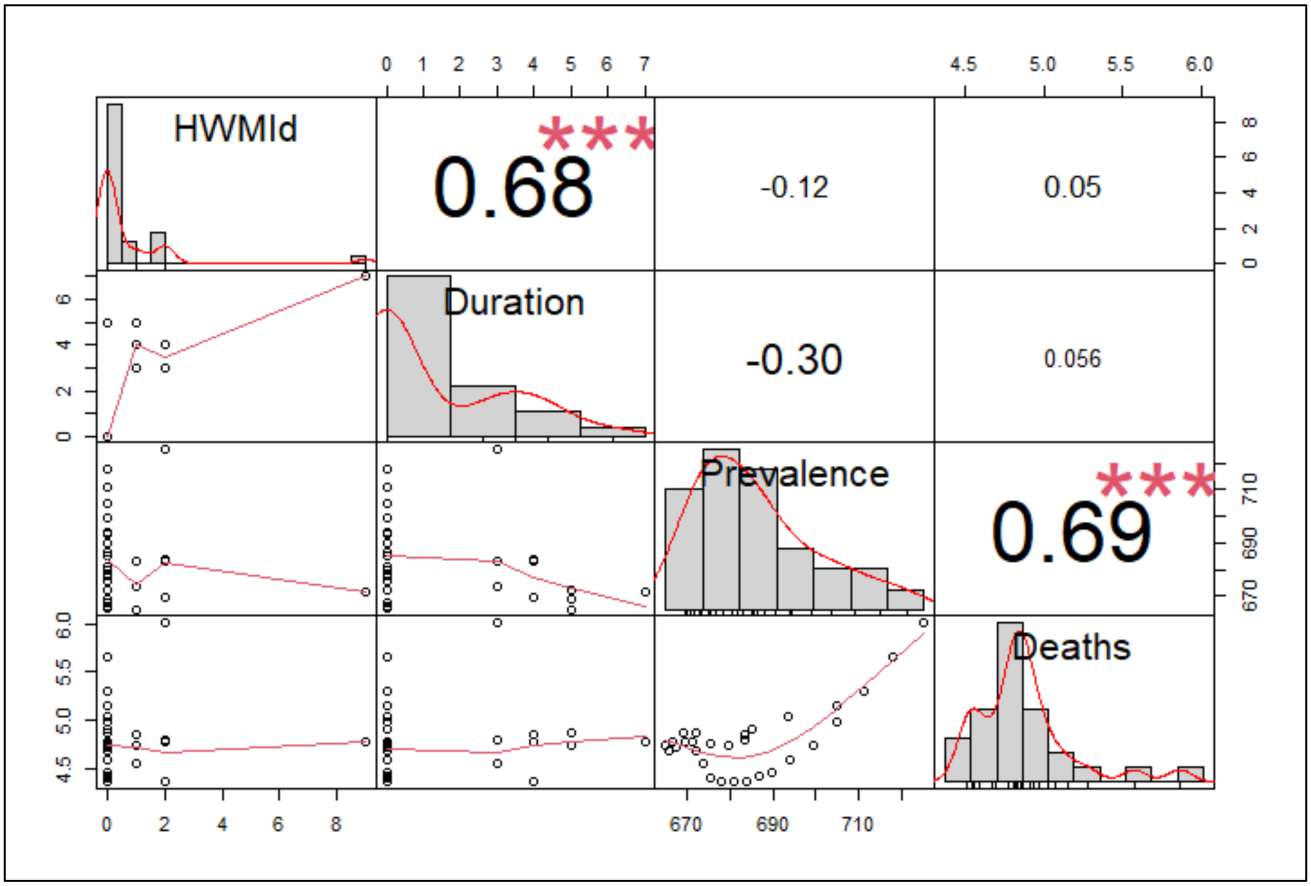

Figure 9: Correlation matrix of Chronic Obstructive Pulmonary Disease prevalence and deaths and heatwave index and duration over Turkana County showing correlation coefficients (top of the diagonal) with red asterisks depicting statistical significance levels (i.e., *, **, and *** show 0.05, 0.01 and 0.001, respectively), bivariate scatterplots (bottom of the diagonal) with a fitted red line, and histograms (diagonal) with red kernel density overlays

6.4 Multivariate Regression Analysis

The combined association between heatwave magnitude and duration and Chronic Obstructive Pulmonary Disease prevalence and deaths was obtained using the multivariate analysis.

6.4.1Generalized Additive Model (GAM) Analysis

The linearity of Chronic Obstructive Pulmonary Disease prevalence and deaths reported at the Nairobi (top), Tana River (middle) and Turkana (bottom) counties between 1991 and 2016 associated with independent variables of Heatwave Magnitude [HWMId] and Heatwave Duration [days] are as shown in *Figure 10*. As is evident, the risk of COPD prevalence and deaths depict different degrees of linearity with the heatwave characteristics over the three Counties. COPD prevalence are linearly and inversely related to heatwave magnitude over the Nairobi and Tana River, and linearly and directly over Turkana County. These varied results are in agreement with Curriero et al. (2002) who have shown that different areas have different sensitivities to extremes in temperature; arguing that the local climate should be considered. Heat waves having gained more attention due to the urban warming attributed to greenhouse gases and other anthropogenic sources, air conditioning and human behavior could explain the inverse relationship over Nairobi due to their substantial modification of the adverse effects of high temperatures.

