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Ambulance Service Resource Planning for Extreme Temperatures: Analysis of Ambulance 999 Calls during Episodes of Extreme Temperature in London, UK

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Abstract: The association between episodes of extreme temperature and ambulance 999 calls has not yet been properly quantified. In this study we propose a statistical physics-based method to estimate the true mean number of ambulance 999 calls during episodes of extreme temperatures. Simple arithmetic mean overestimates the true number of calls during such episodes. Specifically, we apply the physics-based framework of nonextensive statistical mechanics (NESM) for estimating the probability distribution of extreme events to model the positive daily variation of ambulance calls. In addition, we combine NESM with the partitioned multiobjective method (PMRM) to determine the true mean of the positive daily difference of calls during periods of extreme temperature. We show that the use of the standard mean overestimates the true mean number of ambulance calls during episodes of extreme temperature. It is important to correctly estimate the mean value of ambulance 999 calls during such episodes in order for the ambulance service to efficiently manage their resources.

Keywords: ambulance 999 calls; extreme weather; resource planning; London; UK

1. Introduction

The impact of extreme weather on the number of ambulance 999 calls has been reported in many studies but is rarely quantified [1–8]. These studies show a significant increase in the number of calls during periods of extreme weather (e.g., heat waves, cold waves).

Alessandrini et al. [1] applied time series analysis to examine the associations between emergency ambulance dispatches and biometeorological discomfort conditions in Emilia-Romagna, Italy. Their study showed a strong relationship between ambulance dispatches and temperature. Dolney and Sheridan [2] studied the relationship between extreme heat and ambulance data response calls for the city of Toronto, Ontario, Canada. They reported that over a four-year period (from 1999 to 2002), the average number of ambulance calls increased by 10 percent over normal levels on those days considered oppressively hot. In further studies, Mahmood et al. [3] analyzed the impact of air temperature on London ambulance call-out incidents and response times and Nitschke et al. [4] analyzed the impact of two extreme heat episodes on morbidity and mortality in Adelaide, South Australia. Schaffer et al. [5] examined emergency department visits, ambulance calls, and mortality associated with the 2011 heat wave in Sydney, Australia. They concluded that the heat wave resulted in an increase in the number of emergency department visits and ambulance calls, particularly in older persons, as well as an increase in all-cause mortality. Ambulance call-outs and response times in Birmingham and the impact of extreme weather and climate change were studied by Thornes et al. [6], who also considered the impact of cold episodes. Turner et al.'s [7] time-series analysis of the association between hot and cold temperatures and ambulance attendances in Brisbane, Australia, suggested that ambulance attendance records can be used in the development of local weather/health early warning systems. Wong and Lai [8] examined the effect of strong weather on the daily demand for ambulance services in Hong Kong suggesting the potential value of developing of a short-term forecast system of daily ambulance demand using weather variables.

The aim of this study is to examine records of recent extreme temperature periods and to estimate and interpret the expected (mean) value of the positive daily variation of ambulance calls in London. More specifically, it is to estimate how many more 999 calls are likely to be received in London during extreme temperature weather events. We argue and show that use of the standard mean of ambulance 999 calls for examining episodes of extreme temperature overestimates the true level and that a combination of statistical physics and risk analysis-based methods provides a better estimate of the mean number of 999 calls.

It should be also noted that not all 999 ambulance calls are acted upon; between the years 2000 and 2014, London Ambulance Service (LAS) only responded to two-thirds of the 999 calls on average. The remaining third include cases where it is clear that the caller does not require an ambulance and/or can be advised to consult 111 or General Practice (GP) services etc.

When calculating the standard mean of a random variable, it is assumed that the variable is "well-behaved". As an example, consider a random variable which exhibits the random values x_1 to x_n. If the random variable is behaving "normally", then the mean value is given by $(x_1 + \ldots + x_n)/n$. In other words, we are assigning equal probabilities $(1/n)$ for each occurrence. However, when the random variable in question exhibits extreme or complex behavior, we can no longer attach equal probability weights (i.e., $1/n$) to the occurrences of the random variable when calculating the mean. We need to introduce instead some bias to the probability weights to account for extreme behavior of the variable. The standard method for calculating means assumes that the random variable during periods when it exhibits extremes has an equal probability of occurrence [9]. In reality, as the value of the random variable increases, the probability of occurrence decreases. The theory of nonextensive statistical mechanics (NESM) is concerned with understanding and analyzing this complexity using Tsallis probabilistic context [10,11]. In addition, a series of publications demonstrate the effectiveness of NESM for the study of extreme phenomena. Our approach is similar to that of Basili [12] who showed that using NESM gives better forecasts of influenza pandemic outbreaks.

2. Method

The description of the method divided into three sections. The first two sections describe the two theories underpinning the analysis, and the third section outlines the application of the methods in six steps.

2.1. Nonextensive Statistical Mechanics

The theory of nonextensive statistical mechanics (NESM), originally introduced by Tsallis [10], is a method for modelling complex systems exhibiting extreme behavior. These include natural processes such as earthquakes, floods, extreme weather events etc., and non-natural phenomena such as extreme fluctuations in the financial market. Tsallis distribution (q-exponential distribution) characterizes such systems and derives its principles from the concept of nonadditive entropy, which is a generalization of the classical Boltzmann–Gibbs (GB) entropy [10,11]. GB entropy characterizes systems which exhibit normal (Brownian) nonextreme fluctuations. In this study, we apply NESM to characterize the ambulance 999 calls. In this case, the Tsallis complementary cumulative distribution function (CCDF) is expressed as:

$$P(D > x) = \left[1 - (1 - q)\frac{x}{x_0}\right]^{\frac{1}{1-q}}, \tag{1}$$

where P (D > x) is the probability that the positive daily difference of calls is greater than x; q and x_0 are parameters of the distribution. The key parameter is q which measures deviations from classical entropy i.e., it characterizes extreme and behavior. The closer it is to unity the more normally distributed is x and the further it deviates upward from unity the more extreme x is [13–15]. In other words, the estimated value of q reflects the absence or existence of extreme values of ambulance 999 calls (low or high values). If q deviates significantly from unity, the time-series of ambulance 999 calls exhibits extreme values whereas if q tends to one the 999 calls portray normal (i.e., BG-type) fluctuations. Note that Tsallis distribution (i.e., the q-exponential distribution) recovers the exponential distribution in the limit $q \to 1$. Note also that in this study the calculation of the CCDF is based on the concept of escort probability which is a transformation of the ordinary physical probability when dealing with complex systems (for more information see [11,16,17]). Overall, the Tsallis framework is capable of calculating the degree of correlations in a dynamic system and is also capable of describing transitions of a complex system from a normal random phase (Poissonian processes) to a phase where the system self-organizes towards an extreme phase.

