Identification of local heat thresholds and related health impacts: The case of Nairobi, Mombasa, Kisumu Cities in Kenya

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Executive Summary

As the climate warms, more days with extremely hot temperatures are occurring across the world. With thousands of excess deaths every year, the health effects of hot weather are fast becoming a global public health challenge for the 21st century. Studies on the relationship between high temperatures and hospital visits, admissions and mortalities especially in vulnerable parts of the globe e.g. Sub Saharan African cities are however largely absent. In this study, we define local heat thresholds for three Kenyan cities (Nairobi, Kisumu and Mombasa) and use these thresholds to evaluate heat-health impacts of the most recent heatwaves. We utilize daily maximum and minimum temperature data from Kenya Meteorological Department for two stations in each city and monthly health data (visits, admissions and mortalities) from two public health facilities in close proximity to the weather stations. Our results show positive associations between high temperatures and hospital admissions across the three cities. We also see indications of a delayed effect of heat on mortalities albeit not in all cases. We use this analysis to propose heatwave definitions for issuing health alert warnings in each city: daily maximum temperature of 32+ for 3 or more days in Nairobi, daily maximum of 37+ for 3 or more days in Kisumu and a daily max of 36+ for 3 or more days in Mombasa. These thresholds can be used to trigger protocols e.g., the deployment of heat-health action and emergency response plans or mitigate against the effects of extreme heat in the three Kenya's economic hubs. We draw attention to hospital managers and medical practitioners to pay particular attention to patients during such high-temperature periods.

Keywords: extreme heat, heat thresholds, heat-health impacts

1. Purpose

IPCC, (2022) identifies heatwaves as a climate impact driver for human mortality and morbidity from heat and infectious diseases in all regions of Africa. Despite both observations and model projections highlighting heatwaves and their impacts in Kenya and other Sub-Saharan Africa (SSA) countries, these are seldom captured in extreme weather databases (Harrington & Otto, 2020). Kenya, a tropical country in East Africa, is straddled by the equator and is prone to highly variable weather conditions that drive heatwaves. There are however no studies that characterize the thresholds for heatwave events in Kenya and the general East African region. In Africa, most studies that have been conducted have a southern African focus.

The purpose of this study is to identify local heatwave thresholds in Kenya and investigate the impacts of exceeding such thresholds on health in three main cities. Additionally, improved understanding of heatwave patterns in Kenyan cities will be useful in enabling early warning of heat waves and identifying potential impacts for adaptation planning at local and country levels which include reducing losses in productivity, safeguarding lives and overall resilience building.

2. Literature Review

Climate change and its effects on natural and human systems are becoming increasingly obvious all around the world. In comparison to other parts of the globe, Africa is expected to suffer the burden of climate change and variability the most due to the many vulnerability hotspots identified across the continent (IPCC, 2021). At the same time, the African continent is the part of the world with the least available information on changing risks in extreme weather (Seneviratne *et al.,* 2022). Rapid urbanization and population growth interact with climate change to increase the risk of severe impacts from extreme climate events such as droughts, floods and in more recent years' heatwaves (Dodman *et al.,* 2015). Both observations and model projections capture heatwaves and their impacts in Kenya and other Sub-saharan Africa (SSA) countries, however not usually reported by national meteorological services and are seldom captured in extreme weather databases (Harrington & Otto, 2020). A robust understanding of the links between extreme heat and health is crucial to developing effective early warning and adaptation strategies in a rapidly warming world, both to safeguard the lives and livelihoods of the people (Scrovonic *et al* 2018). Among the most vulnerable groups to heatwaves now and in the future are the elderly (over 65 years old), children, outdoor workers and those with pre-existing health conditions such as diabetes, autoimmune conditions, migraines and pregnant women (Manyuchi *et al* 2022). Additionally, people living in informal unplanned settlements in urban areas are disproportionately affected, with a 32% rise in 2019 in those affected compared to the baseline of 1981-2010 (Igun *et al.,* 2022). Kenya, a tropical country straddled by the equator, is prone to weather conditions that drive heatwaves. Temperature is the main component of heat, however, humidity, wind speed and radiant load also determine the severity and impacts of extreme heat. The extent to which populations are negatively affected by heat waves depends on a number of factors including sensitivity, the vulnerability of populations, and the severity of the weather event among others.

Studies have shown that the risk of morbidity and mortality during extreme heat events is a factor of the intensity, duration and timing of heat waves, with those of long duration having the greatest impact on health and mortality (D'Ippoliti *et al.,* 2010). This then means that different public health management strategies are required for longer, slightly warmer extreme heat events that have a greater physiological burden compared to shorter and more intense events (Perkins-kirkpatrick & Lewis, 2020). In many African countries, heatwaves interact with other factors such as a low understanding of extreme heat events and low adaptive capacity thus resulting in greater impacts compared to other regions. Cities, such as Nairobi, Mombasa and Kisumu in Kenya, face the greatest impacts of extreme heat events on health relative to rural regions since ambient temperatures are compounded by the interaction between air pollution and temperature, the 'urban heat island effect' and urban sprawl in many cases characterized by unplanned informal settlements (Egondi *et al* 2012).

Given the severity of the impacts and also the fact that heat extremes are the type of extreme weather changing fastest with global warming (Clarke *et al*., 2022), identifying metrics to characterise heatwaves and develop early warning systems and subsequently heat action plans is the most urgent task towards adaptation to a warmer climate. This study seeks to identify local heat thresholds for three Kenyan cities (Nairobi, Mombasa and Kisumu) that provide heatwave definitions that can be used by Kenya Meteorological Services and city authorities to issue heatwave warnings and advisories. We further assess the impact of heat on hospital visits, admissions and deaths in the three cities. This report is structured as follows. Data and methods are provided in section 4, results are presented in section 5 and the discussion and conclusion are given in section 6.

3. Data and Methods

4.1 Methods

Heatwaves are generally understood to be periods of hot weather considerably above the average temperatures for a given time and location. There is however no one definition of a heatwave that can be applied globally. While there are purely meteorologically based definitions, focusing on the exceedance of a set temperature threshold, e.g. 35C or 40C (indices called TX35deg, or TX40deg) or when night time temperatures are considered instead the exceedance of 20C (TN20deg) might be considered. Other indices are based on percentages, e.g. TX95per is an index based on the exceedance of the 95% long-term average of the maximum temperature for a 15-day window around that calendar day. So the resulting threshold temperature will be different for every day of the year. Other indices combine night and daytime temperatures or include measures of humidity. Perkins and Alexander (2013) provide an overview of such indices.

Heatwaves have adverse impacts (Perkins-Kirkpatrick and Lewis, 2020) on many natural and human systems, including human health, productivity, infrastructure, ecosystems and wildfire danger. Which of all possible indices to measure heat waves is most relevant for any given location depends very much on local weather conditions and the vulnerability of people and ecosystems exposed to heat and the purpose of trying to measure heat waves. E.g., a wide variety of complex indices exist to measure the discomfort of humans or the relationship between human morbidity and mortality. Such indices require a large amount of data to be calculated and are generally only applicable to a small impact group. Based on such calculations and epidemiological assessments heatwaves have been shown to be extremely deadly. This year alone, more than 3000 people died in a heatwave hitting the United Kingdom in July (GovUK, 2022).

It has also been shown that early warning systems and heat action plans can drastically reduce mortality and morbidity during a heatwave (Hajat et al., 2010). The implementation of early warnings requires a location-specific definition of heatwaves that takes the vulnerability of the population into account. Heatwave warnings need to actually protect the population but be infrequent enough so that people do not tire of them.

Over the African continent, no examples exist of what indices might be appropriate, as heatwaves are generally, neither recorded nor reported locally (Harrington and Otto, 2020).

With these requirements in mind, we adopt a method introduced by Harrington and Frame 2022 for New Zealand. While the climate of New Zealand and Kenya is very different, some of the practical characteristics are the same: In both countries, no current definition of heatwaves exists that could be used for heatwave warnings. Similarly, in both countries weather station data is available for stations relatively far away from each other with quite different characteristics. This means, applying meteorological heat wave definitions like hot days (e.g. above 30C) would identify extreme heat days in one location, but very frequent temperatures in another.

We, therefore, use a transparent method to try and identify heat episodes based on the relative rareness of heat extremes at each station.

We first sort the maximum and minimum temperature records at each station, to identify all discrete heat events for which different integer thresholds of daily maximum and minimum temperature were exceeded for a variety of N-days. With N spanning from 1 to 10 days. See tables 1, 2 and 3. We then identify for each separate variable a threshold that leads to approximately 10 events in the record. This gives us a number of heat events per station that is on the order of 20, but smaller as in many cases events identified by maximum or minimum temperature are identical.

This is the first, purely weather-driven part of the analysis.

In the second step, we obtained hospital data, described below for hospitals close to the stations. The hot periods identified above are now compared to hospital data to see if there is a correspondence between the hot periods and heat-related illnesses or mortality. This is to assess whether the meteorological method actually corresponds with the impacts of the heat waves. Here, we focus on the recent heatwave events i.e those that occurred between 2011-2020 as this is the period where hospital data is available.

In a third step we turn the procedure around and identify whether, on days and months, where heat-related hospital visits, admissions and mortalities were high, these correspond with identifiable discrete events in either maximum or minimum temperatures.

Combining the findings from all three steps we aim to identify for each station one or more heat wave definitions that could be used to issue early heatwave warnings if heatwaves meeting the definition are forecast.

4.2 Study area

For this study we chose three major cities in Kenya: Nairobi with a population of just over 5 million people, Mombasa with a population of about 1.2 million people and Kisumu home to about 300,000 people. These cities (Figure 1), being the largest in Kenya and crucial economic hubs for the country, will be ideal pilots for heatwave early warning.

The three cities are varied in climatology by virtue of their locations. Figure 1 shows the location of the three cities in Kenya.

Mombasa is a coastal town at about 50m above sea level in southeastern Kenya along the Indian Ocean. Mombasa's climate is influenced by its proximity to the Indian Ocean with an average annual rainfall of 1060mm (1991-2020). As with the rest of the coastal region, Mombasa benefits from 2 main rainfall seasons, March to May (MAM; 455mm average annual rainfall) and October to December (OND; 323mm average annual rainfall). In addition, however, a 3rd rainfall season with less overall precipitation is experienced between June and August (199mm). The average annual daytime or maximum temperature is 30.5ºC while the average nighttime or minimum temperature is 22.4ºC. The hottest months on average are December to March, temperatures are relatively lower during the peak of the MAM rain season in May and stay under 30ºC on average up to October. Mombasa being adjacent to the Indian Ocean has an average humidity of 80% with November having the highest humidity of 85% and February the lowest at 75%.

Nairobi, the capital city of Kenya, is located in the central highlands of Kenya at altitude of 1795m above sea level. Nairobi is characterized by mixed developments. The central business district is populated with skyscraper offices while the outskirts or suburbs host residential buildings. There are two large informal settlements within a few kilometres of the Central business district, Kibera and Mathare. The annual average rainfall in Nairobi ranges from 700mm to 1028mm, with most of it received during the two main rainfall seasons; March to May and October to December. Average daytime temperatures range from 23.8ºC to 25.6ºC across the 4 stations while average nighttime or minimum temperatures range from 12.9ºC to 13.8ºC. The hottest months on average are January to March and the coolest months are June to August. The average humidity for Nairobi is 75% with the highest monthly average humidity recorded during the month of May (85%) and the lowest average in February (65%).