The risk of COPD prevalence decreases linearly with heatwave duration over Turkana County but varies at different levels of heatwave duration over Nairobi and Tana River. The implied non-linearity over Nairobi for example, depicts that heatwave events lasting shorter than 3-days lead to a decrease in the risk of COPD prevalence. When the duration of the heatwave events increases beyond 4-days, the risk is increased. The opposite is observed in Tana River: heatwave events lasting shorter than 3-days lead to an increase whereas longer events are associated with a decrease in the risk of COPD prevalence. Deaths due to COPD are linearly and constantly related to both heatwave magnitude and duration over the three Counties.

The autocorrelation function (ACF) at default maximum lagging-period for annual Chronic Obstructive Pulmonary Disease prevalence and deaths between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya is as shown in *Figure 11*. As may be deduced from the figure, the ACF of the GAM model did not show a significant autocorrelation.

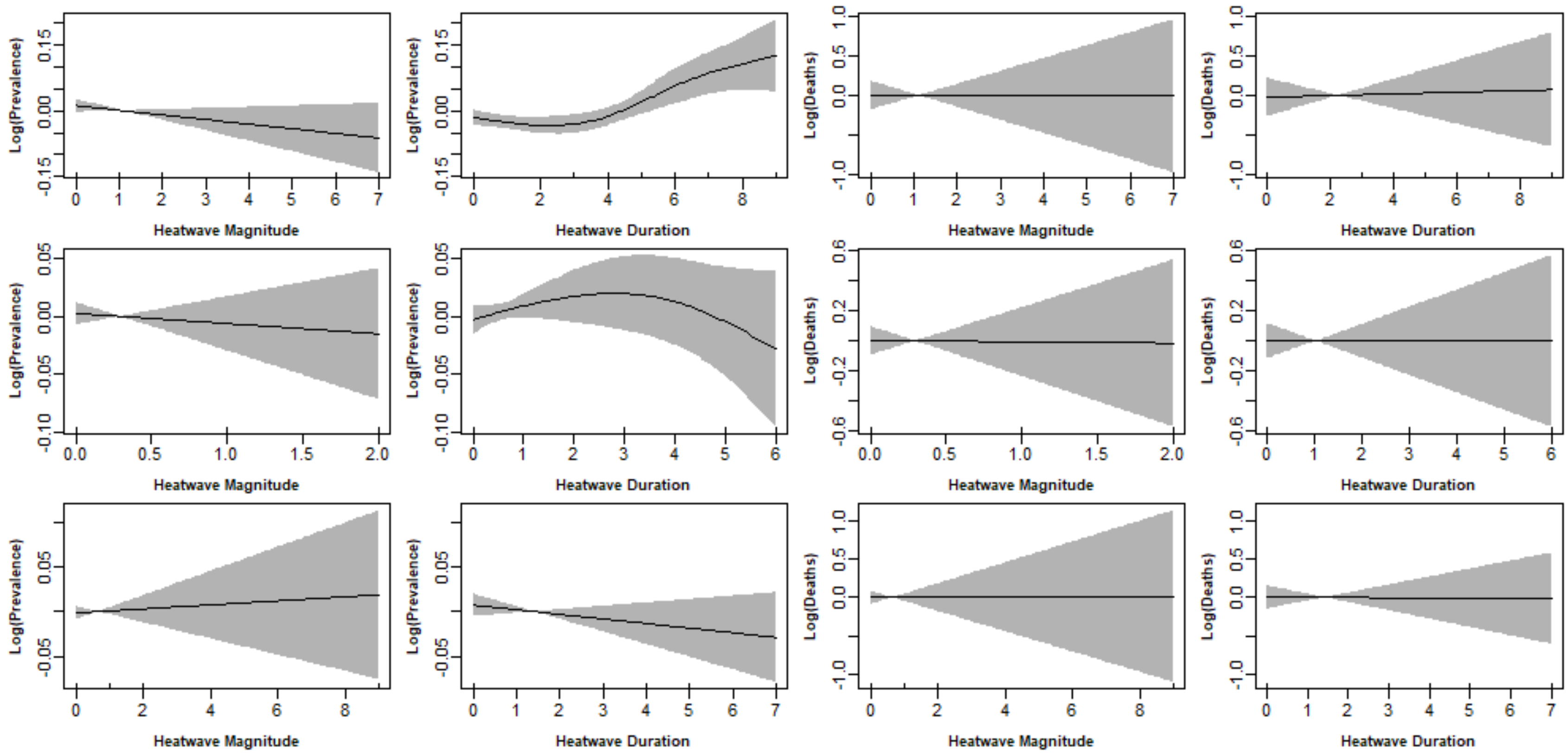

Figure 10: Log (RR)s of Chronic Obstructive Pulmonary Disease prevalence and deaths reported at the Nairobi (top), Tana River (middle) and Turkana (bottom) counties between 1991 and 2016 associated with independent variables of Heatwave Magnitude [HWMId] and Heatwave Duration [days] obtained using a Generalized Additive Model. The shaded area represents the confidence bounds