2.2. The Partitioned Multi-Objective Risk Method

The partitioned multiobjective risk method (PMRM) [18] is a risk analysis method to handle extreme and potentially catastrophic risks. The PMRM calculates conditional expected values for different ranges of the variable of interest from the normal to the extreme range. The ranges are specified according to some criteria which are explained below.

2.3. Application of Methods

We outline the methods in six steps:

1. We focus on four extreme temperature episodes in London (see below) and we calculate the positive daily difference (i.e., difference between successive days) of the total number of 999 emergency incidents (calls) for each episode.
2. We divide each of the four extreme temperature episodes into three periods that correspond to the period before (Period A), during (Period B) and straight after (Period C) the extreme weather episode.
3. We estimate two nonclassical statistical-mechanics-based measures of the daily difference in 999 calls: Tsallis exceedance probability distribution function and Tsallis mean value.
4. We partition the estimated Tsallis probability distribution function for each period into three ranges by using the partitioned multiobjective risk method (PMRM). These ranges correspond to low positive daily difference of calls/high exceedance probability (Range 1), medium positive daily difference of calls/medium exceedance probability (Range 2) and high positive daily difference of calls/low exceedance probability (Range 3). The whole range (Range 4) is defined as the union of the three ranges.
5. We show that (i) the calculated Tsallis mean value in Range 3 of Period B is a measure of the increase of the mean value of the positive daily difference of calls during an extreme weather period; (ii) the calculated Tsallis mean value in Range 4 (unconditional mean value of Period B) is an accurate measure of the mean value of the positive daily difference of calls during extreme weather periods. In other words, we propose that Tsallis mean value estimates the true mean of the underlying distribution which describes extreme events.
6. We estimate the exceedance probability for various thresholds of the positive daily difference of calls.

Figure 1 captures the aforementioned steps.

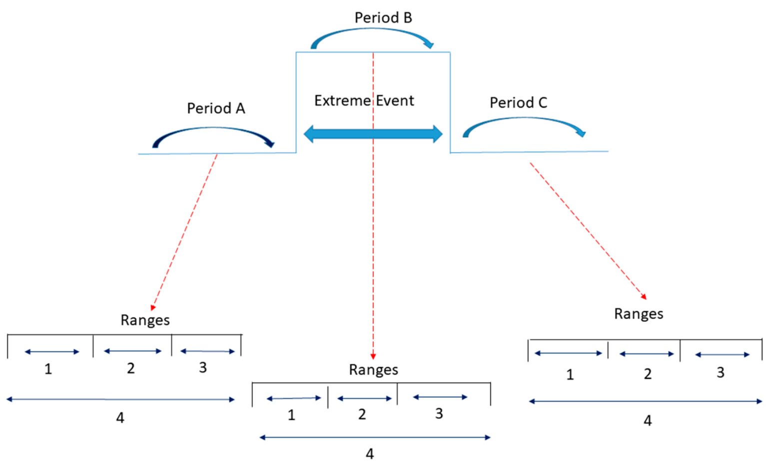

Figure 1. Schematic representation of the methodological steps followed in this study.

3. Data

We examined 999 emergency ambulance calls in London from 1 April 2000 to 31 December 2014. The daily average number of ambulance calls during this period is 3904. Instead of analyzing the whole sequence of 999 emergency ambulance calls (see Figure 2), we chose to focus on four well-reported extreme temperature episodes in the UK as described in Thornes [19,20]. These specific episodes have health relevance. The Heat wave Plan for England [21] defines a heat wave in London expressed as two consecutive days at 32 °C with the night time temperature in between not dropping below 18 °C. On the other hand, the Cold Weather Plan for England [22] gives warnings when the mean temperature for the day is 2 °C or below, which was the case for 16 days out of 31 in December 2010 (Cold spell in December 2010, see Table 1). The choice to study well-documented extreme temperature episodes enables us to scrutinize the probabilistic nature of such episodes. In order to examine the fluctuations of the number of ambulance calls before, during and after the extreme temperature episodes, we selected broader time periods centered at the peak of each episode (for a detailed description see the Analysis section). These periods and the corresponding extreme temperature episodes are given in Table 1.

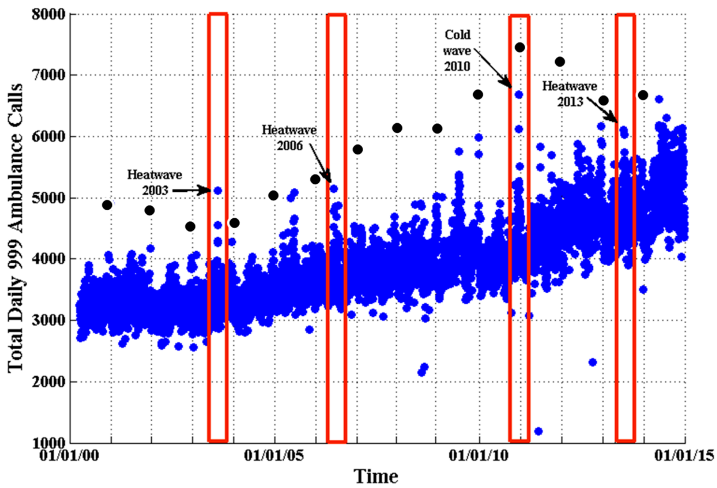

Figure 2. The daily total number of 999 emergency ambulance incidents (calls—blue dots) in London from 1 April 2000 to 31 December 2014. The red rectangles delimit the four extreme temperature episodes which we study in this paper. Seasonal peaks which are the spikes on the 1 January each year are marked with black dots (see text above).