Kisumu city located in Western Kenya in the Lake Victoria basin region is 1131m above sea level. It is the 3rd largest city in Kenya after Nairobi and Mombasa and is also characterized by both commercial buildings and residential ones in the suburbs. A few informal settlements or slums exist within the city as well. Annual average rainfall for Kisumu is 1417mm while seasonal averages are 532mm for March to May, 378mm for October to December and 240mm for June to August. Average daytime/maximum temperatures are 29.7ºC while nighttime/minimum temperatures are 17.1ºC. The hottest months are January to March and October with average temperatures over 30ºC while the coolest months are June to August. Being adjacent to the lake Kisumu experience relatively high humidity levels compared to other highlands west of the Rift Valley regions

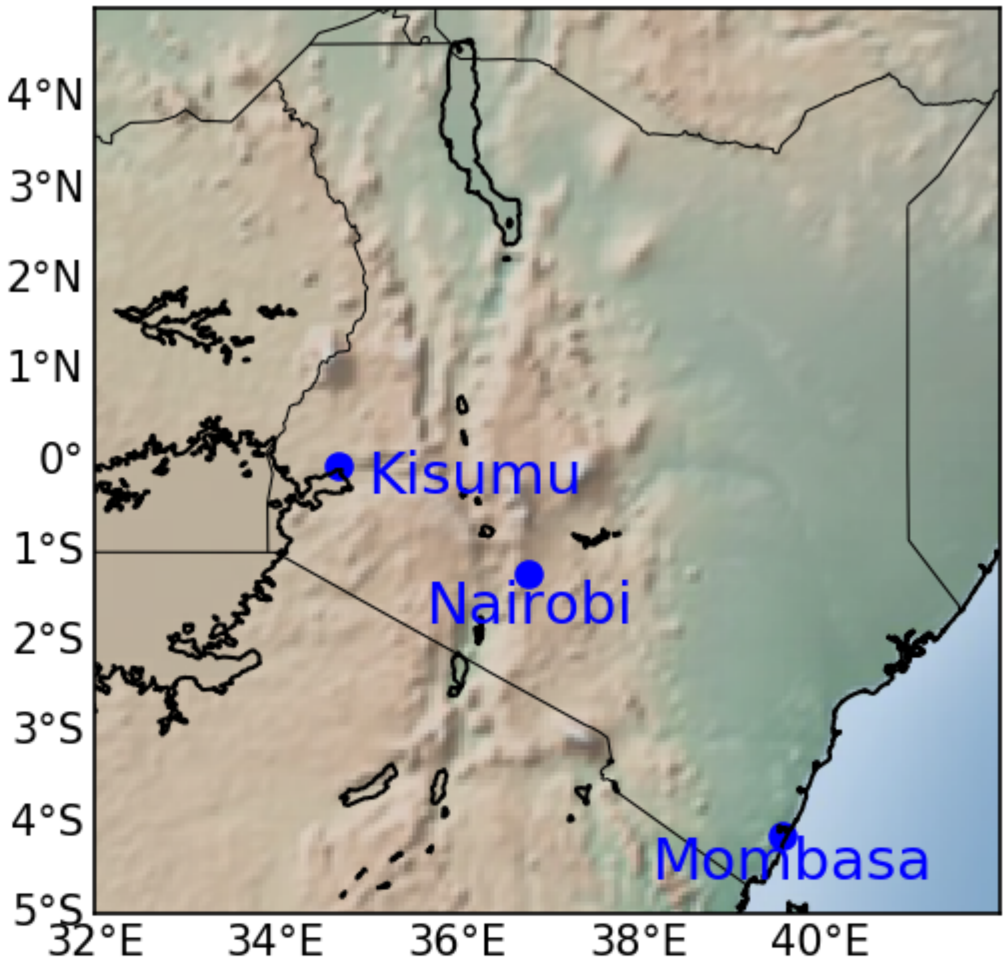

Figure 1: **Location of the three study cities in Kenya**

4.3 Data

The climate data used in this study is sourced from the Kenya Meteorological Department (KMD). The data is a blend of observed station data with satellite data produced by KMD to supplement the station data that shows significant gaps in some stations. We evaluated the data using the available good quality station data and found no obvious bias or inhomogeneities (not shown). We use daily maximum and minimum temperatures for at least two weather stations in each city for the period 1981-2020. For Nairobi city, we utilize data from Dagoretti and Moi Airbase (hereafter, MAB) weather stations, Kisumu Airport station for Kisumu city, and Mombasa International Airport (hereafter, MIA) and Mtwapa stations for Mombasa city.

For hospital data, we utilize data from two hospitals in each city in close proximity to the weather stations. For Nairobi, we obtained data from Mbagathi hospital and Mathari hospital. For Mombasa City, we utilize data from Port Reitz and Bomu hospitals, and Kisumu and Jaramogi General Hospitals for Kisumu city. Table 1 shows the weather stations and the corresponding hospitals used in the study. The hospital data is in the form of hospital visits, admissions, and mortalities. The data is obtained from a central repository operated by the ministry of health, where hospitals across the country transmit cases on a monthly basis. The data is normally the sum of all daily cases reported in that month. Unlike private hospitals, most daily records in public hospitals are currently available in hard copies only which made them unusable for the present study. It is important for this analysis to focus on public hospitals as the population sample of the patients is representative of vulnerable groups. While daily data would be preferable, there are some advantages to using monthly data. Namely, monthly data provides an aggregated view that is less prone to errors and other idiosyncrasies of data, making it more reliable. Additionally, monthly data also allows for easier comparison over time, as it is more likely to show clear trends than daily data. We, therefore, utilized the total monthly cases for the period 2011-2020. For visits, we utilised cases that were classified as heat-related by the doctors submitting the data. Heat exposure is known to have a complex set of physiological effects on multiple organ systems and body functioning, we, therefore, include all admissions and mortality cases with no particular stratification or categorisation in our analysis. Due to unexplained trends and gaps in mortality cases for hospitals in Mombasa city, we only analysed visits and admissions in that location. Ethics approval was obtained for our analysis of the hospital data.

***Table 1*: Weather stations and corresponding hospitals used in the study.**

Weather station	**Health facility**	**City**
Dagoretti	Mbagathi	Nairobi
Moi international Airbase (MAB)	Mathari	Nairobi
Kisumu International Airport	Jaramogi Oginga, Kisumu General	Kisumu
Mtwapa	Port Reitz General	Mombasa
Mombasa International Airport (MIA),	Bomu	Mombasa

4. Results

5.1 Temperature trends

Figure 2 presents trends in annual mean maximum (T_{max}) and minimum (T_{min}) temperatures from 1981-2020 for Dagoretti and MAB stations in Nairobi city. We see an upward trend in temperature in all the cities, particularly for T_{min}. Temperature trends for Kisumu Airport, MIA and Mtwapa stations show a similar pattern and are provided in the Annex.

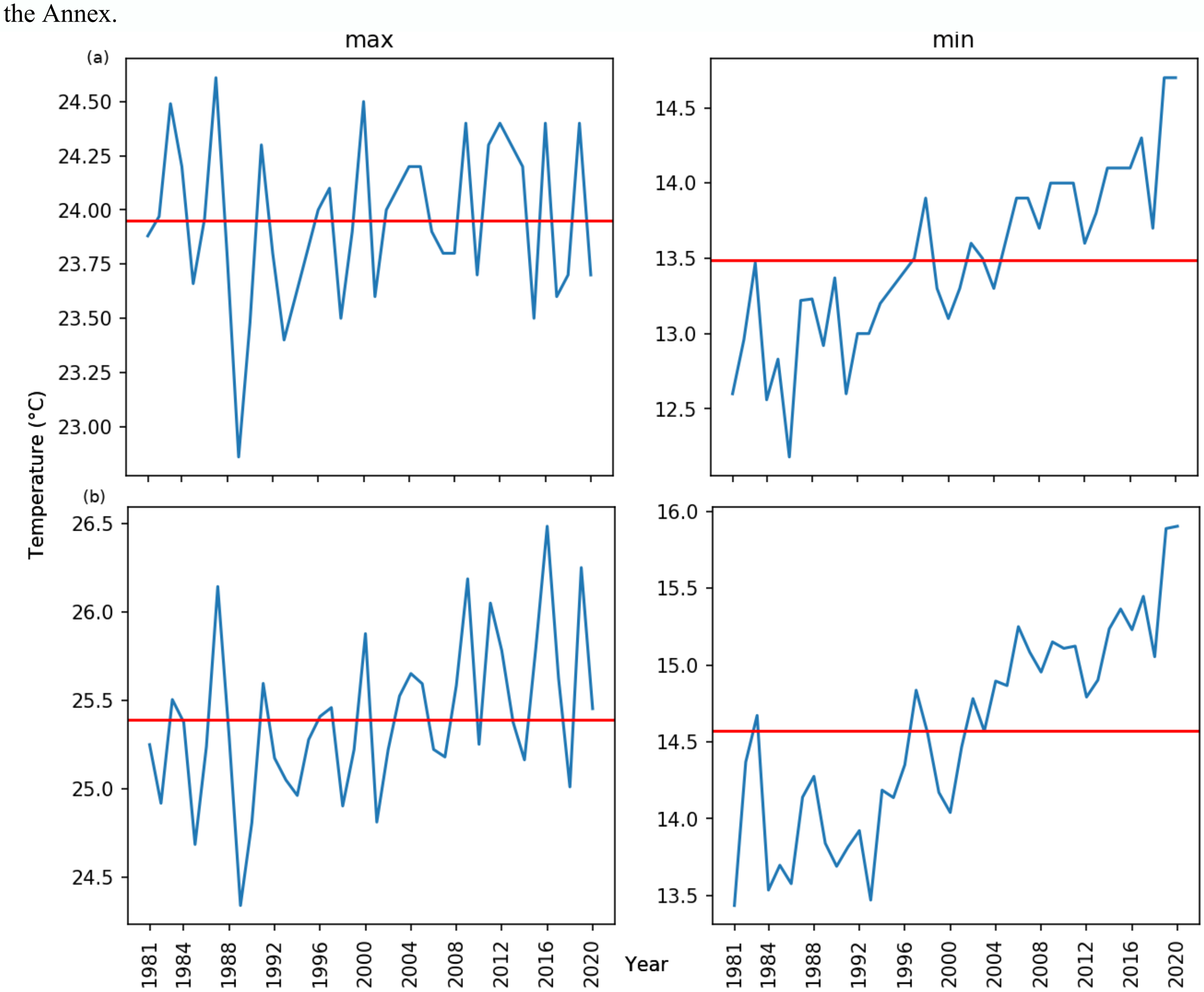

Figure 2. Trends in maximum and minimum tempearture for Dagoretti (a) and Moi Airbase (b) stations in Nairobi city for the period 1981-2020. The red line indicate the climatological mean

5.2 Local heatwave definitions

The daily distribution of maximum and minimum temperatures for the period 1981-2022 in three selected weather stations in Nairobi (MAB), Kisumu (Kisumu) and Mombasa (MIA) are shown in Figures 3(a) and 4(a). It can be noted that December to March is the warmest period of the year across the three cities, particularly for Mombasa. In general, seasonal variation in temperature in Kenya is dependent on the prevailing winds. From October to February the dominant flow is the hot and dry northerlies/northeasterlies from Arabia, while cooler and wetter southeasterlies (westerlies) from the Indian Ocean (Congo basin) prevail from April to September. As expected, Nairobi city which is located on the central highlands, experiences relatively cooler temperatures compared to the low-lying coastal city of Mombasa and the lake-side city of Kisumu (see section 3).

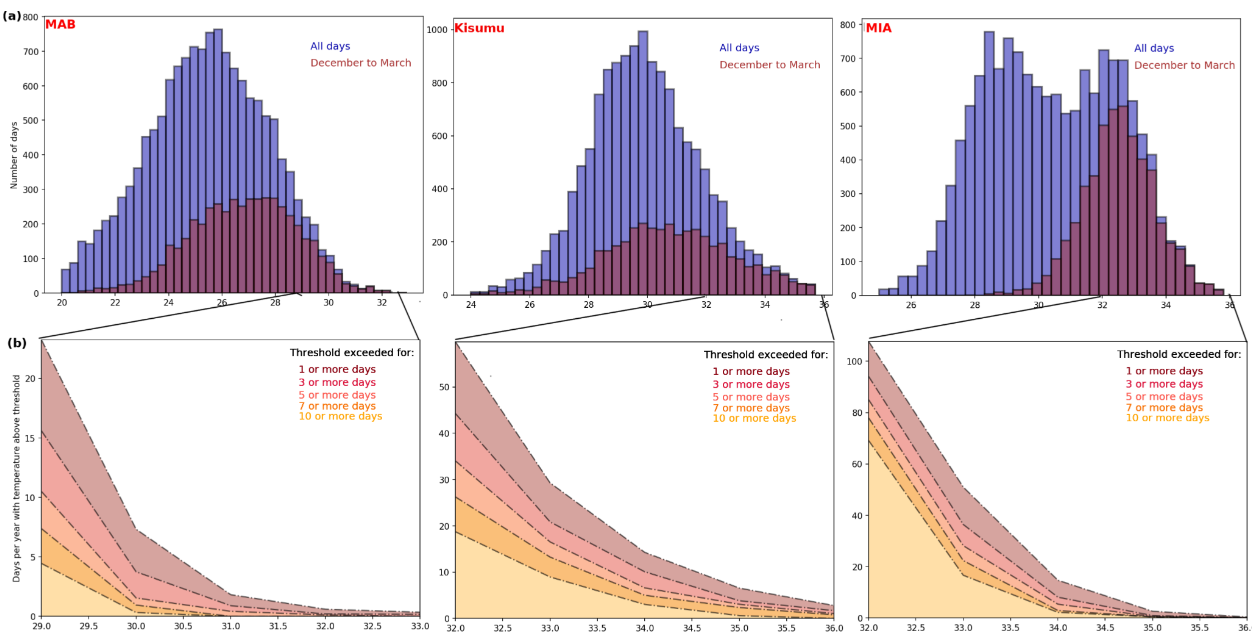

Figure 3. (a) Distribution of daily maximum temperatures for the period 1981-2020 in three selected weather stations: MAB, Kisumu and MIA in Nairobi, Kisumu and Mombasa, respectively. The purple bars show the distribution for all the days while the brown bars represent December to March days over the 40-year period. (b) The average number of days per year in exceedance of a specified daily maximum temperatures for the three selected weather stations.

