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Effects on Public Health of Heat Waves to Improve the Urban Quality of Life

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Abstract: Life satisfaction has been widely used in recent studies to evaluate the effect of environmental factors on individuals' well-being. In the last few years, many studies have shown that the potential impact of climate change on cities depends on a variety of social, economic, and environmental determinants. In particular, extreme events, such as flood and heat waves, may cause more severe impacts and induce a relatively higher level of vulnerability in populations that live in urban areas. Therefore, the impact of climate change and related extreme events certainly influences the economy and quality of life in affected cities. Heat wave frequency, intensity, and duration are increasing in global and local climate change scenarios. The association between high temperatures and morbidity is well-documented, but few studies have examined the role of meteo-climatic variables on hospital admissions. This study investigates the effects of temperature, relative humidity, and barometric pressure on health by linking daily access to a Matera (Italy) hospital with meteorological conditions in summer 2012. Extreme heat wave episodes that affected most of the city from 1 June to 31 August 2012 (among the selected years 2003, 2012, and 2017) were analyzed. Results were compared with heat waves from other years included in the base period (1971–2000) and the number of emergency hospital admissions on each day was considered. The meteorological data used in this study were collected from two weather stations in Matera. In order to detect correlations between the daily emergency admissions and the extreme health events, a combined methodology based on a heat wave identification technique, multivariate analysis (PCA), and regression analysis was applied. The results highlight that the role of relative humidity decreases as the severity level of heat waves increases. Moreover, the combination of temperatures and daily barometric pressure range (DPR) has been identified as a precursor for a surveillance system of risk factors in hospital admissions.

Keywords: climate change; heat waves; human health; multivariate analysis; quality of life; urban planning

1. Introduction

Climate change is a major public health threat due to the effects of extreme weather events on human health and on quality of life in general [1–4]. In the last three decades, many studies have addressed the issue of climate evolution under anthropic pressure and the relative increase of its effects observed in the last century [5–7]. Recently, several studies have suggested that heat exposure reduces emotional wellbeing, increases interpersonal aggression, and diminishes life satisfaction [8–10].

In fact, heat exposure is associated with increased suicide rates [11–13]. Together, these findings indicate that heat exposure may adversely impact mental health and that global climate change, by increasing exposure to extreme heat, could similarly have negative consequences for physical and mental health [2]. A critical literature review on the definition of heat waves, on the impacts of heat waves on health, ecosystems, and the built environment, and on the current mechanisms to deal with impacts of heat waves was reported by Zou et al. [14].

Climate warming, as noted over the past several decades, is consistently associated with changes in a number of components of the hydrological cycle and hydrological systems, such as: changing precipitation patterns, intensity, and extremes; causing a widespread melting of snow and ice; increasing atmospheric water vapor; increasing evaporation; and causing changes in soil moisture and runoff [15].

In this context, mean temperatures are increasing, in particular extreme temperatures, with heat waves (HWs) becoming more frequent, more intense, and longer lasting. In many cities, extreme HWs have drastically increased [16,17]. In an urban area, this effect, called the urban heat island (UHI) phenomenon, may raise the temperature by as much as 10 °C due to different local environments and atmospheric conditions [18].

Several studies carried out in the United States assert that HWs led to the highest 10-year estimates of fatalities and the second-greatest estimated economic damage (after hurricanes) among the main weather and climate disaster events in the USA from 2004 to 2013 [19,20]. In general, HW phenomena are one of the natural hazards with the greatest impact worldwide in terms of mortality and economic losses. [21,22]. In the last 15 years, Europe has suffered a high number of severe summer HWs with devastating health and economic effects. Out of the last 15 years, 2003, 2006, 2007, 2013, 2014, and 2015 should be mentioned due to the major HW events that occurred in Europe for their great magnitude, spatial area, and temporal persistence measured in consecutive days [23–27]. Most of these HWs were included in the top ten HWs that have occurred in Europe since 1950 [20].

In Italy, the summer of 2012 was characterized by high average temperatures (+2.3 °C compared to the period 1970–1999), enough to be considered one of the hottest summers since 1800; since 2000, it was the hottest after the summer of 2003 (with +3.7 °C) [28].