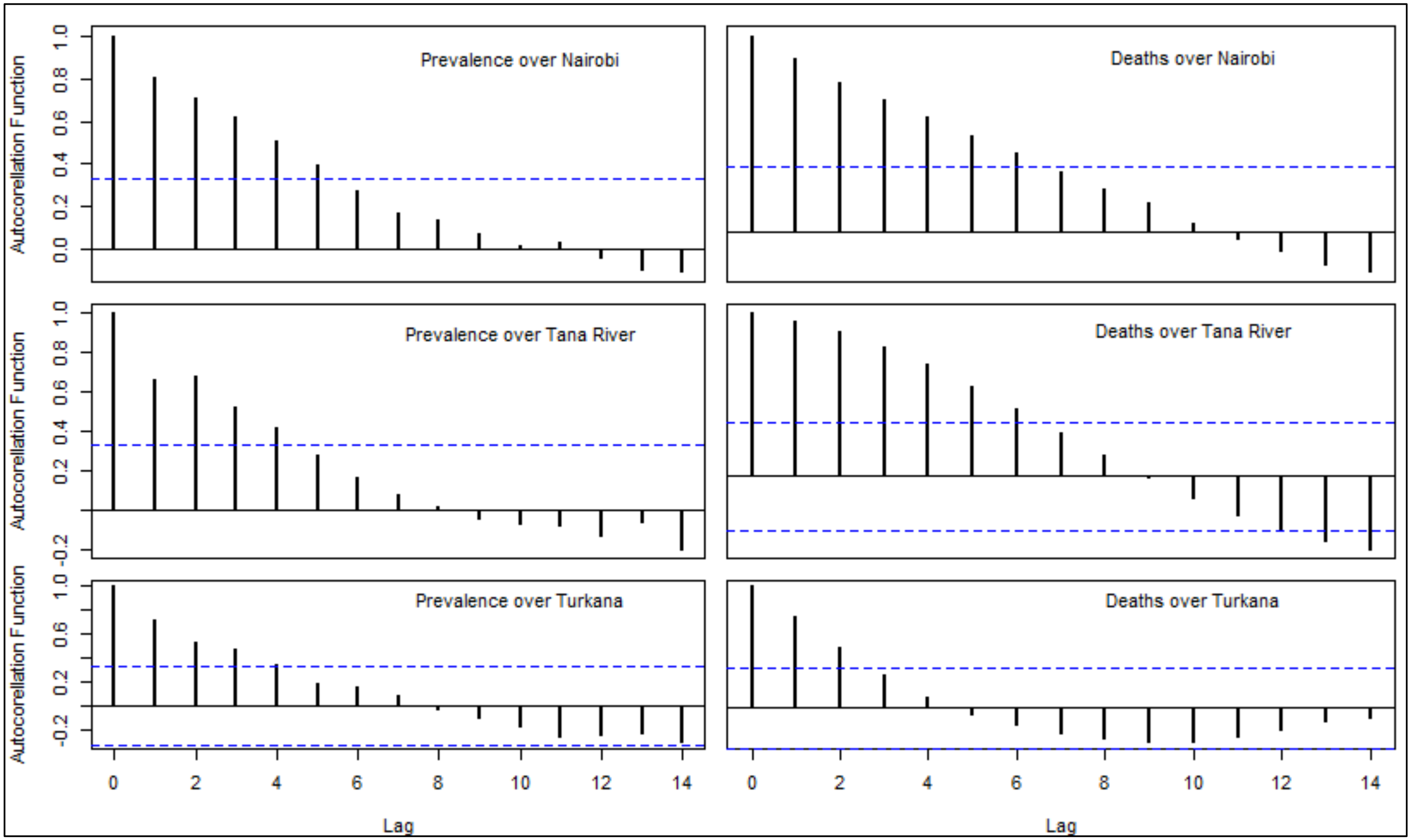

Figure 11: Autocorrelation function (ACF) at default maximum lagging-period for annual Chronic Obstructive Pulmonary Disease prevalence and deaths between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya

6.4.2 Generalized Linear Model (GLM) Analysis

Table 2 sows the percent relative risk for Cardiopulmonary Chronic Obstructive Pulmonary Disease prevalence and deaths based on Generalized Linear Model of heatwave magnitude and duration between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya. It is worth noting that based upon the GAM results, the linearity assumption was deduced to be acceptable between COPD prevalence and heatwave duration over Nairobi and Tana River Counties. It is for this reason that the only statistically significant percent relative risk of COPD prevalence is a 0.76 % ((-1.82 % to 3.32 %)) increase with respect to a one-day increase in the duration of heatwave events over Nairobi. Based on the acceptable linearity assumption, one-day increase in the duration of heatwave events will lead to a 0.03 % ((-0.99 % to 1.04 %)) increase in the risk of COPD prevalence over Tana River. As proposed by Curriero et al. (2002), the low and/or insignificant relative risk for COPD could be attributed to acclimatization. Over Turkana County for example, adaptation of populations to their local climate is evident by the decrease in COPD risk even with prolonged heatwave duration.