Figures 3(b) and 4(b) show the frequency of exceedance for a given threshold in maximum and minimum temperatures respectively in the selected stations in Nairobi, Kisumu and Mombasa cities for the period 1981-2020. While the tails of the distribution seem similar across the three locations, exceedances of high thresholds of maximum temperature are more common in Mombasa and Kisumu compared to Nairobi. For instance, 33°C lasting for 10 days or more is exceeded some ten days per year on average in Mombasa and Kisumu. Furthermore, all the thresholds in maximum temperature are exceeded for at least 7 days in Kisumu. For minimum temperatures, however, the case is different for Nairobi. The distribution tail is relatively longer with a majority of the thresholds exceeded at least for 5 days. This shows that nighttime temperatures could be more significant for the characterization of heatwaves, especially with further global warming, as the tails are steeper and thus exceeding a high threshold, even for a short number of days will feel different for the population.

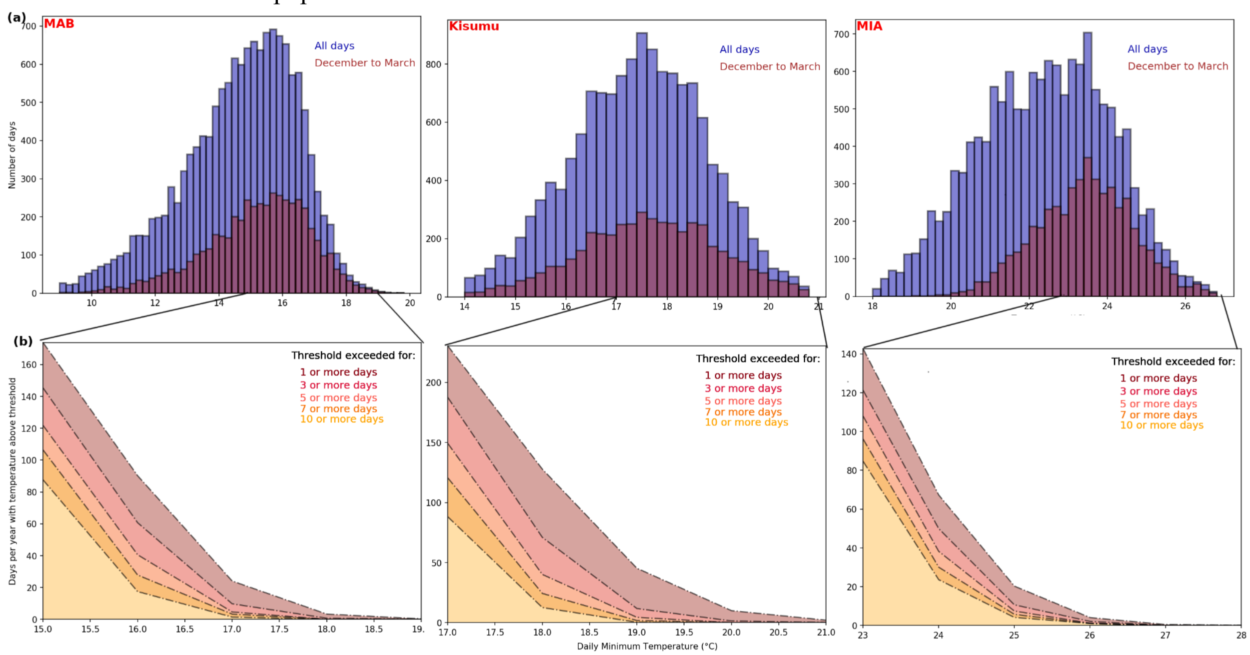

Figure 4. Figure 3. (a) Distribution of daily minimum temperatures for the period 1981-2020 in three selected weather stations: MAB, Kisumu and MIA in Nairobi, Kisumu and Mombasa cities, respectively. The purple bars show the distribution for all the days while the brown bars represent December to March days over the 40-year period. (b) The average number of days per year in exceedance of the specified daily manimum temperatures for the three selected weather stations.

Tables 2, 3 and 4 provide heatwave events defined by different integer thresholds of daily T_{max} and T_{min} exceeded consecutively for 1 to 10 days analyzed over the period 1981-2020 in the cities of Nairobi, Kisumu and Mombasa. These are the number of discrete occasions where exceedance of the specified temperature threshold occurred as part of a hot spell persisting for at least the indicated number of days. Observing the frequency of exceedance in Figures 3(a) and 4(a) for a given threshold in maximum and minimum temperatures, it is evident that acclimatization or 'comfort zone' varies between geographical locations and tends to be higher in warmer climates. Therefore to assess the impact of heat on health, we consider long-duration exceedance on high thresholds in defining local heatwaves in the three cities. For Nairobi city, we use 29°C T_{max} exceeded for 10 days or more in Dagoretti station (Table 2(i), green) and 30°C T_{max} exceeded for 10 days or more in MAB station. We consider nighttime temperatures of 17°C and 18°C exceeded for 4 days or more in two stations respectively. For Kisumu, we use 37°C T_{max} exceeded for 7 or more and 20°C T_{min} exceeded for 4 or more. For Mombasa, thresholds of 35°C T_{max} and 26 °C T_{min} exceeded for 10 days or more in MIA and 34°C T_{max} and 26 °C T_{min} exceeded for 10 days or more in Mtwapa are used to define the heatwaves.

Table 2. **Heat events defined by daily maximum and minimum temperature threshold equalled or exceeded for a given consecutive number days for Dagoretti (i) and Moi Airbase (ii) stations in Nairobi City from 1981-2020**

(i)

Number of consecutive days equal to or above threshold	Threshold (°C): Daily maximum temperature									
	23	24	25	26	27	28	29	30	31	32
1	1345	1360	1165	831	517	250	101	28	5	6
2	935	866	707	514	273	131	45	12	5	3
3	723	635	475	339	186	75	23	5	3	1
4	578	485	350	234	126	47	10	2	2	0
5	475	379	282	175	93	32	6	2	2	0
6	394	324	231	136	71	26	3	2	1	0
7	342	271	188	106	55	17	1	0	0	0
8	304	238	161	90	47	12	1	0	0	0
9	276	217	134	73	39	8	1	0	0	0
10	243	196	121	65	34	6	1	0	0	0

Number of consecutive days equal to or above threshold	Threshold (°C): Daily minimum temperature									
	11	12	13	14	15	16	17	18	19	20
1	897	1299	1541	1546	1301	431	69	10	4	3
2	718	982	1064	1004	648	136	17	3	1	0
3	601	767	777	691	362	66	7	0	0	0
4	515	611	565	510	225	31	1	0	0	
5	445	505	474	393	156	20	0	0	0	0
6	388	420	395	309	107	10	0	0	0	0
7	355	358	318	249	78	8	0	0	0	0
8	314	312	281	205	57	5	0	0	0	0
9	279	273	251	168	44	2	0	0	0	0
10	244	251	225	147	40	1	0	0	0	0

(ii)

	Threshold (°C): Daily maximum temperature									
	25	26	27	28	29	30	31	32	33	34
1	1354	1202	937	659	351	146	38	13	7	6
2	884	756	581	380	185	67	17	7	4	1
3	673	530	391	243	115	35	9	2	2	0
4	525	406	295	166	71	15	4	1	1	0
5	421	324	224	119	53	8	3	1	0	0
6	355	276	178	93	40	8	2	0	0	0
7	301	231	148	71	30	4	0		0	0
8	256	203	122	60	25	3	0	0	0	0
9	222	177	102	53	17	3	0	0	0	0
10	201	153	86	47	15	1	0	0	0	0

	Threshold (°C): Daily minimum temperature									
	12	13	14	15	16	17	18	19	20	21
1	784	1161	1468	1516	1332	553	96	12	3	2
2	626	876	1029	950	700	195	25	0	0	0
3	527	683	734	663	426	88	9	0	0	0
4	425	547	553	492	283	41	2	0	0	0
5	364	444	455	385	189	25	0	0	0	0
6	308	379	377	323	140	19	0	0	0	0
7	278	332	317	272	96	15	0	0	0	0
8	245	300	290	234	76	8	0	0	0	0
9	224	265	257	197	63	6	0	0	0	0
10	207	242	227	176	44	5	0	0	0	0

Table 3. **Heat events defined by daily maximum and minimum temperature threshold equalled or exceeded for a given consecutive number days for Kisumu Airport station in Kisumu City from 1981-2020**

Number of consecutive days equal to or above threshold	Threshold (°C): Daily maximum temperature									
	30	31	32	33	34	35	36	37	38	39
1	1472	1145	756	391	210	111	46	18	4	1
2	906	645	394	192	102	48	24	5	1	1
3	640	462	265	123	72	25	13	2	1	0
4	513	350	182	92	47	20	10	2	1	0
5	416	273	142	72	31	16	6	1	0	0
6	356	219	111	59	23	14	5	1	0	0
7	308	172	85	48	19	11	4	1	0	0
8	258	145	70	37	14	7	2	0	0	0
9	225	125	59	33	13	4	1	0	0	0
10	200	109	47	26	9	2	0	0	0	0

	Threshold (°C): Daily minimum temperature									
	14	15	16	17	18	19	20	21	22	23
1	128	459	1299	2324	2373	1244	327	72	16	2
2	118	394	1007	1446	1072	334	50	7	1	0
3	109	364	818	1026	586	118	17	1	0	0
4	100	327	692	751	329	56	4	0	0	0
5	94	301	597	574	213	29	0	0	0	0
6	92	287	520	450	138	15	0	0	0	0
7	91	267	454	362	95	9	0	0	0	0
8	88	253	406	294	66	3	0	0	0	0
9	87	241	356	241	45	1	0	0	0	0
10	83	227	327	197	34	1	0	0	0	0

Table 4. **Heat events defined by daily maximum and minimum temperature threshold equalled or exceeded for a given consecutive number days for Mombasa International Airport (i) and Mtwapa (ii) stations in Mombasa City from 1981-2020**

(i)

Number of consecutive days equal to or above threshold	Threshold (°C): Daily maximum temperature									
	28	29	30	31	32	33	34	35	36	37
1	743	904	745	670	736	663	274	62	9	2
2	546	561	446	417	441	331	112	17	2	1
3	431	427	325	324	316	206	61	6	2	0
4	358	330	263	255	246	144	38	4	2	0
5	310	270	226	219	208	108	28	2	1	0
6	272	239	196	194	174	83	18	1	0	0
7	251	216	175	171	155	65	10	1	0	0
8	225	199	158	155	139	58	7	1	0	0
9	209	182	143	140	127	48	6	1	0	0
10	194	160	134	128	111	37	6	1	0	0

Number of consecutive days equal to or above threshold	Threshold (°C): Daily minimum temperature									
	19	20	21	22	23	24	25	26	27	28
1	238	566	912	999	1081	839	386	83	15	2
2	175	386	561	599	609	417	136	25	3	1
3	148	283	379	446	416	281	68	15	1	0
4	126	217	285	347	329	190	48	[illegible]	0	0
5	112	184	230	289	261	141	31	4	0	0
6	102	160	195	238	212	102	21	4	0	0
7	94	146	168	209	174	80	18	3	0	0
8	88	124	155	188	146	67	14	3	0	0
9	82	108	136	168	129	53	13	3	0	0
10	78	99	122	148	115	47	10	3	0	0