The intensity, duration, and timing of HWs can influence the risk of heat-related mortality. In the EuroHEAT study of the health effects of HWs in a number of European cities, it was found that in prolonged HW events, mortality was 1.5–5 times higher than for HWs of short duration, with the highest increases for prolonged heat events found in several cities (Athens, Budapest, London, Rome, and Valencia) in the 75+ age group [29–31]. There are various approaches to detecting climate variations on a local scale. Common methods include the use of climate data and their analysis with satellite imagery or mathematical modeling that compares a climate variable or an indicator between different locations at different local scales [32–35]. Recent studies report on the use of satellite monitoring of extreme heat events in urban areas and estimations of associated public health impact. Satellite thermal data can depict the spatial gradient of radiometric surface (and not ambient) temperature [36].

Detailed observations and monitoring, as well as real-time dissemination of meteo-climatic information, quantification by remote sensing (radar and satellites), and derived indices and operational services are important for decision development plans in different contexts (public health, agricultural, water resources, energy), for example in terms of managing and optimizing data monitoring networks [37,38].

The present study examines the interactions between heat waves and daily-diagnosis-related emergency admission to the hospital in Matera in the period June 2012 to August 2012. In particular, the focus was on temperatures, relative humidity, and variations of barometric pressure through the combination of multivariate statistical techniques and linear multiple regression analysis.

In this study, identification of a heat wave day was based on the suggestion made by the Intergovernmental Panel on Climate Change (IPCC) to define an extreme weather event. The World Meteorological Organization (WMO) defines HWs as periods of at least six days with a maximum temperature exceeding the 90th percentile of daily maximum temperature calculated on each calendar day in the base period CLINOs (Climatological Normals), the average values of meteorological elements for a 30-year period (1961–1990 or 1971–2000) [39,40].

Multivariate statistical analysis allows rapid definition of descriptor profiles and their interpretation in terms of the measured variables. In particular, Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables by transforming the dataset into a smaller number of artificial variables (called principal components) that will account for most of the variance of the observed variables.

In order to reduce the number of weather variables collected at the meteo-climatic stations and to define their correlation structure with the number of emergency hospital admissions on each day, PCA was applied in the present investigation [37,41–43].

2. Data Source

The study was conducted in Matera, located in southern Italy. In 2015, Matera was home to approximately 60,500 citizens in an area of about 390 km^2. The city attracts many visitors, causing an increase in population fluctuation, especially in summer, of approximately 300% from 2000 to 2015. Matera presents a typical Mediterranean climate with mild winters and hot humid summers, with an annual average temperature of 14 °C and average humidity of 65%.

Data were collected from two representative meteorological stations (see Figure 1). They were chosen according to type and significant duration of variables of interest in the study area:

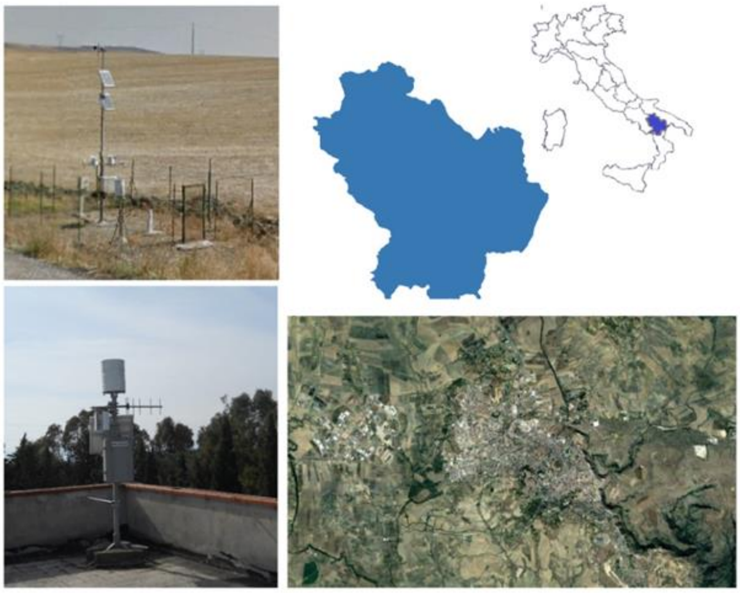


Figure 1. Meteorological stations in Matera (MaTera Alsia station in the upper left corner; MaTera Civil Protection station in the lower left corner; Matera orthophoto in the lower right corner; Basilicata region localization in upper right.