Table 2: : Percent Relative risk for Cardiopulmonary Chronic obstructive pulmonary disease prevalence and deaths based on Generalized Linear Model of heatwave magnitude and duration between 1991 and 2020 over Nairobi, Tana River and Turkana Counties in Kenya

Location	Heatwave Characteristic	% Relative Risk (95 % CI)	
		Prevalence	**Deaths**
Nairobi County	Magnitude	-0.46 % (-4.47 % to 3.48 %)	-0.14 % (-5.89 % to 5.47 %)
	Duration	0.76 % *** (-1.82 % to 3.32 %)	1.04 % (-2.69 % to 4.71 %)
Tana River County	Magnitude	-0.66 % (-3.55 % to 2.22 %)	-0.89 % -12.38 % to 10.45 %
	Duration	0.03 % (-0.99 % to 1.04 %)	-0.04 % (-4.09 % to 3.94 %)
Turkana County	Magnitude	0.22 % (-0.53 % to 0.97 %)	0.18 % (-2.7 % to 2.99 %)
	Duration	-0.51 % (-1.11 % to 0.08 %)	-0.25 % (-2.53 % to 2 %)

7. CONCLUSION AND RECOMMENDATION

The main objective of this research was to investigate the temporal distribution of heatwave events and its concomitant effect of human health. To do so, the study relied on both daily observed and satellite maximum temperature data for Nairobi, Tana River, and Turkana Counties from 1991 to 2020. Heatwave Magnitude Index daily (HWMId) was employed as a measure of heatwave events. For Pearson's correlation analysis between annual records of heatwave magnitudes and duration, annual records of Chronic Obstructive Pulmonary Disease (COPD) prevalence and deaths were obtained from the Institute of Health Metrics and Evaluation, University of Washington

The linear relationship between heatwave magnitude and duration and COPD prevalence and deaths was first confirmed using non-parametric Generalized Additive Model (GAM). A parametric multivariate analysis was then conducted using a Generalized Linear Model (GLM) in order to determine percentage change in relative risk.

From the research that has been carried out, it is concluded that the observed heatwave events ranging from normal to very extreme have had a negative impact on the human respiratory health. the risk of COPD prevalence and deaths depict different degrees of linearity with the heatwave characteristics over the three Counties. A statistically significant percent relative risk of COPD prevalence of 0.76 % ((-1.82 % to 3.32 %)) increase with respect to a one-day increase in the duration of heatwave events over Nairobi was observed. As proposed by Curriero et al. (2002), the low and/or insignificant relative risk for COPD could be attributed to acclimatization. Nevertheless, Pyrgou (2018) argues that even if populations became fully acclimatized to extremely high temperatures, the poorer air quality associated with the such temperatures may still negatively affect their health.

On the basis of the findings presented in this report, it is recommended that, in order to establish cause effect, cause specific (e.g., emphysema, chronic bronchitis etc.) morbidity and mortality data segregated along age and gender and for specific health facilities should be incorporated. Research therefore examining whether socio-economic or demographic variables or other comorbidities could have a potential confounding or modifying effect on the mortality–temperature relationship are recommended.

Regarding humanitarian work, the observed seasonality in the occurrence of the heatwave event point to the need for accurate and timely seasonal forecast of maximum temperature and the accompanying triggers i.e., wind and humidity. With such forecasts humanitarian work can be deployed to manage extremely hot and humid days with the understanding that there is no better way to avoid a COPD flare-up than to stay indoors. In acute forecasts the populace who have pre-existing respiratory health conditions would be advised to even move to parts of the country where weather temperatures are more moderate e.g., highlands west and east of the Rift Valley and the western parts. Additionally, and given that studies have demonstrated that air pollution worsens the effect of weather on human respiratory health, the populace should protect itself from both indoor and outdoor pollutants particularly over crowded urban built areas in the ASALs. While outdoor, one ought to limit the level of physical activity.

8. STUDY LIMITATIONS

The study recognition of the critical role of accurate and finer resolution climate data, and private and confidential aggregated health data records in epidemiology justifies (i) the complimentary use of high-resolution satellite data as a remedy for data gap, and (ii) aggregated (ward level) and gender-segregated health records.