(ii)

	Threshold (°C): Daily maximum temperature									
	27	28	29	30	31	32	33	34	35	36
1	392	775	723	598	731	676	313	55	8	1
2	331	529	428	389	455	366	132	14	2	0
3	293	411	326	305	338	256	82	6	2	0
4	258	342	272	249	272	194	50	3	2	[illegible]
5	241	282	222	221	233	151	33	1	1	0
6	218	254	199	191	196	120	21	1	0	0
7	202	232	181	173	176	104	15	1	0	0
8	194	201	166	162	155	85	14	1	0	0
9	179	187	153	145	137	71	13	1	0	0
10	168	170	137	136	127	66	7	1	0	0

	Threshold (°C): Daily minimum temperature									
	19	20	21	22	23	24	25	26	27	28
1	74	295	803	1326	1387	1141	567	152	25	3
2	71	236	562	823	767	555	234	43	7	1
3	63	204	417	563	518	357	130	19	1	0
4	60	185	332	421	380	237	67	12	0	0
5	56	169	279	339	300	180	45	8	0	0
6	54	154	236	277	246	134	30	7	0	0
7	54	143	210	244	210	107	25	5	0	0
8	51	132	185	219	183	85	18	3	0	0
9	48	122	167	192	166	69	15	3	0	0
10	45	113	155	165	149	62	11	3	0	0

5.3 Heat-health associations

Extreme heat is likely to trigger thermal discomforts which may increase incidence of heat-related illnesses and/or death. For every heatwave identified in section 2 (based on both T_{max} and T_{min}), we identify the number of hospital visits, admissions and deaths in the corresponding month in comparison with cases in that particular month over the entire period. Focusing on a particular month i.e. assessing individual months separately, we avoid the possible effect of the seasonal cycle of temperature on the hospital cases or other seasonality effects which could be related to things independent of the weather, e.g. holiday season. As a case study, we focus our heat-impact analysis on March 2016 since most of the identified heatwaves occurred during this period. For hospital visits, we only utilize heat-related visits while all reported cases of admissions and deaths are considered.

In the other approach, we assess the temperature conditions that prevailed when the highest number of visits, admissions and mortalities were recorded in each of the hospitals. Taking the highest spike in particular cases, we check for any coinciding identifiable discrete events in either maximum or minimum temperatures. We also note any elevated cases reported in the preceding or succeeding month in an attempt to highlight the probable delayed effect of heat on health, especially on mortality. The results are discussed per city in the subsections below.

Further to the assessments based on already identified heat waves, we statistically tested for correlations between the monthly time series of T_{max} and T_{min} at each weather station with the monthly admissions, visits and deaths at the nearest hospital. A t-test of significance of the correlations was carried out at the 5% significance level. Because six correlations were calculated between dependent variables for each station-hospital pair, a Bonferroni correction was applied to reduce the risk of falsely identifying spurious correlations due to carrying out multiple tests. The threshold for significance is therefore 0.05 / 6 = 0.00833. Pearson correlation coefficients and p-values for those pairs of variables for which the correlation was found to be significantly different from zero are shown in Table 5 (see, section 5.4).

5.3.1 Nairobi city

Based on the thresholds defined in section 5.2, four heatwaves events were identified in Nairobi city in the period 2011- 2020: 10-day 29°C T_{max} (March 22-31 2016), 4-day 17°C T_{min} (April 16-19 2020) in Dagoretti station, 13-day 30°C T_{max} (March 19-31 2016) and 4-day 18°C T_{min} (March 30- April 02 2016) in MAB station (Table1). Figures 5 and 6 show the total monthly visits, admissions, and mortalities for March (2011-2020) for Mbagathi and Mathari hospitals (green), respectively. The dotted black line shows the mean monthly maximum (5a, 6a) and minimum (5b, 6b) temperatures in March (2011-2020) for Dagoretti and MAB weather stations, respectively. The dots indicate the 2016 value.

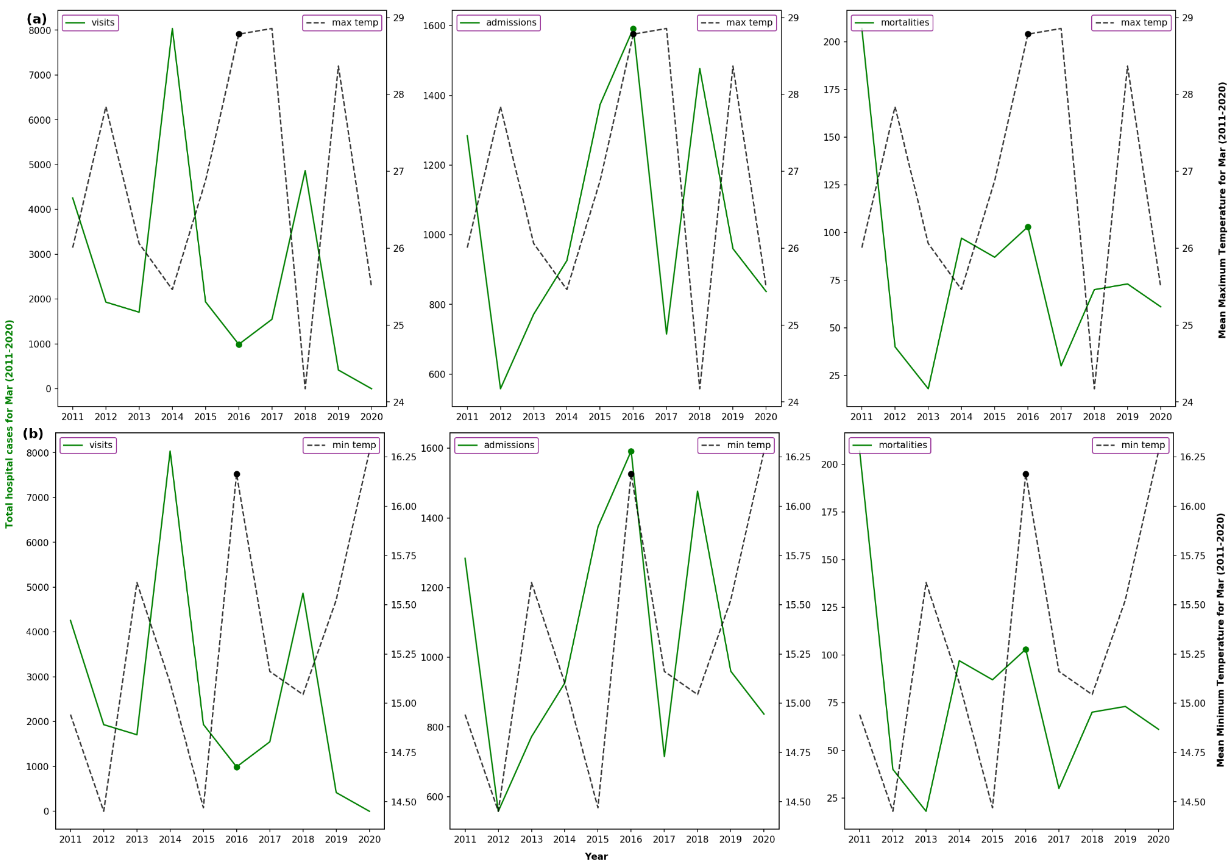

Figure 5. **Total monthly visits, admissions & mortalities in Mbagathi hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at Dagoretti weather station for March (2011-2020) in Nairobi city. The dot indicates the March 2016 value.**

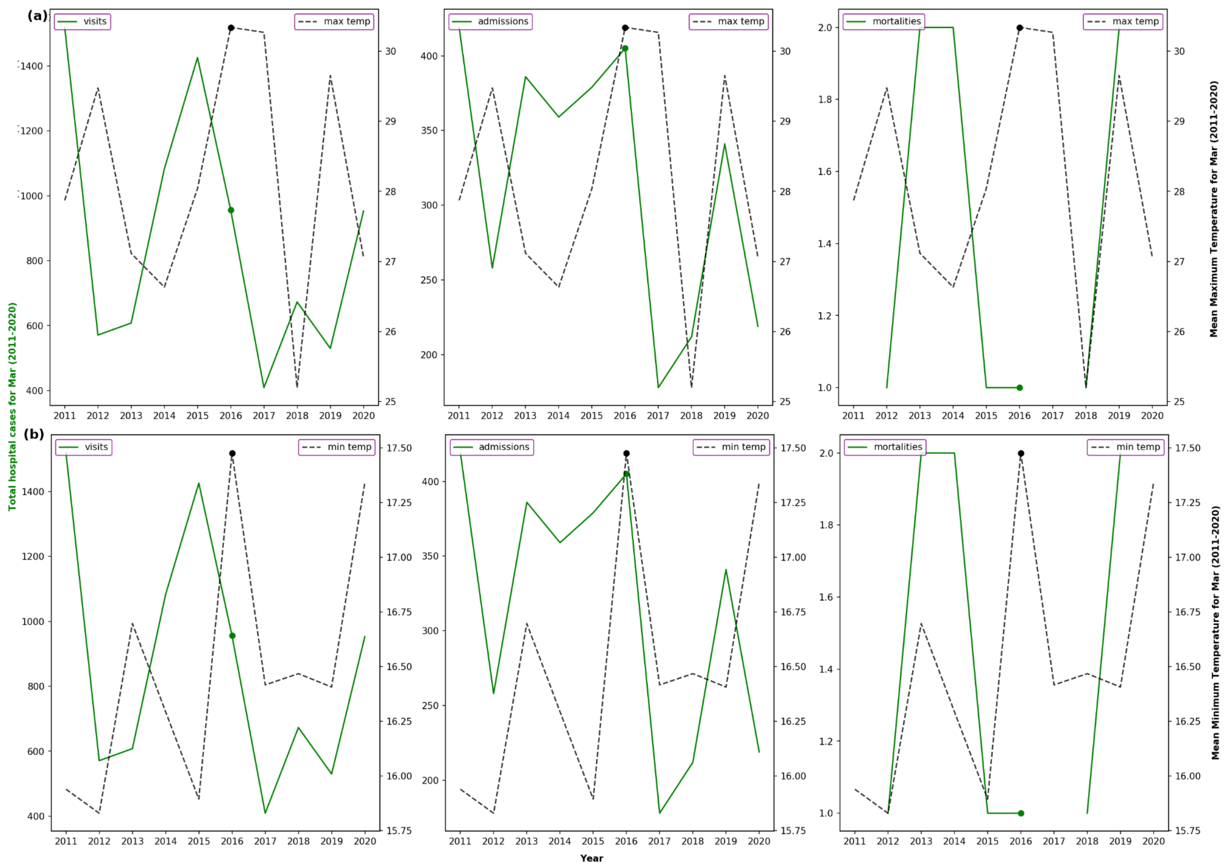

Figure 6. **Total monthly visits, admissions & mortalities in Mathari hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at MAB weather station for March (2011-2020) in Nairobi city. The dot indicates the March 2016 value.**

Figure 7 shows the total monthly hospital cases (visits, admisions, mortalities) in Mbagathi and Mathari hospitals, respectively for the period 2011-2020. The annotated texts show the period (year-month) in which the highest number of cases were reported. In Mbagathi hospital, a spike in visits was experienced in March 2014, while a spike in admissions and deaths occurred in October 2019 and March 2011, respectively. For Mathari, the highest number of visits was recorded in March 2011 while admissions and deaths reached highest levels in September 2016 and August 2013.