MTA (MaTera Alsia): A historical monitoring station managed by the regional Agency for Development and Innovation in Agriculture (Italian acronym, ALSIA); hourly air temperatures (maximum and minimum) and precipitation, from 1918 to present;

MTCP (MaTera Civil Protection): an urban station managed by the National Civil Protection Department; sub-hourly summer data of maximum and minimum temperatures (°C), maximum and minimum relative humidity (%), and maximum and minimum barometric pressure (hPa), from 2000 to present.

Daily admissions data were made available by the emergency department of the Matera hospital "Madonna delle Grazie" from 1 June 2012 to 31 August 2012.

The data included admission date (day and hour), diagnostic code (International Classification of Diseases) of each admission, residence zone, age, and sex of the patient, ward type, diagnosis, and triage. The total number of patients admitted to the emergency department in the three months investigated was 7895. The heat-related illnesses analyzed in this study, usually attributed to heatstroke, were fever, headache, myalgia, dehydration, palpitations, dizziness, tachycardia, syncope, etc. The selected cases, referred to as Daily Emergency Admissions (*DEA*), are 1079 and represent 14% of total admissions for the Matera hospital (330 in June, 378 in July, and 371 in August). Figure 2 reports daily emergency admissions (*DEA*) from 1 June 2012 to 31 August 2012. The *DEA* data for this period show an average of 12 patients per day and a maximum value of 23 patients per day.

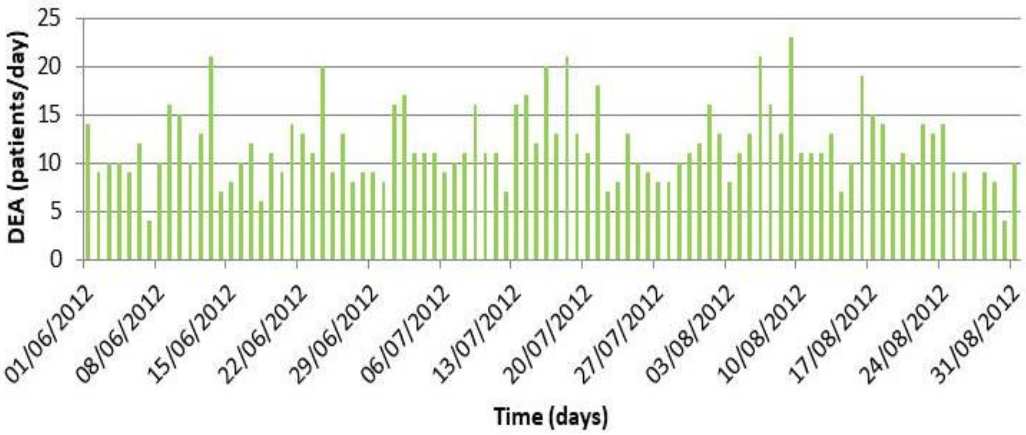


Figure 2. Daily emergency admissions (DEA) trend in summer 2012.

3. Methodology

3.1. Methodological Approach

In order to better explain the methodological approach applied in this paper, in Figure 3 a block diagram is reported. It shows the main steps of the proposed analytical framework.

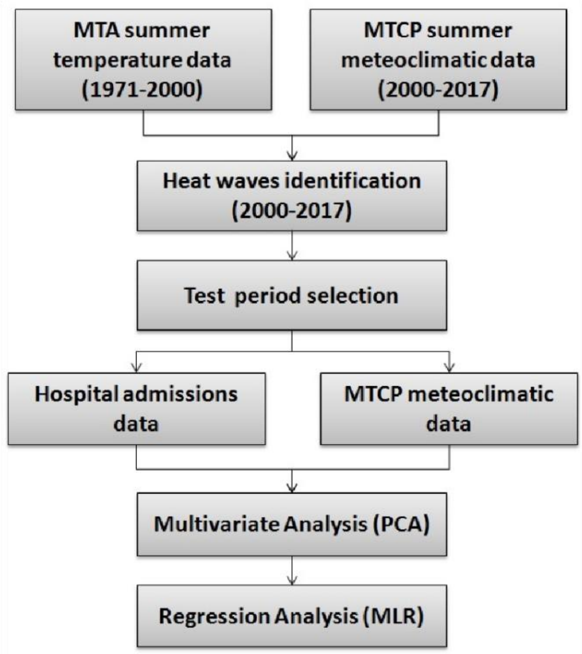


Figure 3. Flow chart of the methodological approach. MTA: Matera Alsia; MTCP: Matera Civil Protection; PCA: principal component analysis; MLR: multiple linear regression.