Table 1. Selected periods of study and the associated number of days for four extreme temperature episodes.

Extreme Temperature Episode	Selected Period	Number of Days
Cold spell in December 2010	1 October 2010–28 February 2011	151
Heat wave in August 2003	25 May 2003–24 October 2003	153
Heat wave in July 2006	15 April 2006–16 September 2006	155
Heat wave in July 2013	19 April 2013–21 September 2013	156

Figure 2 shows the daily total number of 999 emergency ambulance incidents (blue dots) in London from 1 April 2000 to 31 December 2014. The red rectangles delimit the four extreme weather episodes which we study in this paper. Significant peaks in the number of calls are observed in December 2010 [6], in August 2003, in July 2006 and in July 2013. It is worth noting that the daily average number of calls has dramatically increased from 2000 to 2014. For example, the daily average number of calls during 2000 was 3235 whereas for 2014 was 5055. Note that this increasing trend has been removed from our analysis by windowing the extreme weather episodes of interest (see next section). Figure 2 suggests that rapid daily variations in urban temperature are strongly related to the 999 ambulance calls particularly during extreme temperature periods. These temperature increases or decreases over short time periods are fully reflected in Figure 3, which shows the positive daily difference of the total number of 999 emergency calls in London from 1 April 2000 to 31 December 2014. The positive daily difference is equal to the difference between the number of calls on one day and that of the previous day if the difference is positive, otherwise it is zero. We used the positive daily difference instead of the absolute number of calls because the time-series is nonstationary and because we are only interested in extreme positive daily deviations. There are also seasonal peaks that correspond to surges in calls on the 1 January each year during New Year's Eve celebrations [19] (see Figure 2) and which seem to disappear from 2013 onwards. We substituted these peaks by the average number of calls. The rationale for windowing the extreme weather episodes (red rectangles) is explained in detail in the following section.

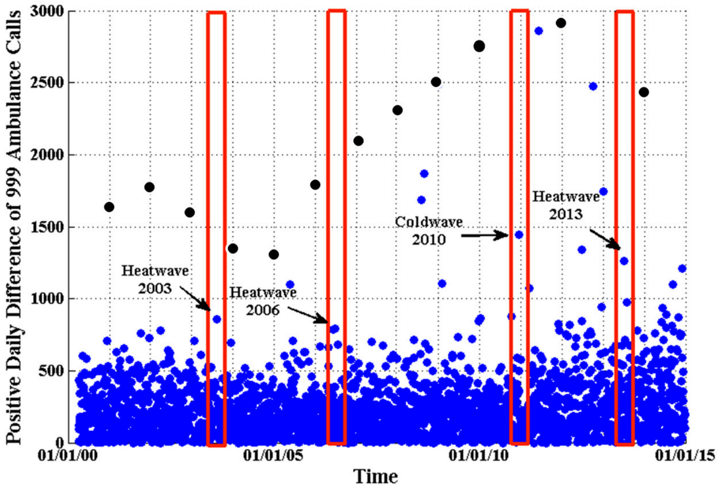

Figure 3. The positive daily difference of the total number of 999 emergency ambulance calls (blue dots) in London from 1 April 2000 to 31 December 2014. The red rectangles delimit the four extreme temperature episodes which we study in this paper. Seasonal peaks which are the spikes on the 1 January each year are marked with black dots (see text above).

4. Analysis

This section presents the method we use to estimate the Tsallis mean value of the positive daily variations of calls during an extreme weather period. We describe the method giving as an example the 2010 cold wave period. Figure 4 shows the daily total number of 999 emergency ambulance calls in London from 1 July 2010 to 31 May 2011. Note that the minimum number of calls for this period is chosen to be 3500. We need to set a minimum threshold (baseline) for the number of calls for each extreme weather episode to avoid analyzing very low numbers of calls that are not caused by temperature variations. They could be due to other causes such as an ambulance operations problem. Overall, despite the fact that our study gives special attention to the occurrence of high numbers of calls, we try to avoid analyzing extremely low numbers of calls unrelated to temperature changes. In other words, we do not calculate positive daily differences for calls below this baseline. For example, we can clearly see in Figure 1 that a plausible baseline for the number of ambulance calls during the 2010 cold wave period is 3500. However, there are two days within this episode which had 3000 calls. If we keep those two days in the dataset the positive daily difference of calls would be erroneously high and unrelated to temperature. In addition, to focus only on peaks that are caused solely by extreme temperature, we substituted the peak observed on the 1 January 2011 (7455 calls) by the average number of calls (4201).

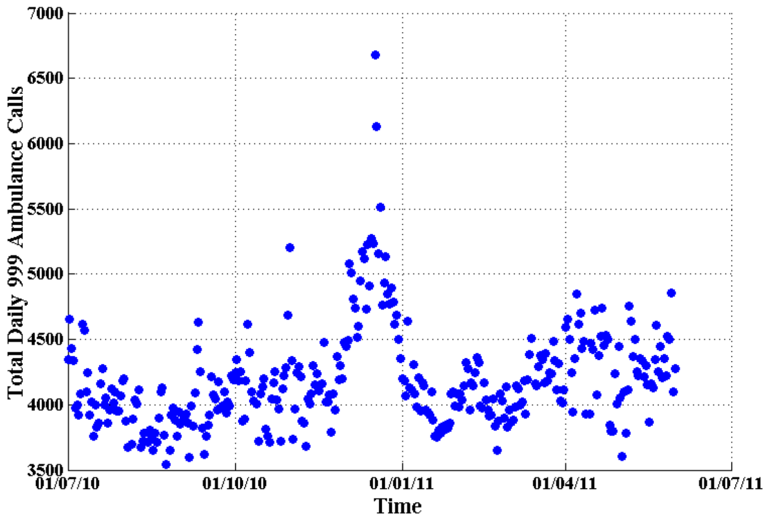

Figure 4. The daily total number of 999 emergency ambulance calls (blue dots) in London from 1 July 2010 to 31 May 2011.