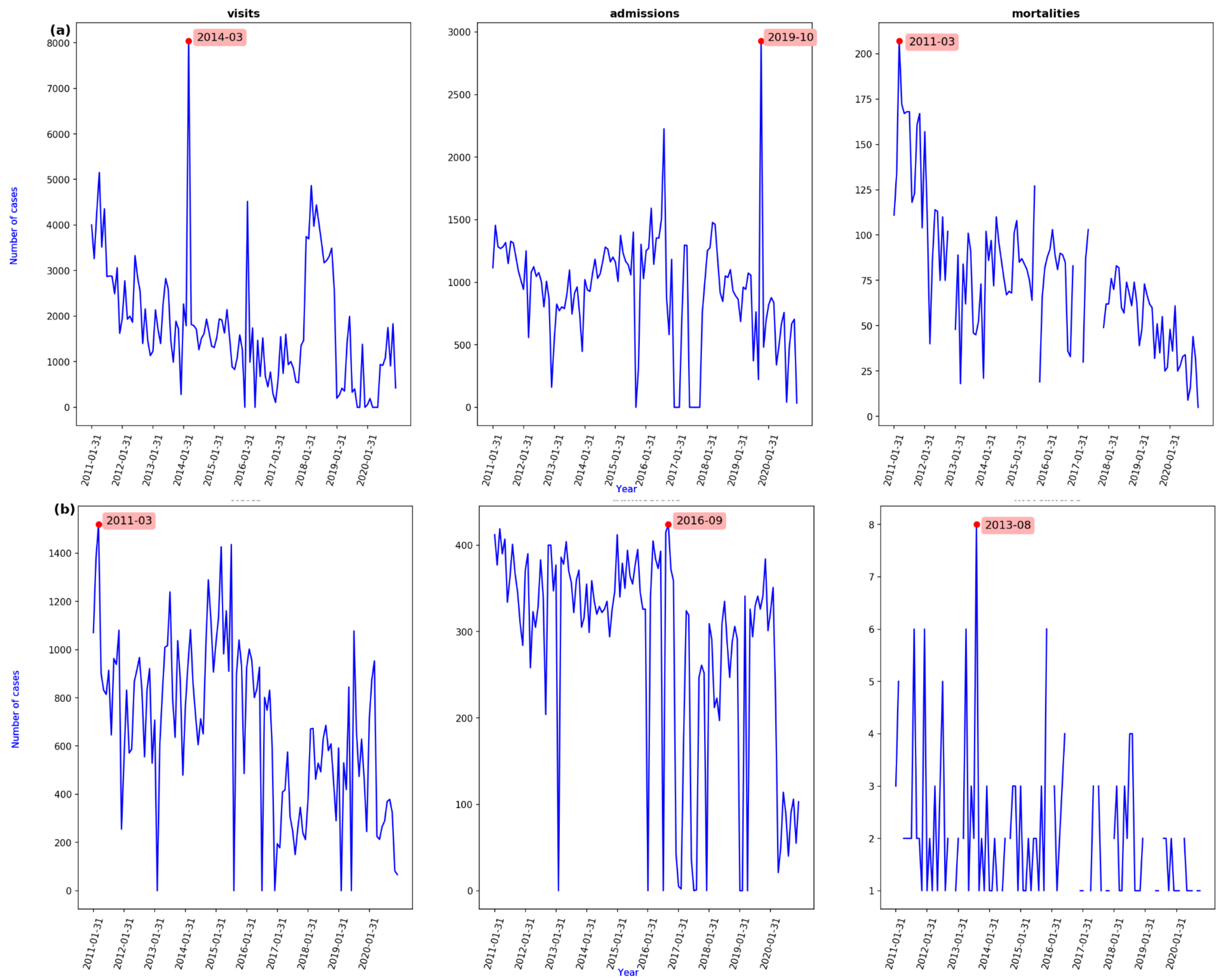

Figure 7. **Total monthly visits, admissions, and mortalities reported in Mbagathi (a) and Mathari (b) hospitals in Nairobi city for the period 2011-2020. The annotation indicates the period (year-month) in which the highest number of cases were reported.**

5.3.2 Kisumu city

From table 2, four heatwave events were identified for Kisumu city: 7-day 37°C T_{max} (March 25-31 2016) , 4-day 20°C T_{min} (March 08-11 2014), 4-day 20°C T_{min} (January 08-11 2016) and 4-day 20°C T_{min} (March 01-04 2016). Figures 8 and 9 show the total number of visits, admissions, and mortalities reported in Kisumu and Jaramogi General hospitals (green), respectively and mean monthly maximum (black; 8a, 9a) and minimum (black; 8b, 9b) in Kisumu station for March in the period 2011-2020.

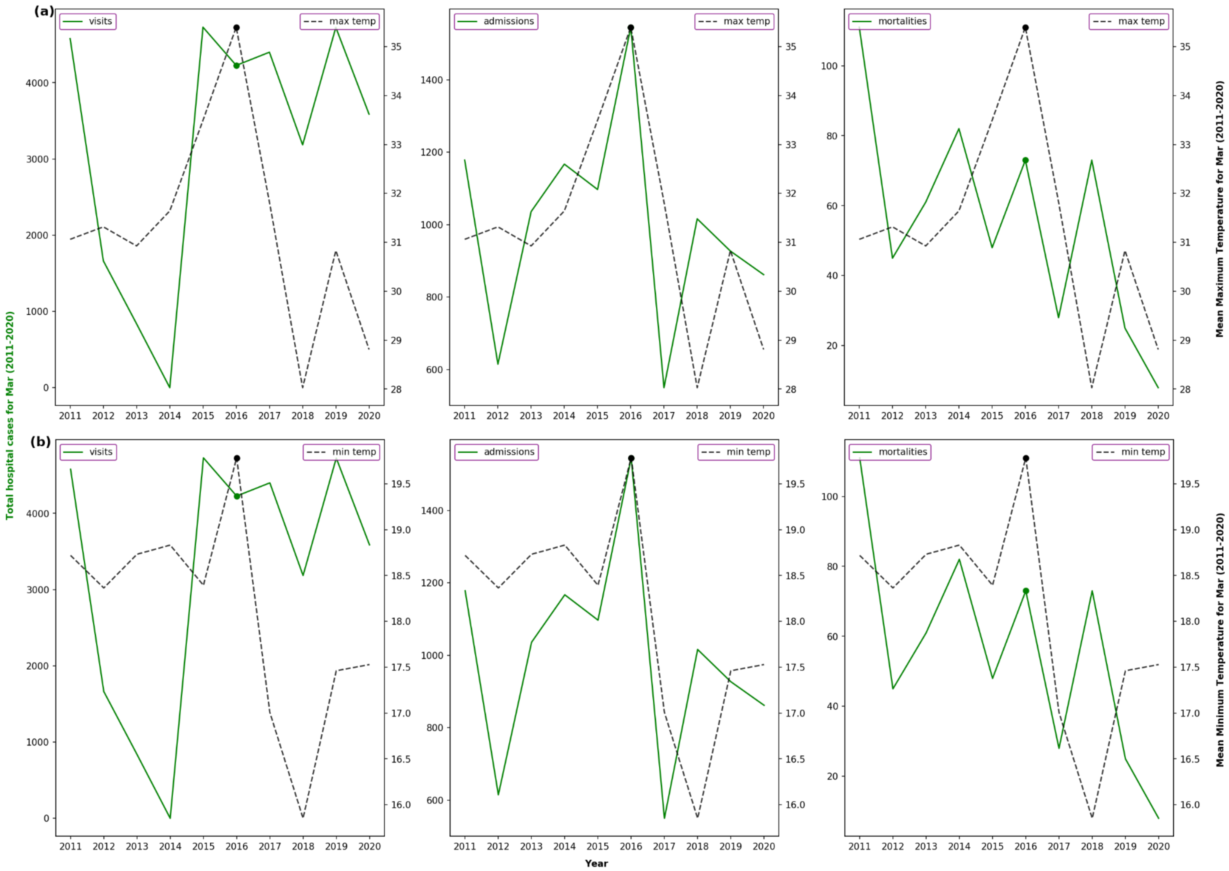

Figure 8. **Total monthly visits, admissions and mortalities in Kisumu General hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at Kisumu weather station for March (2011-2020) in Kisumu city. The dot indicates the March 2016 value.**

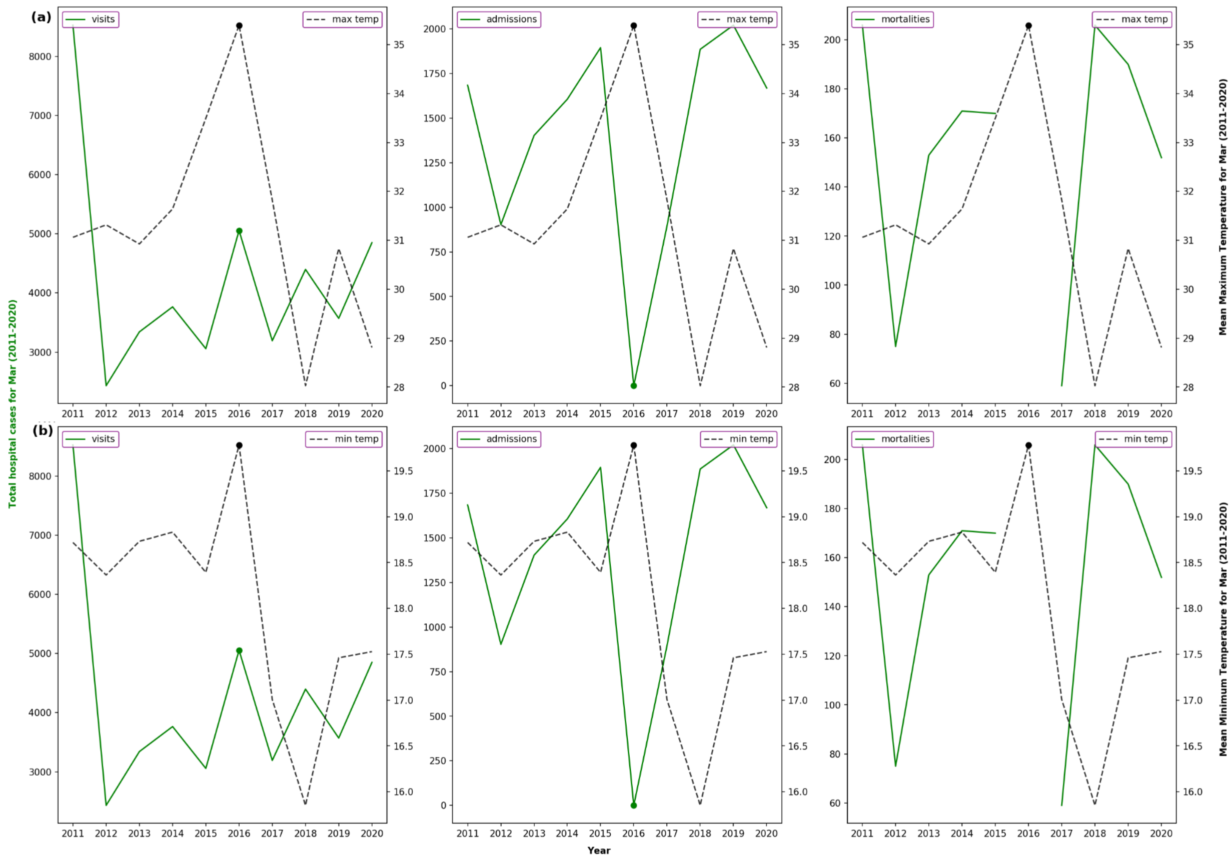

Figure 9. **Total monthly visits, admissions and mortalities in Jaramogi General hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at Kisumu weather station for March (2011-2020) in Kisumu city. The dot indicates the March 2016 value.**

Figure 10 shows the total monthly hospital cases (visits, admissions, mortalities) reported in Kisumu (a) and Jaramogi (b) General hospitals for the period 2011-2020. The annotated texts show the period (year-month) in which the highest number of cases were reported. In Kisumu General Hospital, the highest number of visits was recorded in January 2016, admissions in June 2016 and deaths April 2016. For Jaramogi, highest visits were recorded in February 2011, admission in June 2015 and deaths in May 2017.