There exist several limiting factors that informed and justified the choice of both limited space and scope of this study. Even though data on health outcomes and environmental risk factors (in this case maximum temperature) would be needed at the smallest possible unit (e.g., sub-county) since larger areas may conceal the local-level variations, data availability limited the spatial range of the assessment. Therefore, data was aggregated at County level. Some of the datasets may be national in scope and may not provide sufficient detail for County governments. Additionally, the exclusion of other variables which are known risk factors e.g., air pollution, smoking, level of exercise, may be a source of uncertainty.

Human health data insufficiency and confidentiality informed the use of coarse time and space -resolved data, especially WHO country annual statistics. Moreover, a study participants' informed consent was not obtained from the Ministry of Health and a research approval was not sought from the KNH/UoN ERC, implying that only records of selected climate-sensitive disease data were considered, and not individual patients' data.

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GLOBAL HEAT HEALTH INFORMATION NETWORK

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Appendix A: Total Monthly All-Cause Outpatient Data Reported at AMURT Health Centre, Nairobi, Kenya

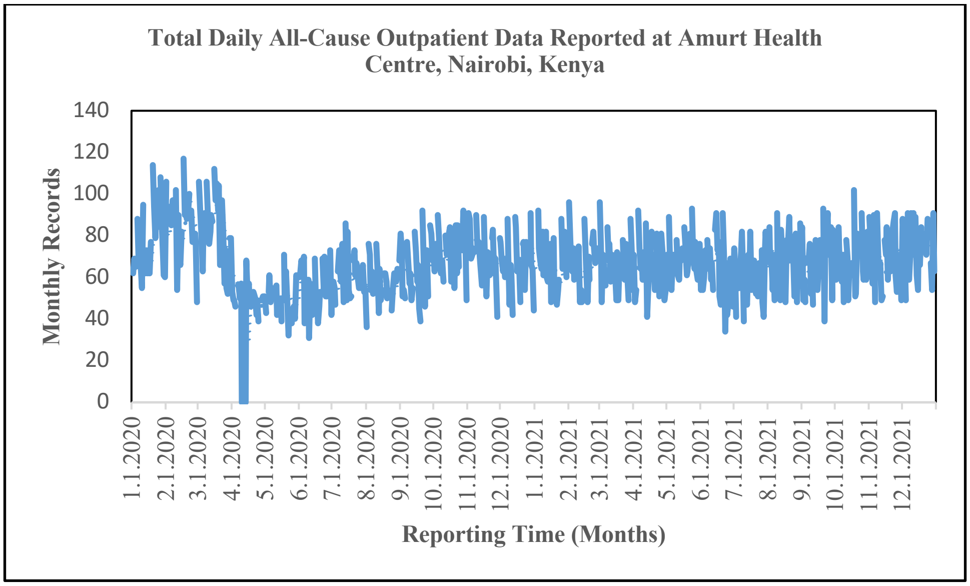

Figure 12: Total Monthly All-Cause Outpatient Data Reported between 2020 and 2021 at AMURT Health Centre, Nairobi, Kenya

Appendix B: Total Monthly All-Cause Visits, Hospitalizations and Deaths Reported at Mathari Hospital, Nairobi, Kenya

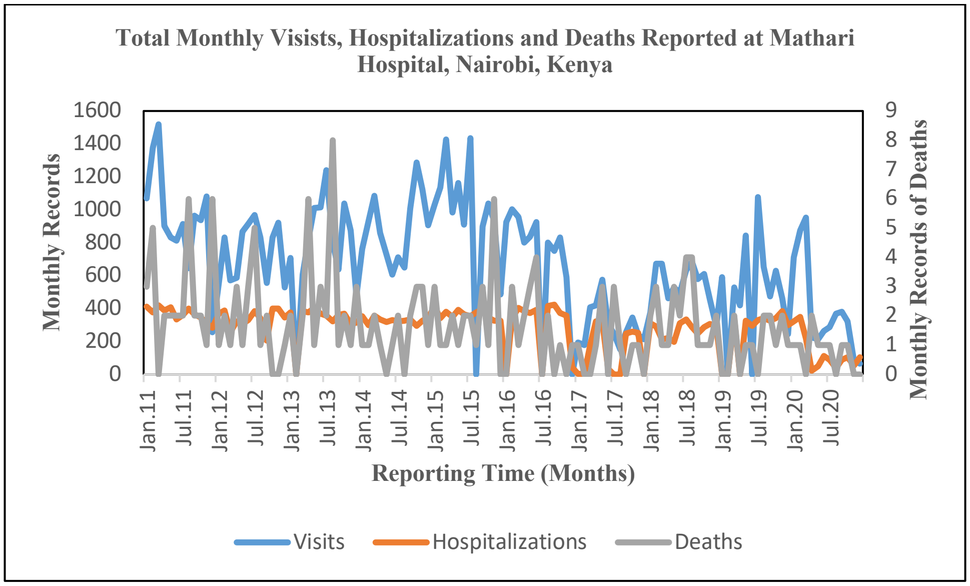

Figure 13: Shows the Total Monthly All-Cause Visits, Hospitalizations and Deaths Reported between 2011 and 2020 at Mathari Hospital, Nairobi, Kenya