For each extreme weather episode, we specify three periods. We define the extreme weather period as Period B. This is a period of one month in duration centered at the peak of the positive daily difference of calls (Figure 5). Other durations were chosen for sensitivity analysis purposes (see below). Although usually extreme temperature episodes last for a few days (few events) we choose a period of one month in order to have a sufficient number of events (31 events) for calculating the associated probability distribution. Using the actual number of days that concern the extreme temperature episode would lead us to a poor estimation of the probability distribution due to the small number of events selected. We define further two associated periods, one before (Period A) and one straight after (Period C) the extreme weather period (Period B). Periods A and C are two-month periods where we expect "normal" numbers of calls (i.e., corresponding to "normal weather conditions") to be recorded.

As we have explained, we use the positive daily difference of ambulance 999 calls (x) as the measure for analysis and we estimate the parameter q and the Tsallis CCDF for each one of the extreme temperature periods. We estimate the Tsallis probability distribution of the time series and the associated Tsallis expected value (referred as generalized q-expectation value in NESM's theoretical framework, see Tsallis 2009) for each of the datasets. Tsallis probability distribution and the associated expected value are calculated for each period of the four selected extreme weather episodes (i.e., before (Period A), during (Period B) and right after (Period C) the episode). We focus on the Tsallis expected value of the extreme temperature in Period B because it measures the increase of the mean value of the positive daily difference of calls relative to periods A and C. Moreover, as we show in the following sections, by analyzing Period B we obtain an accurate measure of the true mean of the positive daily difference of calls.

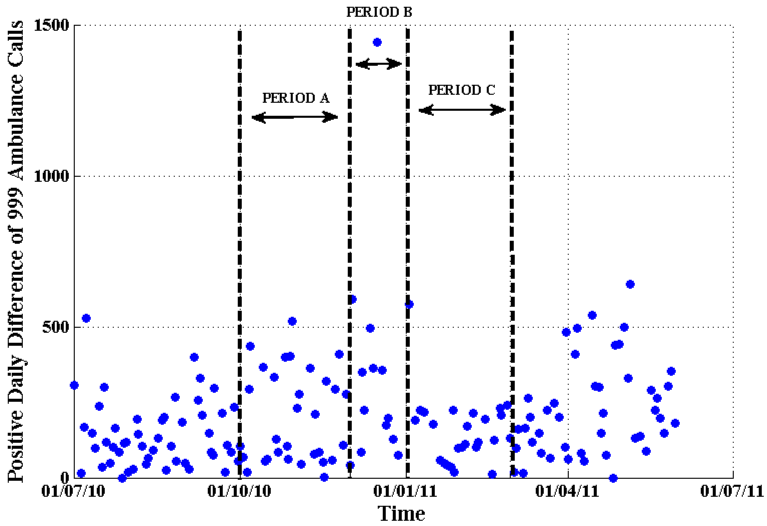

Figure 5. The positive daily difference of calls of 999 emergency ambulance incidents (blue dots) in London from 1 July 2010 to 31 May 2011. The dataset is divided into three periods. Period A corresponds to the period before the extreme temperature, Period B is the extreme temperature period and Period C is after the extreme temperature.

Parameter q is calculated by fitting Tsallis CCDF to the dataset using the Levenberg–Marquardt (LM) algorithm [23] (Figure 6). The LM algorithm is an iterative numerical procedure that is suited to solving nonlinear least squares problems [24–26]. Figure 7 shows the exceedance probability distribution function corresponding to each period for the 2010 cold wave. When the time series exhibits extremes (i.e., during the extreme weather period) the q value acquires its highest value and the distribution becomes "fatter" at the tail end, which means that the probability of getting high values of calls (x) is not small.

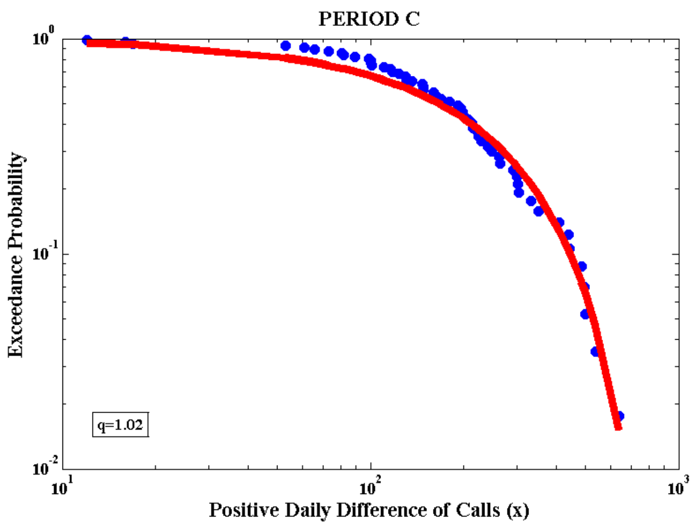

Figure 6. Log–log plot of the exceedance probability distribution function. The dataset (blue dots) and the Tsallis fitting curve (Equation (1), red line) for period C of the 2010 cold wave. The q value is calculated equal to 1.02.