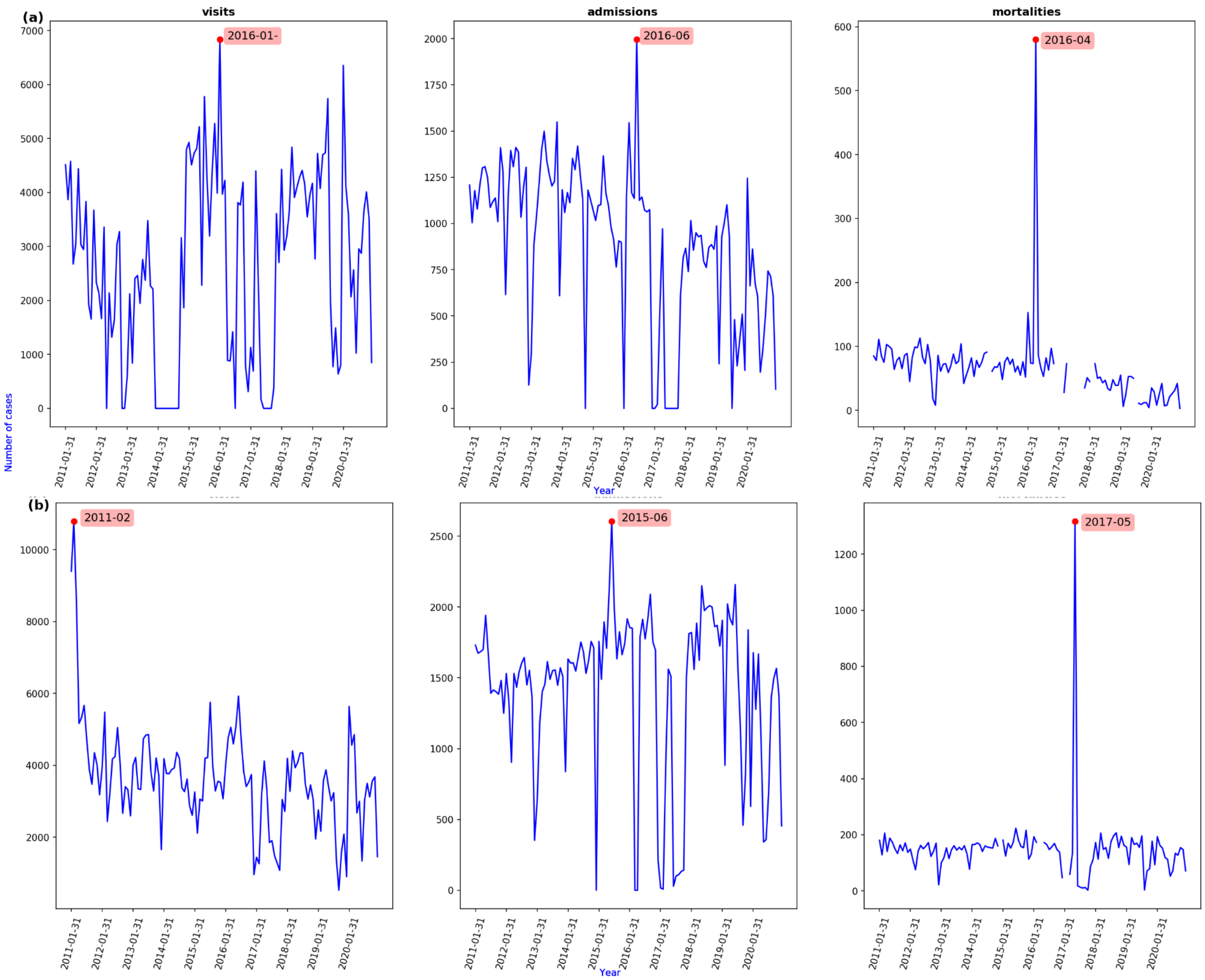

Figure 10. **Total monthly visits, admissions and mortalities reported in Kisumu General (a) and Jaramogi General (b) hospitals in Kisumu city for the period 2011-2020. The annotation indicates the period (year-month) in which the highest number of cases were reported.**

5.3.3 Mombasa city

We identified eight heatwave events in Mombasa city: 20-day 35°C T_{max} (March 13-31, 2016), 16-day 26°C T_{min} (April 16-31, 2016), 10-day 26°C T_{min} (25 April- 04 May 2019), 15-day 26°C T_{min} (March 07-21, 2020) in MIA station, and 19-day 34°C T_{max} (March 12-31, 2016), 17-day 26°C T_{min} (March 15-31, 2016), 11-day 26°C T_{min} (April 25- May 04, 2019), 16-day 26°C T_{min} (March 06-21, 2020) in Mtwapa station (Table 3). Figures 11 and 12 show the total monthly hospital visits, admissions and deaths (green) in March for the period 2011-2020 in Bomu (a) and Port Reitz (b) hospitals. The black dotted lines indicate the mean monthly maximum (11a, 12a) and minimum (11b, 12b) temperatures for March in the period 2011-2016. We opted to omit mortality cases in our analysis for Mombasa due to huge gaps in the data.

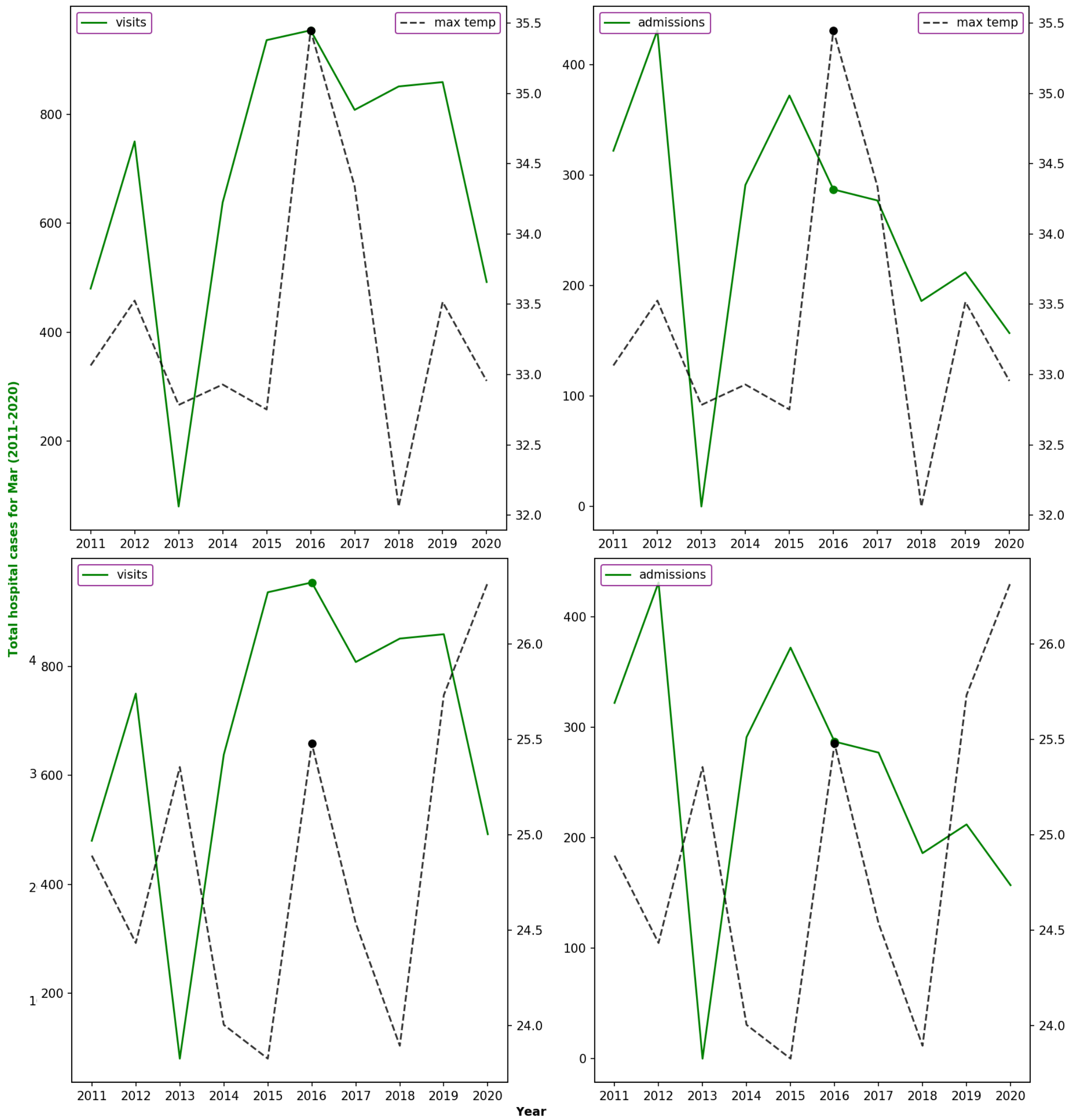

Figure 11. **Total monthly visits, admissions and mortalities in Bomu hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at MIA weather station for March (2011-2020) in Mombasa city. The dot indicates the March 2016 value.**

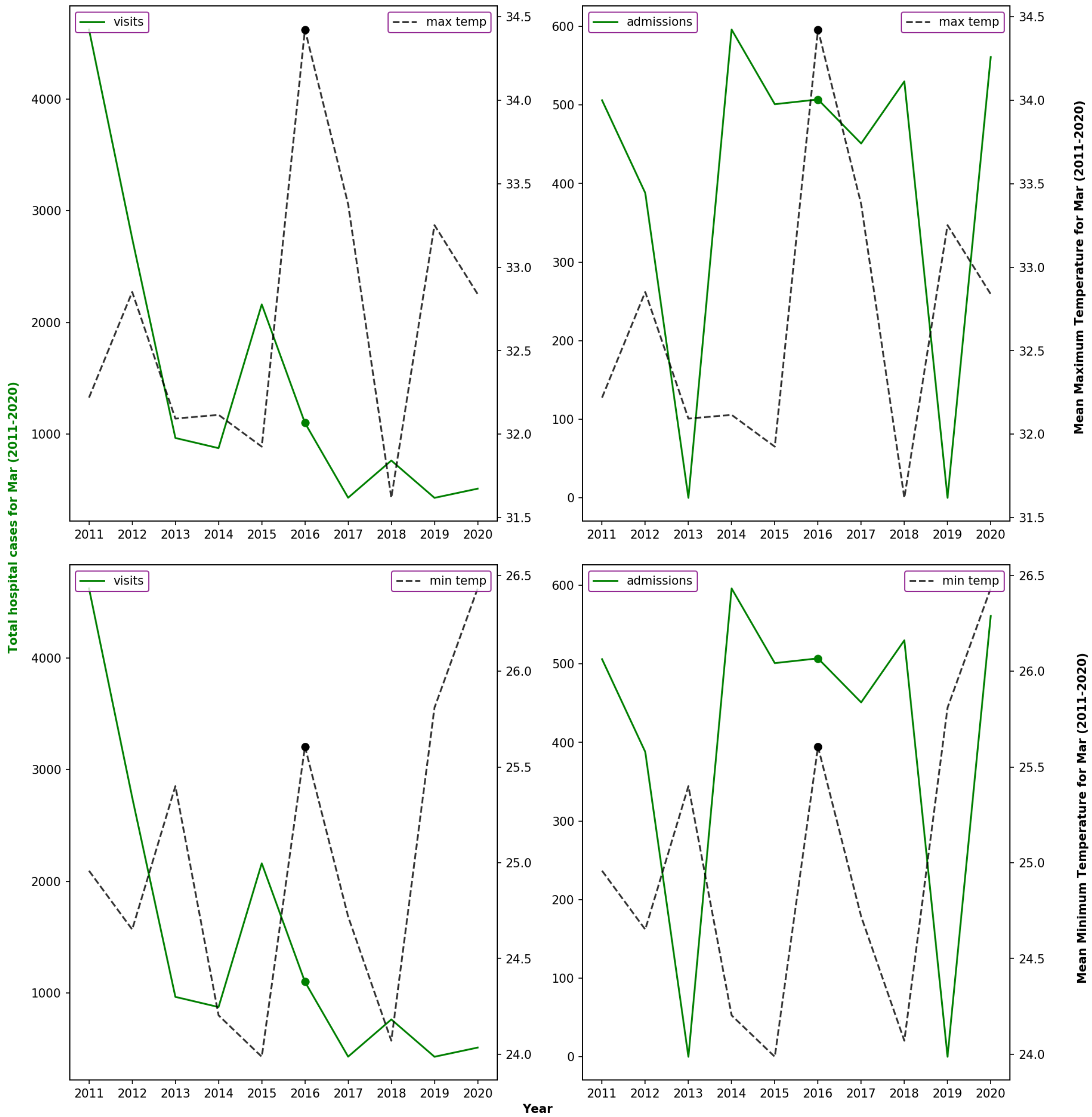

Figure 12. **Total monthly visits, admissions and mortalities in Port Rietz hospital (green; a,b), and mean maximum (black; a) and minimum (black; b) temperature at Mtwapa weather station for March (2011-2020) in Mombasa city. The dot indicates the March 2016 value.**

Analysis of trends in total monthly cases in Mombasa city (figure 13) shows that Bomu hospital recorded its highest visits in May 2018 and admissions in January 2012 while Port Rietz recorded spikes in hospital visits in March 2011 and admissions in June 2015.