Appendix C: Total Monthly All-Cause Visits, Hospitalizations and Deaths Reported at Mbagathi Hospital, Nairobi, Kenya

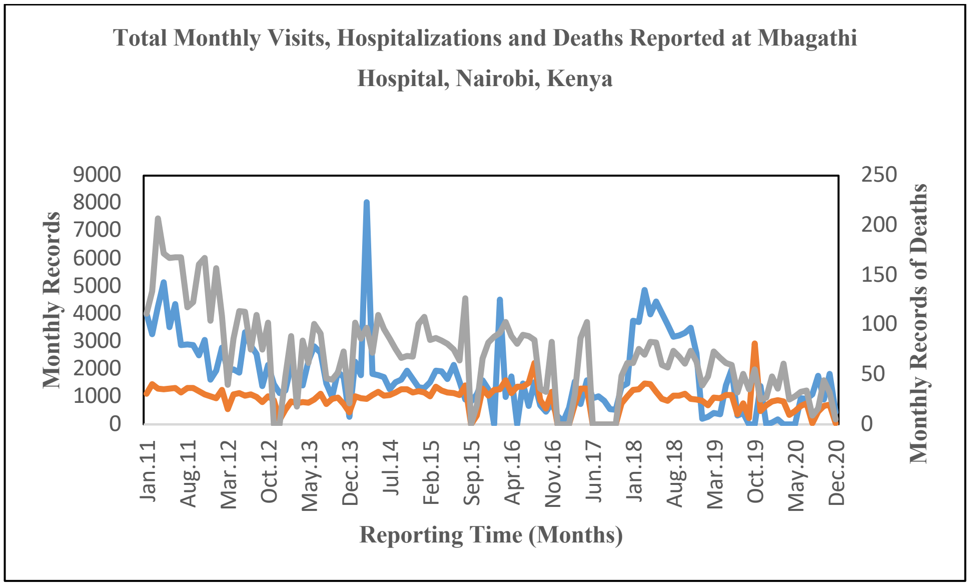

Figure 14: Shows the Total Monthly Al-Cause Visits, Hospitalizations and Deaths Reported between 2011 and 2020 at Mbagathi Hospital, Nairobi, Kenya

Appendix D: Total Monthly All-Cause Inpatient Admission, Inpatient Discharge and Inpatient Deaths at Mbagathi Hospital, Nairobi

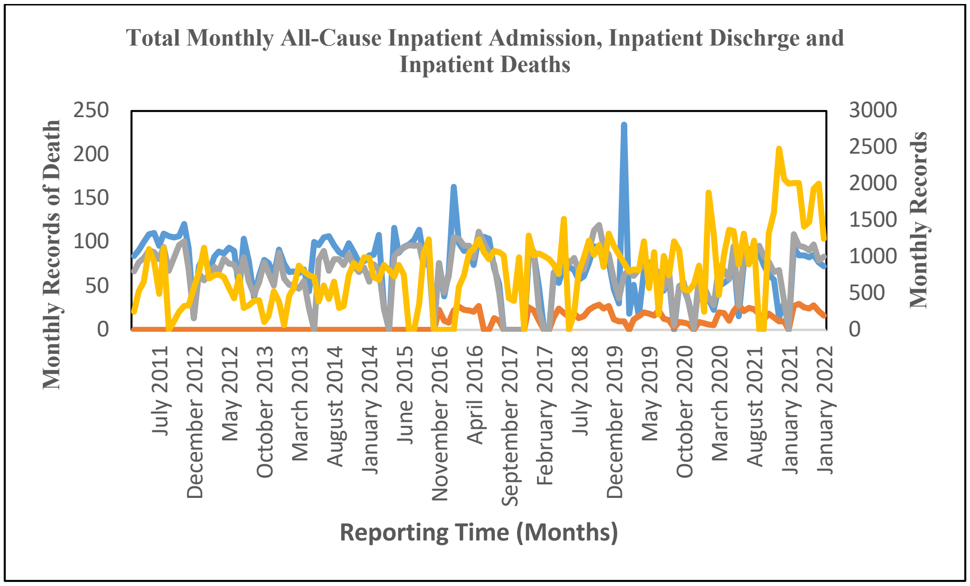

Figure 15: Shows the Total Monthly All-Cause Inpatient Admission, Inpatient Discharge and Inpatient Deaths between 2011 and 2020 at Mbagathi Hospital, Nairobi

Appendix E: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Death at Hola Hospital, Tana River