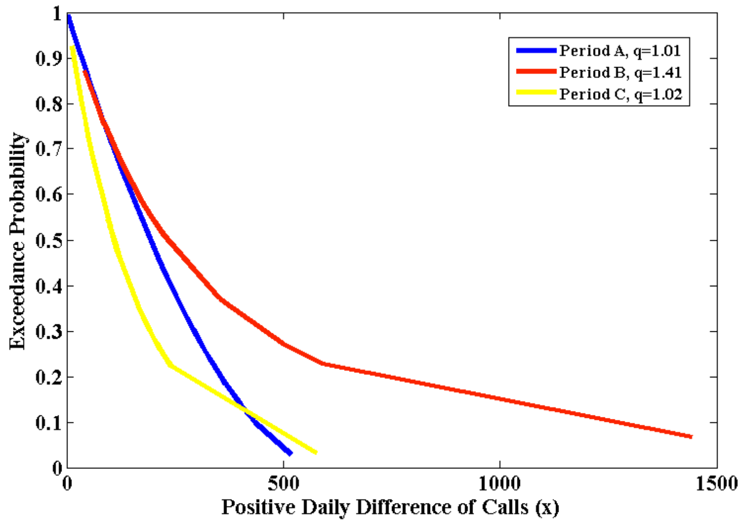

Figure 7. The exceedance probability distribution function corresponding to each period. It should be noted that the axis in this plot is not in logarithmic scale as in Figure 6.

Based on the PMRM method, we partition the exceedance probability distribution function of the positive daily difference of ambulance calls-outs (D) into a number of ranges; three ranges are selected here: low D/high exceedance probability (Range 1), medium D/medium exceedance probability (Range 2) and high D/low exceedance probability (Range 3) (Figure 8). In terms of extreme events, Range 3 is the most important, and the PMRM provides a robust method for its interpretation and analysis. Range 4 includes all the three ranges 1 to 3 (Figure 8).

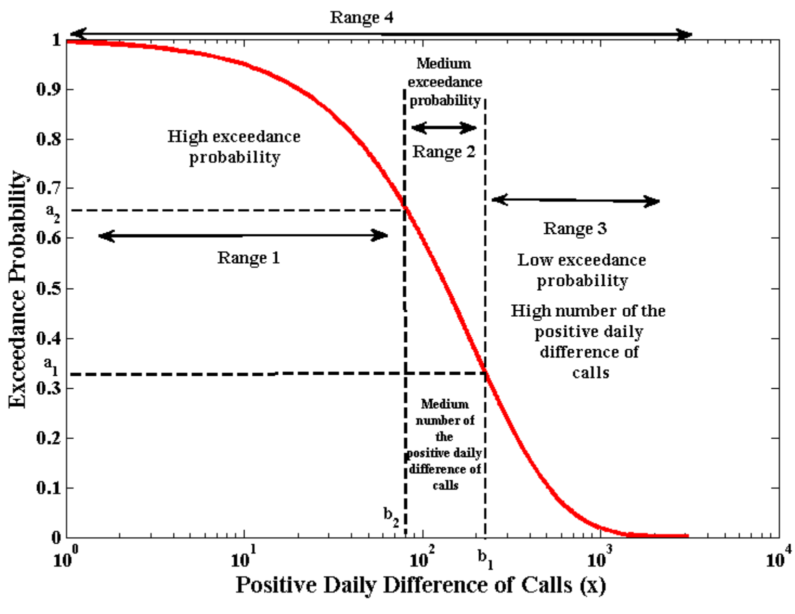

Figure 8. The partition of the positive daily difference of calls into three ranges of the exceedance probability (red line), i.e., high, medium and low exceedance probability, for the whole dataset, in London from 1 July 2010 to 31 May 2011. The x-axis is in logarithmic scale.

Figure 8 shows the partition of the exceedance probability function of the positive daily difference of calls into three ranges of the exceedance probability, i.e., high, medium and low exceedance probability, for the whole dataset, in London from 1 July 2010 to 31 May 2011. Without loss of generality, the partitioning probabilities a_1 and a_2 are selected to be 0.35 and 0.68 respectively (y-axis).

The associated positive daily difference of calls (x-axis) is b_1 = 220 and b_2 = 80. This selection of the partition probabilities defines Range 2 (medium exceedance probability) as the linear part of the curve of the exceedance probability (red line) shown in Figure 8. The same partitioning probabilities are used throughout this paper to calculate the unconditional and conditional expected values of the positive daily difference of the ambulance 999 calls in the four ranges.

In the analysis, the conditional and unconditional Tsallis expected values are calculated for each of the three periods (A, B, and C) and four ranges by using NESM and the partitioned multi-objective risk method. The results are presented in the following section.

5. Results

5.1. Cold Wave: December 2010

Table 2 shows the estimated q value and Tsallis expected value for the four ranges of each period.

Table 2. The estimated q value and Tsallis expected value for the four ranges of each period.

Period	q	Range 1 (Tsallis Mean Value)	Range 2 (Tsallis Mean Value)	Range 3 (Tsallis Mean Value)	Range 4 (Tsallis Mean Value)
A					
1 October 2010–30 November 2010	1.01	46	28	42	116
B					
1 December 2010–31 December 2010	1.41	37	72	98	207
C					
1 January 2011–28 February 2011	1.02	14	43	45	102

Sensitivity Analysis

To test the sensitivity of the results to the selected duration of periods A, B and C, we performed a sensitivity analysis by changing the duration of Period B. Table 3 shows the estimated q value and Tsallis expected value for the three ranges of each period when Period B is set to last 2 months (instead of one month) centered at the peak of the positive daily difference of calls. Comparing results between Tables 2 and 3 we observe that the estimated values are not affected by the change of the duration of Period B.

Table 3. Sensitivity analysis. The estimated q value and Tsallis expected value for the four ranges of each period when Period B is set to last 2 months.

Period	q	Range 1 (Tsallis Mean Value)	Range 2 (Tsallis Mean Value)	Range 3 (Tsallis Mean Value)	Range 4 (Tsallis Mean Value)
A					
15 September 2010–14 November 2010	1.01	50	26	34	110
B					
15 November 2010–15 January 2011	1.43	25	82	86	193
C					
16 January 2011–15 March 2011	1.02	14	40	41	95

5.2. Heat Wave: August 2003

Figure 9 shows the daily total number of 999 emergency ambulance calls in London from 1 March 2003 to 31 December 2003. The minimum number of calls for this period is chosen to be equal to 2800.