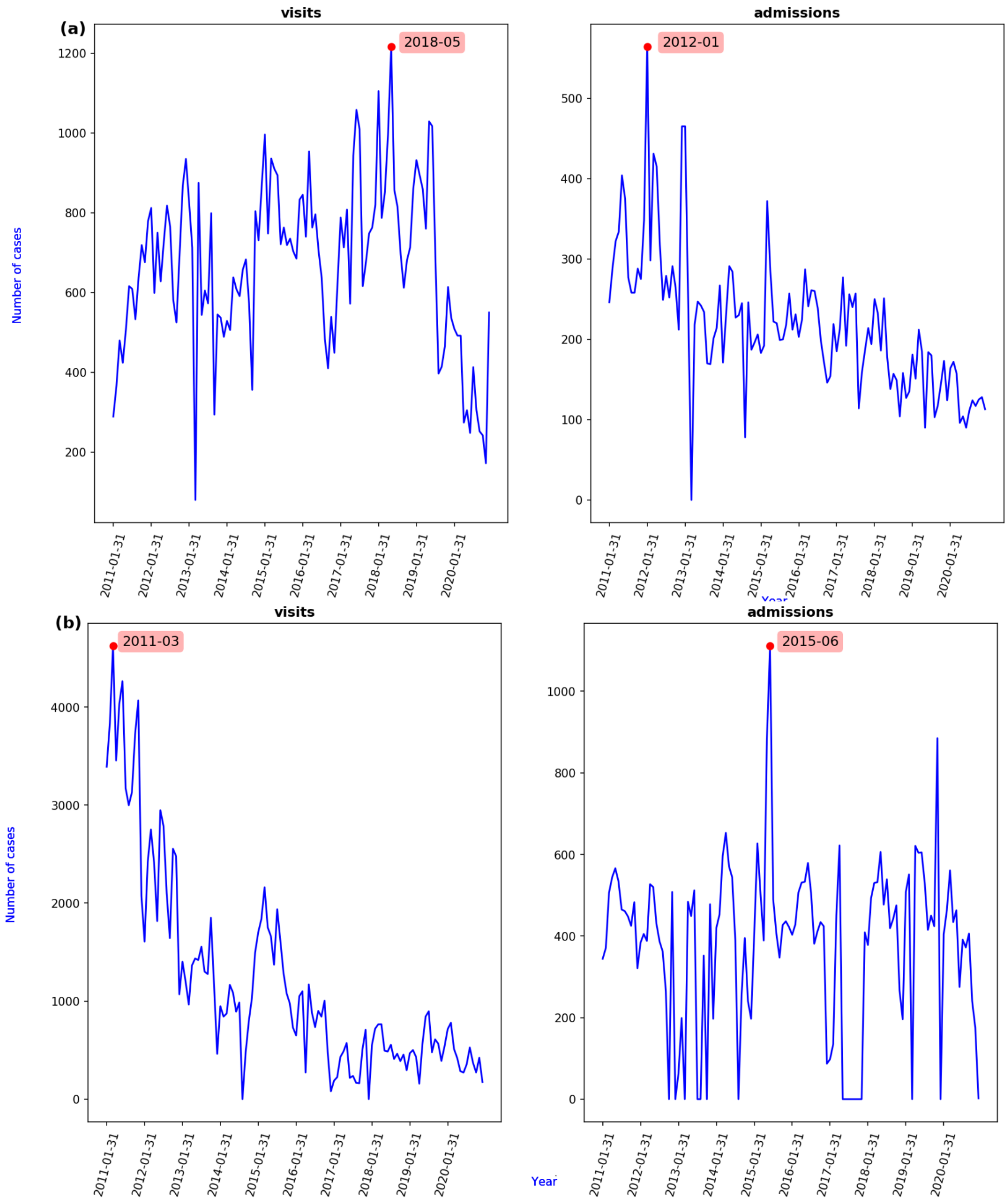

Figure 13. **Total monthly visits, admissions and mortalities reported in Bomu (a) and Port Reitz (b) hospitals in Mombasa city for the period 2011-2020. The annotation indicates the period (year-month) in which the highest number of cases were reported.**

5.4 Statistical testing

There are only significant correlations between maximum temperatures and admissions and deaths in Mombasa. For Nairobi and Kisumu, we find a significant correlation between minimum temperatures and deaths, and in Kisumu also between minimum temperatures and admissions. No statistically significant correlations between hospital visits and temperatures were found. The correlations that were found, although statistically significant, were all very low, and do not suggest a common relationship between either maximum or minimum temperatures and hospital admissions or deaths. As we will discuss further below (section 6), this should not be interpreted as evidence that no such relationships exist, it does only mean that they cannot be detected in the data available to us.

***Table 5.* Pearson correlation coefficients and p-values for pairs of variables i.e hospital data and temperature with significant correlations in the three cities**

Hospital	Temp variable	Hosp variable	Correlation	p-value
Bomu	T_{max}	Deaths	0.26	0.0044
Bomu	T_{max}	Admissions	0.26	0.0036
Kisumu	T_{min}	Deaths	0.36	0.0001
Kisumu	T_{min}	Admissions	0.30	0.0015
Mathari	T_{min}	Deaths	-0.28	0.0059

5. Discussions and Conclusions

6.1 Heatwave definitions for early warning

This study constitutes the first systematic analysis of heat-health association in three Kenyan cities in an attempt to identify heatwave definitions for each city that can be used by the met services and city authorities to issue heatwave warnings. In each city, we have analyzed approximately 10 heatwave events in the period 2011-2020 based on thresholds in maximum or minimum temperature. In many cases, the events identified are identical across the three cities, in terms of duration and time of occurrence. By far most extreme and outstanding event is an episode of extreme heat in March 2016 that lasted for at least 7 days in each city. We therefore have a particular focus of our heat-health impact analysis on March 2016, and we also assess the month of March individually across the period. For Mbagathi hospital in Nairobi, the results show a spike in admissions in March 2016 with the second highest mortality records (figure 5). Visits, however, were among the lowest in the entire period. We see a somewhat similar pattern in the annual variation of admissions and mean T_{max} and T_{min} across all Marchs in the period i.e. higher admissions at higher temperatures and vice versa across the period. Visits and mortalities do not exhibit any correlation with maximum or minimum temperatures. This could have several reasons. On the one hand, due to a lack of awareness of heat related illnesses people might underestimate the seriousness of a situation and not go to hospital. On the other hand, associations between meteorological conditions and health effects can be non-linear and with delayed effects (e.g Yu et al., 2022) and so a correlation exists but does not show up in this initial analysis. The correlations between either maximum or minimum temperatures and hospital admissions or deaths are statistically significant, albeit very low.

Given the monthly resolution and short length of the health records, the data might simply not be detailed enough to identify correlations. We thus take this lack of correlation not as evidence of the absence of such a correlation.

Mathari hospital also recorded among its highest admission cases in March 2016 (figure 6). Like Mbagathi, no considerable changes in visits and deaths were observed. However, only a maximum of two deaths were reported at the hospital over the entire period, thus limiting our ability to deduce any meaningful information on heat-mortality relationship. A correlating pattern in temporal variations in the admissions and temperature exists albeit not entirely consistent across the periods. Looking at periods when the two hospitals had their largest spikes in hospital cases (figure 7; all months in the period 2011-2020), we do not identify any coinciding heatwave events. During these periods, the average temperatures at Dagoretti station were 25.4 T_{max} and 15.1 T_{min} in March 2014 (highest visits in Mbagathi), 23.1 T_{max} and 15.0 T_{min} in October 2019 (highest admissions in Mbagathi) and 26.1 T_{max} and 14.9 T_{min} in March 2011 (highest mortalities in Mbagathi). For MAB station, averages were 27.8 T_{max} and 15.9 T_{min} in March 2011 (highest visits in Mathari), 26.6 T_{max} and 13.7 T_{min} in September (highest admissions in Mathari) and 22.8 T_{max} and 13.2 T_{min} in August (highest deaths in Mathari). It's noteworthy that a 6-day hotspell of 30°C T_{max} was recorded in February 2011 in MAB station. This could be a possible case of delayed heat-health impact on mortalities and admission recorded in Mbagathi and Mathari, respectively.

For Kisumu city, Jaramogi hospital recorded the second-highest visits and lowest cases of admissions in March 2016 (figure 8). No mortalities were recorded. In Kisumu hospital, highest admissions and relatively high visits and deaths albeit no remarkable spikes were also recorded (figure 9). We see a similar trend in the variation of heat and health impacts in both hospitals, especially for admissions. Looking at spikes in hospital data first, we see that Kisumu recorded its highest visits in Jan 2016, admission in June 2016 and mortalities in April 2016 (figure 10). The April spikes in mortalities could be linked to the two heatwaves events in March, another possible case of delayed effect of heat on mortalities. A 4-day heatwave in 2016 January (exceeding 20°C T_{min} ; see annex, Figure) could explain the spikes in hospital visits. No identifiable hot spells were found in June 2016; the average T_{max} and T_{min} were 31.2°C and 17.9°C respectively. In Jaramogi hospital, the highest number of visits, admissions and deaths were recorded in February 2011; June 2015 and May 2017, respectively. No heatwaves were recorded during these periods as average temperatures in 2011 February stood at 32°C T_{max} and 17.5°C T_{min} ; 2015 June at 28.5°C T_{max} and 18.5°C T_{min} and May 2017 at 29.8°C T_{max} and 18.1°C $T_{min.}$

For Mombasa city, analysis of hospital cases in March 2016 shows the highest spike in visits and relatively high admissions in Bomu hospital (figure 11). Due to gaps and unexplained variations, we do not analyze mortality data for Mombasa. Relatively high admissions were also reported in Port Rietz (figure 12). We see a somewhat similar pattern in variations of admissions and Tmax in the two hospitals across the period. No identifiable heatwaves occurred when the highest cases were recorded in the two hospitals in Mombasa (figure 13). In May 2018 (highest visits in Bomu) average temperatures in MIA station were 29.4°C T_{max} and 21.3°C T_{min}; 32.8T_{max} and 23.9T_{min} in January 2012 (highest admissions in Bomu); 33 T_{max} and 24.9 T_{min} in March 2011 (highest visits in Port Rietz) and 29.6 T_{max} and 22 T_{min} in June 2015 (highest admissions in Port Rietz).

Although it is difficult to conclude that the spikes in hospital cases have been caused by the extreme heat conditions in March, we do see a very consistent pattern with admissions that allows us to tie admission spikes to the heat in the three cities. In all cases, Nairobi, Kisumu and Mombasa, our findings show that high temperatures are positively associated with admissions. We also see similar patterns in temporal variation of admissions and temperatures during the period 2011- 2020 in all the hospitals across the three cities. Excessive heat can cause an increase in dehydration, cardiac output and respiratory problems. This can exacerbate conditions of patients with pre-existing conditions, the elderly, very young, overweight or pregnant patients. Also, certain medications can increase patients' risk of adverse outcomes during extreme heat (Nitschke et al. 2011). Our results further indicate potential delayed effects of heat on health mortality. Evidence that heat waves raise hospital admissions across numerous demographic and disease categories (e.g Davis and Novicoff, 2018; Bobb et al. 2014; Zhang et al. 2016) suggests that extreme heat exerts comorbidity influences that extend beyond the more well-studied direct relationships such as heat strokes and cardiac arrest. Our ability to draw conclusions between observed heat extremes and their subsequent health impacts is inherently constrained by the quality and consistency of available health data. High levels of variability in hospital visits and admissions data - including unexplained "zero-admission" months and other unusually extreme peaks - suggest that any results which show an absence of health impacts associated with extreme hot spells should be viewed as preliminary rather than definitive and as absence of evidence rather than evidence of absence. The results we observe corroborate however the meteorology-based definitions and we thus conclude that these are a good starting point for early warning. Our second approach, based on heat-health associations does not provide additional definitions or suggest modifications, at least for an initial early warning definition. This might change however with longer available health data and global warming (6.2).

In conclusion, we suggest to use the following heatwave definitions for issuing heat-health alert warnings in Nairobi, Kisumu and Mombasa respectively:
Nairobi: daily max of 32°C+ for 3 or more days.
Kisumu: daily max of 37°C+ for 3 or more days
Mombasa: daily max of 36°C+ for 3 or more days.
Further research is needed to disaggregate the relative importance of extreme daytime temperatures versus persistently high overnight temperatures when identifying heat-related health impacts, particularly for cities like Mombasa. This question is all the more critical since overnight warming rates are much higher than corresponding trends in daily temperature maxima for all cities considered in this study. Further disaggregating the cause of these contrasting warming trends and particularly the role of urbanization versus climate-only drivers will also be important to topics of future research. Additional research is also needed to understand the relative risks associated with chronic exposure to high temperatures (i.e. thresholds which are exceeded for weeks at a time) versus punctuated spells of several days where those same thresholds are only exceeded by another two or three degrees. Also, there is scope for further work to investigate the potential exposure-lag response association between temperature and in-hospital mortality.