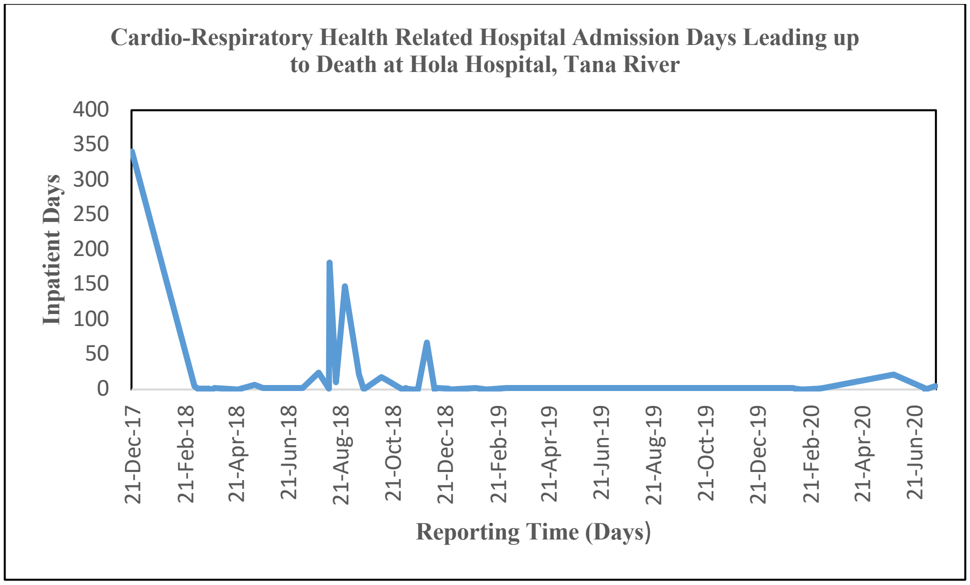

Figure 16: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Death between 2017 and 2020 at Hola Hospital, Tana River

Appendix F: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Discharge at Hola Hospital, Tana River

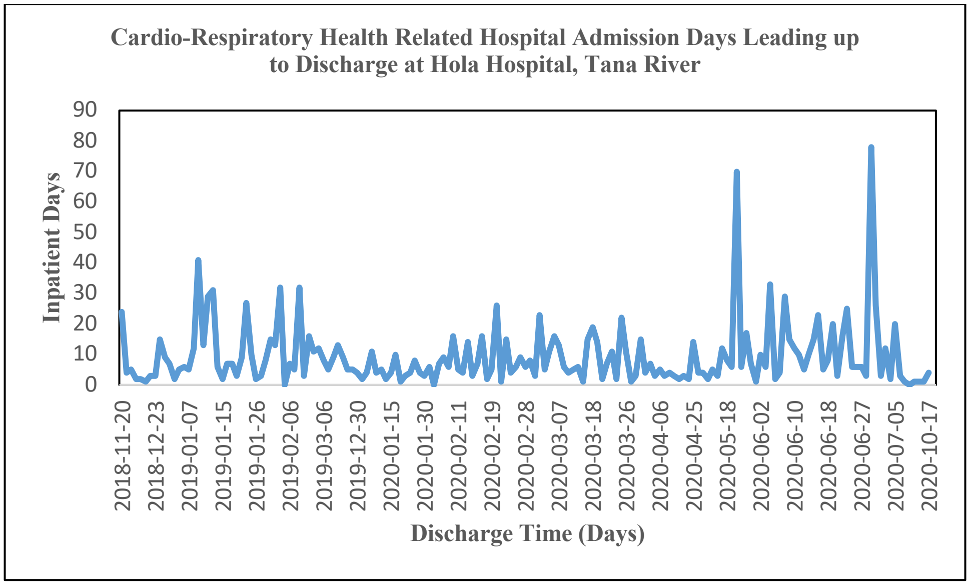

Figure 17: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Discharge between 2018 and 2020 at Hola Hospital, Tana River

Appendix G: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Deaths at Ngao Hospital, Tana River

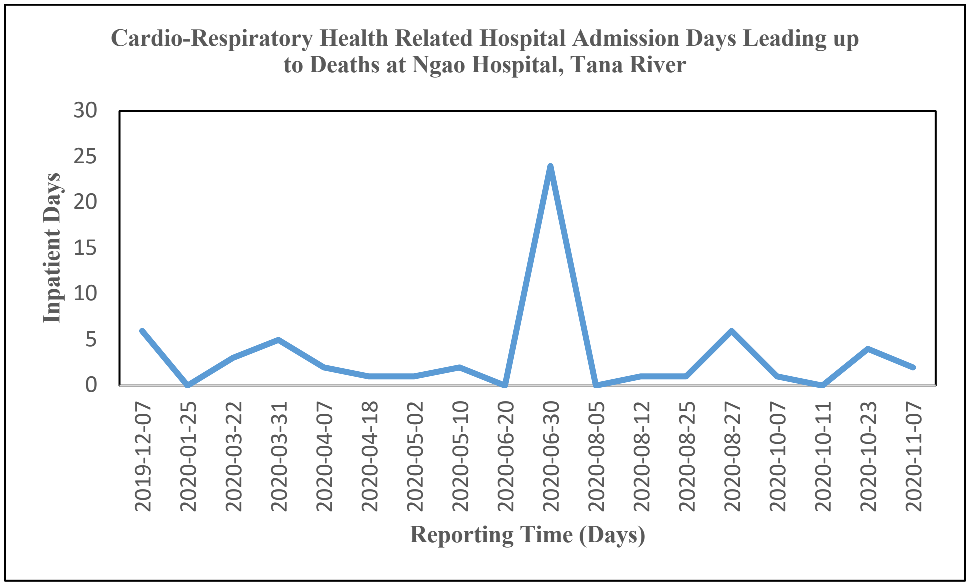

Figure 18: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Deaths between 2019 and 2020 at Ngao Hospital, Tana River