Figure 10 shows the positive daily difference of calls of 999 emergency ambulance calls (blue dots) in London from 1 March 2003 to 31 December 2003.

Table 4 shows the estimated q value and Tsallis expected value for the three ranges of each period.

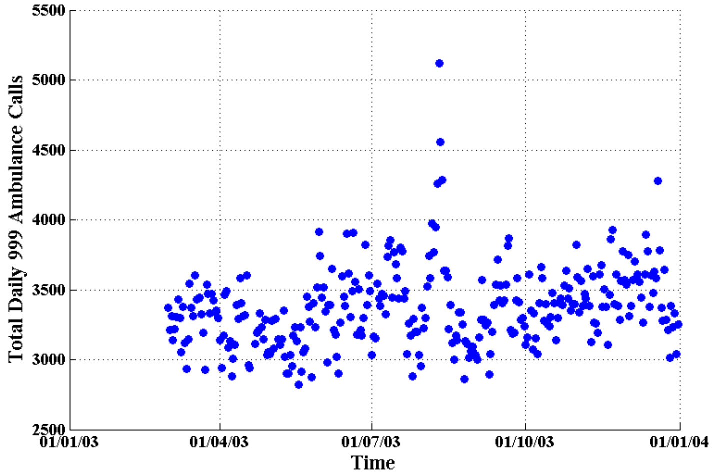

Figure 9. The daily total number of 999 emergency ambulance calls (blue dots) in London from 1 March 2003 to 31 December 2003.

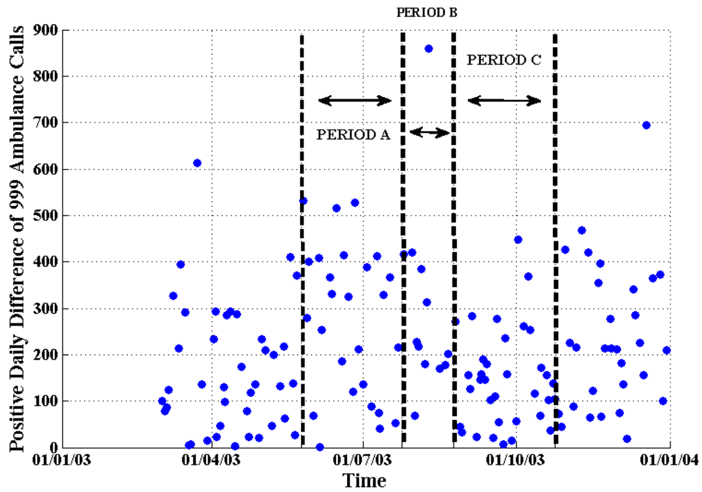

Figure 10. The positive daily difference of calls of 999 emergency ambulance incidents (blue dots) in London from 1 March 2003 to 31 December 2003.

Table 4. The estimated q value and Tsallis expected value for each range of each period.

Period	q	Range 1 (Tsallis Mean Value)	Range 2 (Tsallis Mean Value)	Range 3 (Tsallis Mean Value)	Range 4 (Tsallis Mean Value)
A					
25 May 2003–24 July 2003	1.01	25	60	45	130
B					
25 July 2003–24 August 2003	1.10	47	80	100	227
C					
25 August 2003–24 October 2003	1.01	17	49	28	94

5.3. Heat wave: July 2006

Figure 11 shows the daily total number of 999 emergency ambulance calls in London from 1 February 2006 to 30 November 2006. The minimum number of calls for this period is chosen to be equal to 3200.

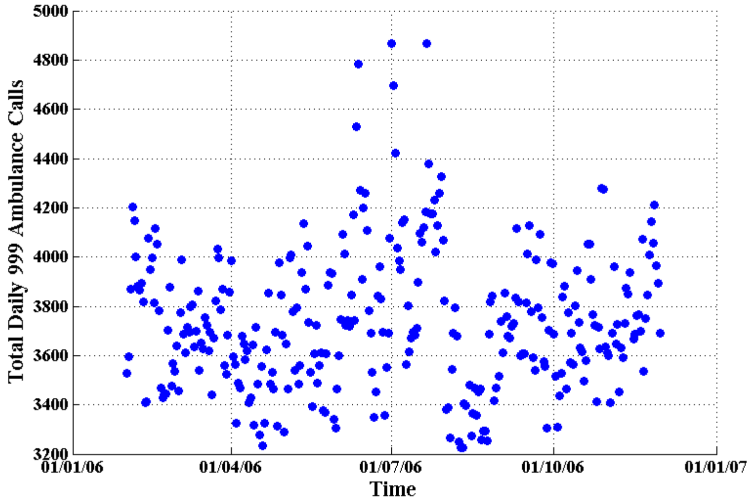

Figure 11. The daily total number of 999 emergency ambulance calls (blue dots) in London from 1 February 2006 to 30 November 2006.

Figure 12 shows the positive daily difference of calls of 999 emergency ambulance calls (blue dots) in London from 1 February 2006 to 30 November 2006.