6.2 Evolution of heatwave definitions in a warming climate

As the climate continues to warm, understanding of the time-varying behaviour of extremes and their associated impacts is crucial for risk management. The fact that the thresholds are mainly based on maximum temperature, which have comparably weak trends means the thresholds will be usable for a while. This is in contrast to other parts of the world, where trends in maximum temperatures are extremely strong (Fischer et al., 2021). Strong trends means that current trend assessments or attribution studies are comparably useless for adaptation and long-term health planning (Harrington et al. 2022), given the strong trends and steep tails in minimum temperatures in all three cities it is thus important to monitor these trends and continue to assess them against hospital data, in order to better identify whether there is a need to have additional minimum temperature based heatwave definitions for early warning.

The latter gains additional importance as not only current trends are stronger but minimum temperatures are also projected to rise faster than maximum temperatures under future warming (Seneviratne *et al.,* 2021). With the projected rate of urbanization in African cities (e.g Marcotullio *et al*., 2021) on top of the general trend, temperatures will continue to rise at higher than background levels and so will associated impacts if preparedness and adaptation is not improved. Both urbanization and heat extremes will increase, even under a low-emission 1.5°C-scenario, rendering heat preparedness one of the most pressing issues to increase resilience in a warming climate. This study is a very first step and offers immediately applicable heatwave definitions to issue early warning if heatwaves meeting these definitions are forecast. Warnings alone will not save lives however, they need to be embedded in heat action plans enabling administration and population to act on these warnings.

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Appendix A: Temperature Trends

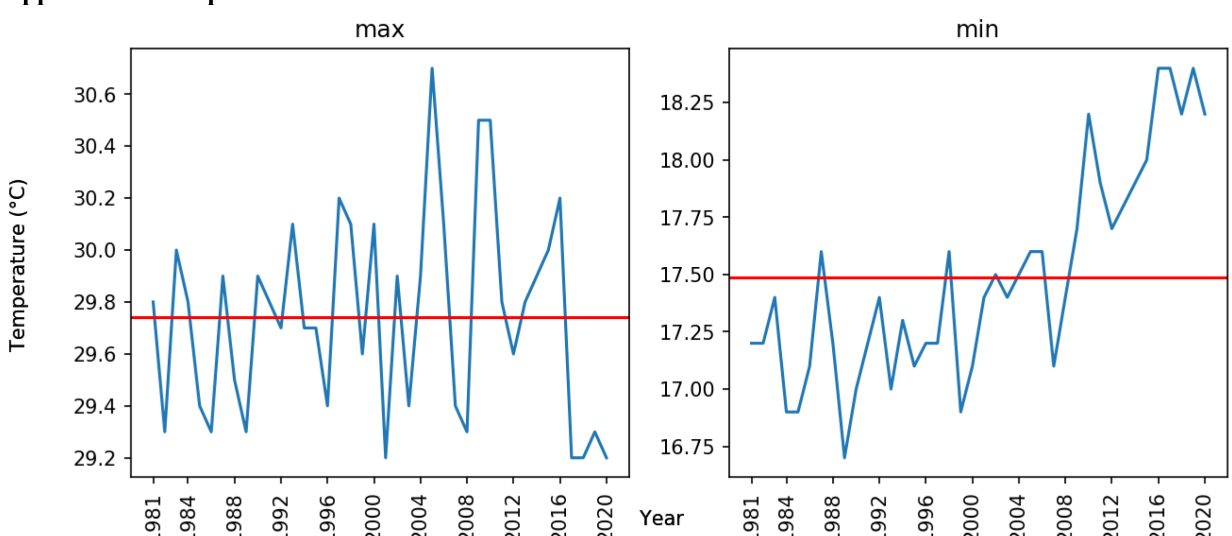

Figure A-1: **Annual trend in maximum and minimum temperature for Kisumu airport station in Kisumu city for the period 1981-2020. The red line shows the climatological mean**

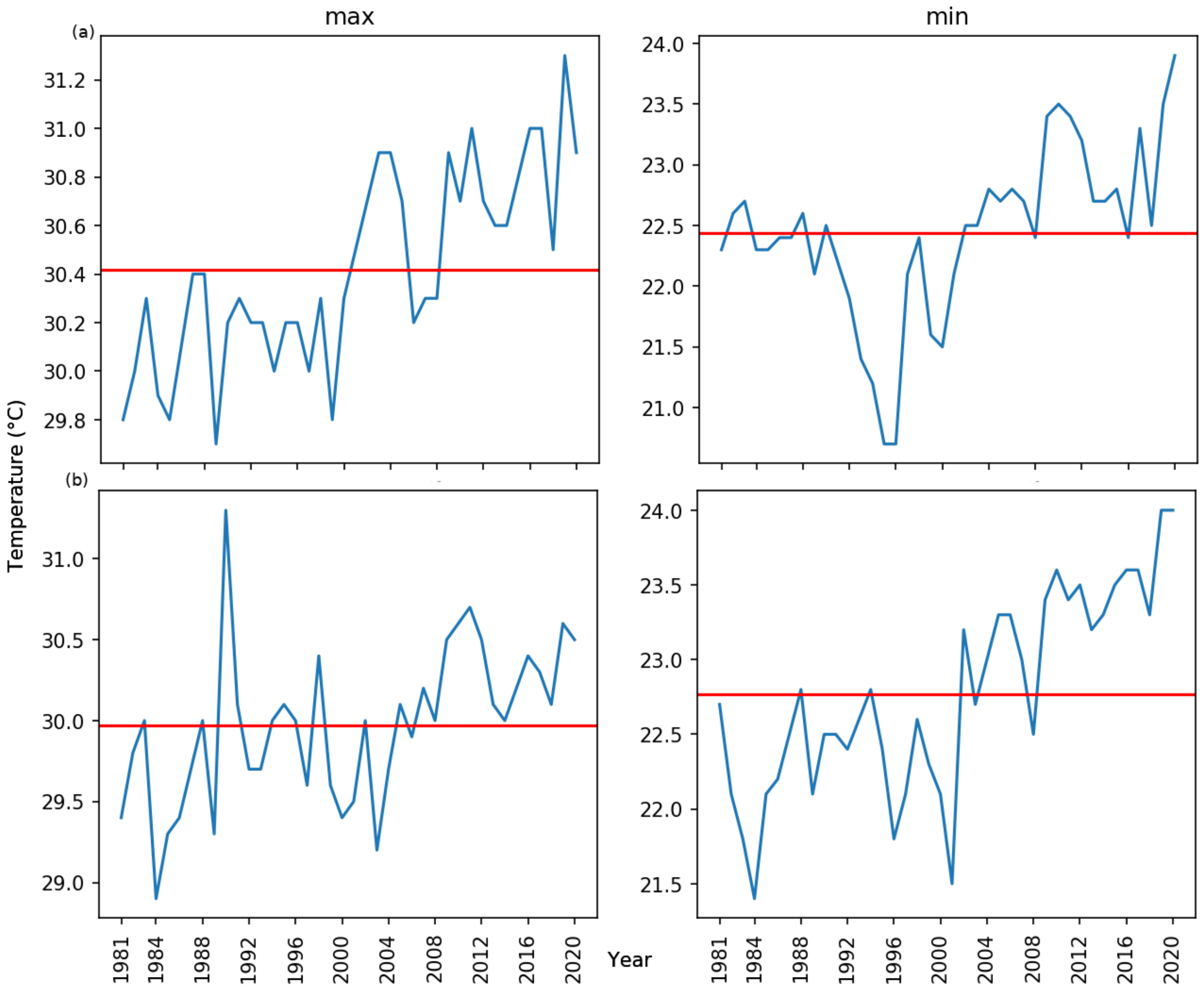

Figure A-2: **Annual trend in maximum and minimum temperature for Mombasa Airport (a) and Mtwapa (b) stations in Mombasa city for the period 1981-2020. The red line shows the climatological mean**

Appendix B: Heat-health associations

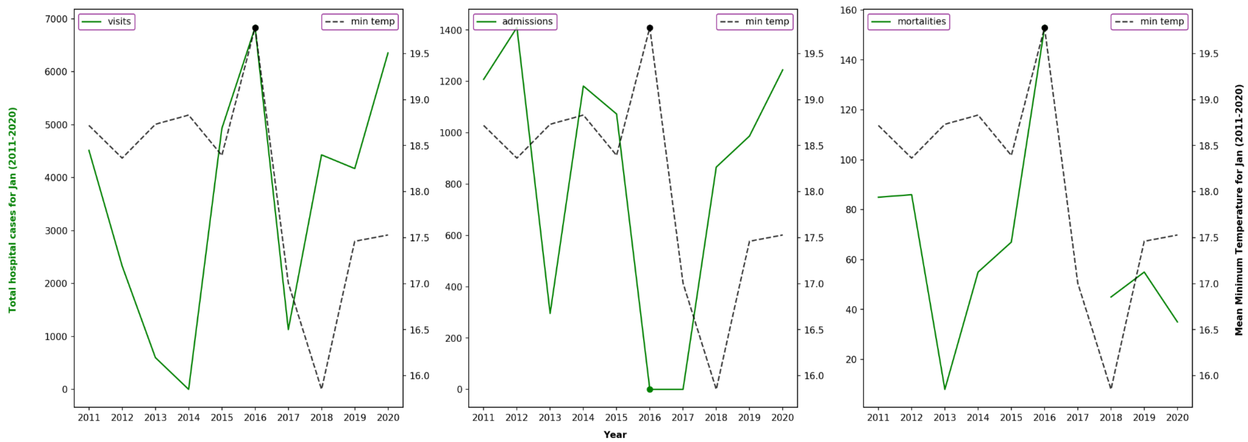

Figure B-1: **Total monthly visits, admissions & mortalities in Kisumu General hospital (greeen), and mean minimum (black) temperature at Kisumu weather station for January (2011-2020) in Kisumu city. The dot indicates the January 2016 value.**

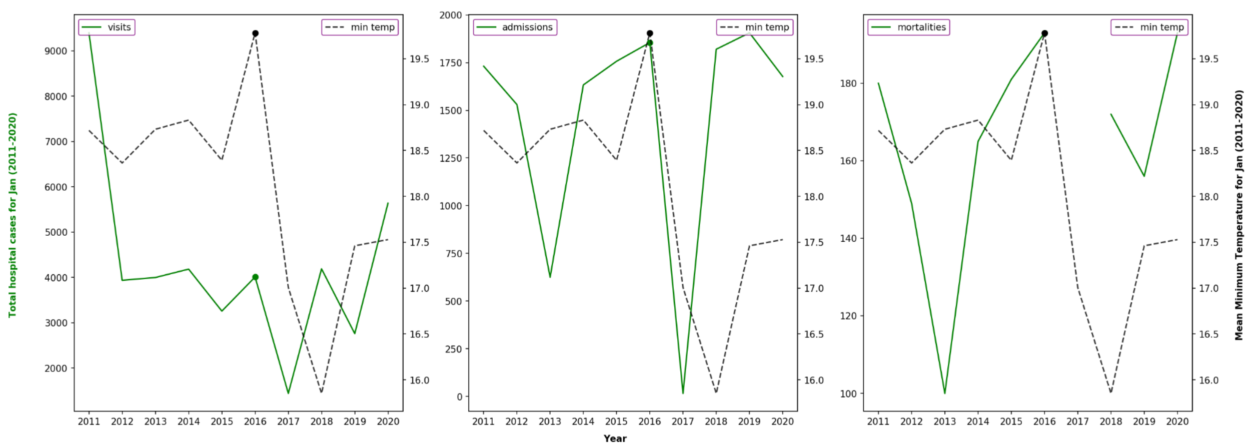

Figure B-2: **Total monthly visits, admissions & mortalities in Jaramogi General hospital (greeen), and mean minimum (black) temperature at Kisumu weather station for January (2011-2020) in Kisumu city. The dot indicates the January 2016 value.**