Appendix H: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Discharge at Ngao Hospital, Tana River

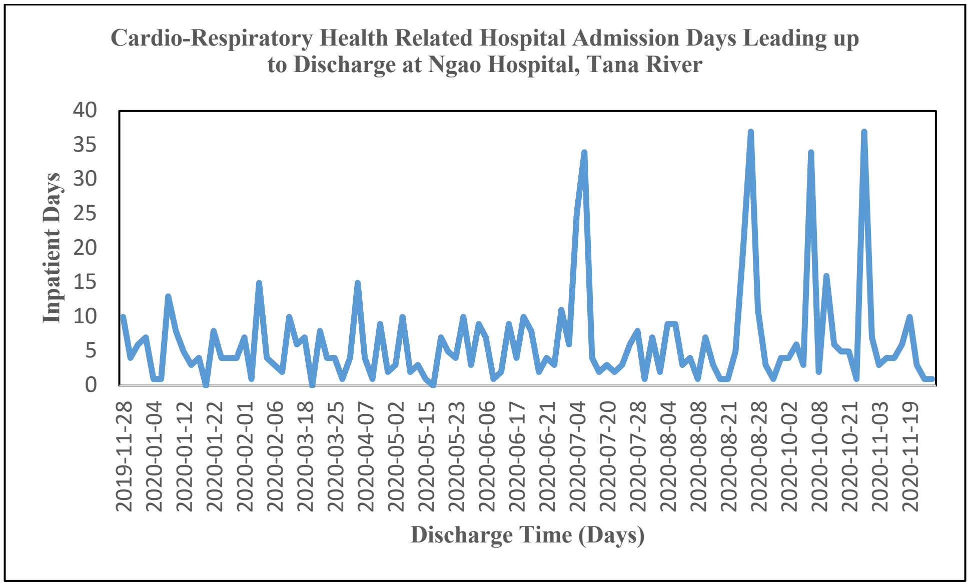

Figure 19: Cardio-Respiratory Health Related Hospital Admission Days Leading up to Discharge between 2019 and 2020 at Ngao Hospital, Tana River

Appendix I: Upper Respiratory Tract Infections (URTI) and Other Diseases of the Respiratory System (ODRS) at Lodwar County Referral, Turkana

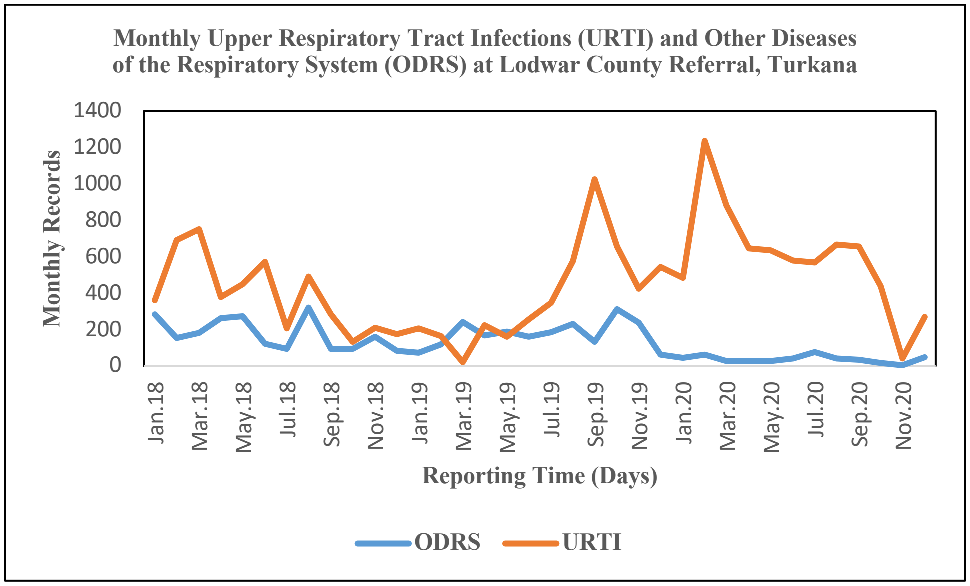

Figure 20: Monthly Upper Respiratory Tract Infections (URTI) and Other Diseases of the Respiratory System (ODRS) between 2018 and 2020 at Lodwar County Referral, Turkana