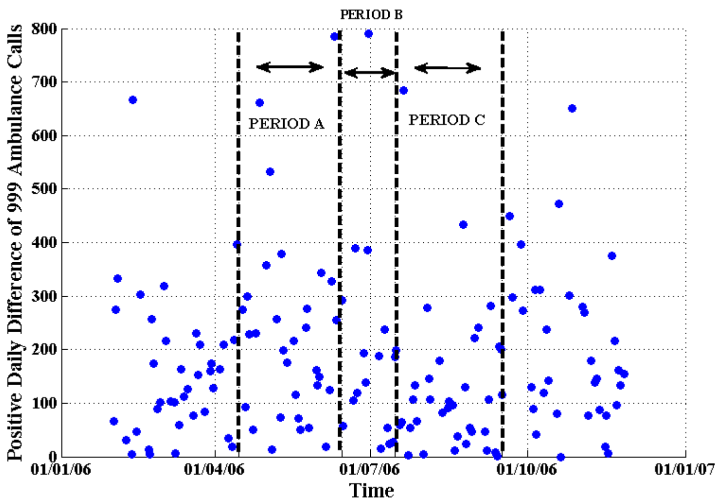

Figure 12. The positive daily difference of calls of 999 emergency ambulance calls (blue dots) in London from 1 February 2006 to 30 November 2006.

Table 5 shows the estimated q value and Tsallis expected value for the four ranges of each period.

Table 5. The estimated q value and Tsallis expected value for the four ranges of each period.

Period	q	Range 1 (Tsallis Mean Value)	Range 2 (Tsallis Mean Value)	Range 3 (Tsallis Mean Value)	Range 4 (Tsallis Mean Value)
A					
15 April 2006–14 June 2006	1.01	18	39	33	90
B					
15 June 2006–15 July 2006	1.38	27	60	61	148
C					
16 July 2006–16 September 2006	1.04	10	34	33	77

5.4. Heat wave: July 2013

Figure 13 shows the daily total number of 999 emergency ambulance calls in London from 1 May 2013 to 30 September 2013. The minimum number of calls for this period is chosen to be equal to 4100.

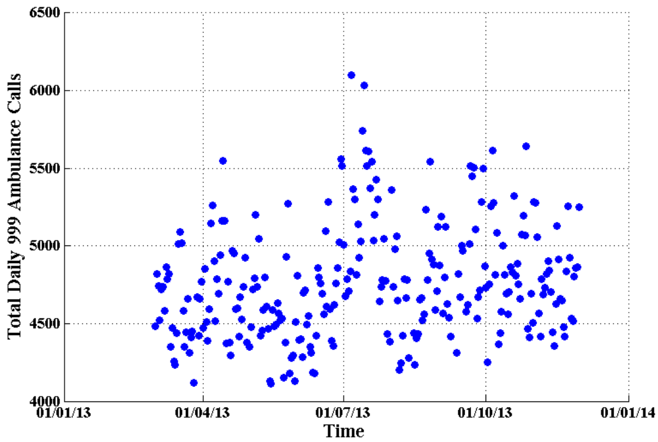

Figure 13. The daily total number of 999 emergency ambulance calls (blue dots) in London from 1 March 2013 to 30 November 2013.

Figure 14 shows the positive daily difference of calls of 999 emergency ambulance calls (blue dots) in London from 1 March 2013 to 30 November 2013.

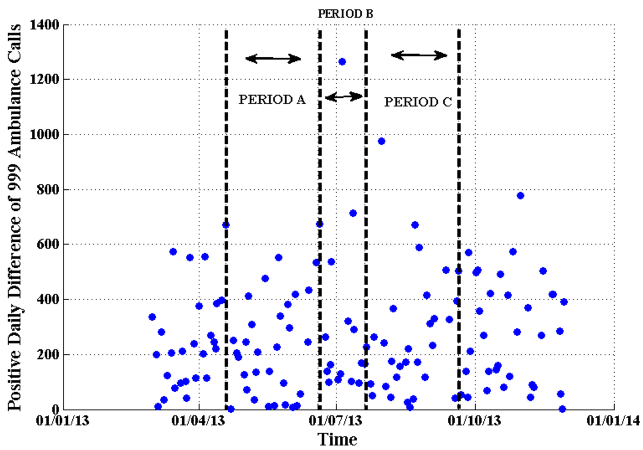

Figure 14. The positive daily difference of calls of 999 emergency ambulance calls (blue dots) in London from 1 March 2013 to 30 November 2013.

Table 6 shows the estimated q value and Tsallis expected value for the four ranges of each period.

Table 6. The estimated q value and Tsallis expected value for the four ranges of each period.

Period	q	Range 1 (Tsallis Mean Value)	Range 2 (Tsallis Mean Value)	Range 3 (Tsallis Mean Value)	Range 4 (Tsallis Mean Value)
A					
19 March 2013–19 June 2013	1.01	21	54	50	125
B					
20 June 2013–20 July 2013	1.24	63	62	77	202
C					
21 July 2013–26 September 2013	1.03	22	60	52	134

6. Discussion and Conclusions

Results show that during extreme temperature periods (Period B) the q parameter deviates from unity and varies from 1.10–1.41. Moreover, Tables 2–6 show that the estimated Tsallis expected value in Range 3 of Period B equals approximately the difference between the estimated Tsallis expected values in Range 4 of Periods B and A. This finding signifies that the calculated expected value in Range 3 of Period B is a measure of the increase of the expected value of the positive daily difference of calls during an extreme temperature period in respect to periods A and C. In addition, the estimated Tsallis expected value in Range 4 (unconditional expected mean of Period B) is a true measure of the expected positive daily difference of calls during extreme weather periods. Table 7 shows that for the four case studies, the mean daily difference of ambulance 999 calls in Range 4 and Range 3 varies between 148–227 and 61–100, respectively. In other words, the positive daily difference of calls (Period B, Range 4) varies between 148 and 227 and the increase of the positive daily difference of calls during an extreme temperature period (Period B, Range 3) varies between 61 and 100. Another significant finding presented in Table 7 is that the use of the standard mean overestimates the true positive daily difference of calls in cases of extreme weather. The standard mean is simply the sum of the positive daily difference of calls divided by their number. This finding shows the importance of using Tsallis distribution to derive the expected values of calls during extreme temperature periods. Assuming that for London each ambulance call-out costs about £250, it is straightforward to appreciate that an inaccurate estimate of the mean of calls when planning ahead for resources can lead the ambulance authorities to overestimate the required resources. In addition, we can approximately determine how many staff and ambulances need to be available in reserve in a near future event of an extreme temperature episode.

Table 7 also shows that with the exception of results for 2006 heat wave, the Tsallis expected value (Range 4) was close to 200. Moreover, Tsallis expected value associated with extreme temperature conditions (Range 3), i.e., the increase of the expected increase in the positive daily difference of calls during an extreme weather period, was estimated to be close to 90.

Table 8 shows the exceedance probability for various thresholds of the positive daily difference of calls. With the exception of the 2006 heat wave similar exceedance probabilities are estimated for the rest of the extreme temperature episodes.

Table 7. The standard and Tsallis values, and the additional Tsallis value due to extreme weather (Range) 3 for the four case studies (extreme weather periods).

Period B	Standard Mean	Tsallis Mean (Mean Value of Calls for Range 4)	Additional Tsallis Mean at Extreme Temperature (Mean Values of Calls for Range 3)
Cold wave: December 2010	348	207	98
Heat wave: August 2003	303	227	100
Heat wave: July 2006	195	148	61
Heat wave: July 2013	338	202	77

Table 8. The exceedance probability for various thresholds of the positive daily difference of calls.

Period B	Exceedance Probability for			
	Positive Daily Difference of Calls $\geq$ 100	Positive Daily Difference of Calls $\geq$ 200	Positive Daily Difference of Calls $\geq$ 400	Positive Daily Difference of Calls $\geq$ 700
Cold wave: December 2010	0.72	0.54	0.34	0.2
Heat wave: August 2003	0.76	0.56	0.31	0.15
Heat wave: July 2006	0.59	0.37	0.16	0.09
Heat wave: July 2013	0.74	0.56	0.34	0.17

How Would the Method Be Used in Practice for Planning Resources? An Illustrative Example

Assume that we are planning ahead now for a future extreme temperature event and we wish to estimate the expected variation in the positive daily difference of ambulance calls in London. We have at our disposal a dataset consisting of the 999 calls on the cold wave in December 2010, the heat wave in August 2003, the heat wave in July 2006 and the heat wave in July 2013. Following the methodology described in this paper, we end up with Tables 7 and 8. By studying these tables, we ascertain that the true positive daily difference of calls during the next extreme temperature episode will vary between 148 and 227 (Table 7 Period B, Range 4). Moreover, we estimate that the increase in the positive daily difference of calls during the next extreme temperature period will vary between 61 and 100 (Period B, Range 3). We can also estimate the probability of occurrence of different levels of the positive daily difference of calls. If instead of the Tsallis mean we used the standard mean, we would have overestimated the true mean value of the positive daily difference of calls for both ranges. Tsallis distribution secures that we assign a legitimate probabilistic context to all calls without neglecting the probability of extreme events (in our case positive daily difference of calls $\geq$700, see Table 8).

Stakeholders can use our findings for resource planning. For example, the ambulance service could estimate the likely consequences of a future extreme temperature weather event as follows. Assuming that the average positive daily difference of 999 calls during 'normal temperature periods' in London is 125 (Table 6, Period A, Range 4), then the ambulance service would expect an increase between of 61 and 100 calls (Table7, Range 3) on day 1 (and for each day) of the extreme temperature episode. If the extreme temperature period lasts for 7 days, then the total increase of the average positive daily difference will vary between 427 and 700 calls. The expected total number of the average positive daily difference of 999 calls during each day of this period will vary between 148 and 227 (Table 7 Period B, Range 4).

By using the estimates obtained in Table 7, we present in Table 9 the expected total number of the positive daily difference of 999 calls during a hypothetical seven-day extreme temperature period using the standard and Tsallis mean for comparison. In addition, we present the expected number of the positive daily difference of additional 999 calls due to the seven-day extreme temperature period relative to a seven-day "normal temperature" period. To obtain Table 9, we simply multiplied the values obtained in Table 7 by seven (number of days of the extreme temperature period). Because the values in Table 7 cover a range over the four modelled extreme events, we present the values in Table 9 as ranges too.

Table 9. The expected number of the positive daily difference of calls during a hypothetical seven-day extreme temperature period using the standard and Tsallis means for comparison (first and second rows). The third row gives the expected number of the positive daily difference of additional calls during the seven-day extreme temperature period relative to a normal seven-day period.

Seven-Day Period of Extreme Temperature	
Standard Mean	1365–2436 is the spread of the total number of the positive daily difference of calls during the seven-day period of extreme temperature.
Tsallis Mean (Range 4)	1036–1589 is the spread of the total number of the positive daily difference of calls during the seven-day period of extreme temperature.
Additional Tsallis mean at extreme temperature (Range 3)	427–700 is the spread of the positive daily difference of additional calls due to the seven-day extreme temperature compared to a normal temperature period.

The spread of values in the cells in Table 9 correspond to those of Table 7 across the four extreme events. It is obvious that the standard mean (first row) overestimates the expected number of 999 calls during this extreme seven-day period compared to the Tsallis mean (second row). Furthermore, in this approach we are able to calculate the true expected additional number of 999 calls compared to a normal period (third row). This shows that the standard method of calculating means during extreme temperature events overestimates the true number.

The conclusions of this study would be strengthened by examining more records of 999 calls during episodes of extreme temperature in other cities in the UK and worldwide. Moreover, future work should include analyzing the temporal variation of the Tsallis q parameter by using event-based moving windows. Such analysis should elucidate further the behavior of 999 calls and the existence of possible patterns or distinct correlations before, during and after an extreme temperature period.

Our findings are not meant to be used for day-to-day operational planning. Table 8 shows that the probability of occurrence of an extreme positive daily difference of calls is not negligible and can be used as a guide for the authorities to plan ahead for the occurrence of the extreme temperature period. Using the current standard mean methods, the ambulance call-out rate during periods of extreme weather is being overestimated. This increases costs and utilized scarce resources. By using the Tsallis mean, a better estimation can be derived that will improve the planning of ambulance resources.

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