3.2. Temperature Analysis for the Base Period (1971–2000)

For the WMO standardized base period 1971–2000, the series of daily mean values and corresponding standard deviations were calculated as follows, starting from the summer maximum temperature BPT_{ij}^{max} temperature (with $i = 1, \ldots, M$; $M = 92$ days and $j = 1, \ldots, N$; $N = 30$ years) collected at the MTA station:

$$\overline{BPT}_i^{max} = \frac{\sum_{j=1}^{N} BPT_{i\,j}^{max}}{N} \text{ with } i = 1, \ldots, M,$$

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^{N}\left(BPT_{i\,j}^{max} - BPT_i^{max}\right)^2}{N-1}} \text{ with } i = 1, \ldots, M,. \quad (1)$$

Starting from these values, three threshold series indicating an increasing level of severity with respect to the occurrence of extreme values of maximum temperature were defined:

- First threshold series:

$$\{Ts_1^I, \ldots, Ts_M^I\} \text{ where } Ts_i^I = (\overline{BPT}_i^{max} + \sigma_i) \;\text{ with } i = 1, \ldots, M, \quad (2)$$

- Second threshold series:

$$\{Ts_1^{II}, \ldots, Ts_M^{II}\} \text{ where } Ts_i^{II} = (\overline{BPT}_i^{max} + 2\sigma_i) \text{ with } i = 1, \ldots, M, \quad (3)$$

- Third threshold series:

$$\{Ts_1^{III}, \ldots, Ts_M^{III}\} \text{ where } Ts_i^{III} = (\overline{BPT}_i^{max} + 3\sigma_i) \text{ with } i = 1, \ldots, M. \quad (4)$$

3.3. Extreme Temperature Analysis from 2000 to 2017

In order to characterize the occurrence of extreme events in maximum summer temperature data from 2000 to 2017, hot days (*HDs*) are defined according to the following criteria:

- the *i*-th summer day ($i = 1, \ldots, M$) in the *k*-th year ($k = 1, \ldots, N'$ $N' = 18$ years) is classified as a hot day of the first degree

$$\boldsymbol{HD_{L1}} \textbf{ if } \boldsymbol{T_{ik}^{max} > Ts_i^I} \quad (5)$$

- the *i*-th summer day ($i = 1, \ldots, M$) in the *k*-th year ($k = 1, \ldots, N'$ $N' = 18$ years) is classified as a hot day of the second degree

$$\boldsymbol{HD_{L2}\ if\ T_{ik}^{max} > Ts_i^{II}} \quad (6)$$

- the *i*-th summer day ($i = 1, \ldots, M$) in the *k*-th year ($k = 1, \ldots, N'$ $N' = 18$ years) is classified as a hot day of the third degree

$$\boldsymbol{HD_{L3}} \textbf{ if } \boldsymbol{T_{ik}^{max} > Ts_i^{III}}. \quad (7)$$

Furthermore, to measure the persistence of these events, the occurrence of *HWs* was defined with the following criteria:

- occurrence of at least six consecutive days classified as

$$\boldsymbol{HD_{L1}} = \textbf{occurrence of heat wave of the first degree } \boldsymbol{HW_{L1}} \quad (8)$$

- occurrence of at least six consecutive days classified as

$$\boldsymbol{HD_{L2}} = \textbf{occurrence of heat wave of the second degree } \boldsymbol{HW_{L1}} \quad (9)$$

- occurrence of at least six consecutive days classified as

$$\boldsymbol{HD_{L3}} = \textbf{occurrence of heat wave of the third degree } \boldsymbol{HW_{L3}}. \quad (10)$$

For each *HW*, the corresponding length or determined intensity (as the number of consecutive days in which a *HD* occurred) was also reported.

3.4. Correlation Analysis of Weather Conditions and Daily Emergency Admissions

To investigate the correlation structure between weather data and daily emergency admissions (number of daily cases), a Principal Component Analysis (PCA) technique and a Multiple Linear Regression (MLR) model were applied [37,43–46].

To apply PCA, minimum and maximum daily temperatures (T^{min} and T^{max}), minimum and maximum daily relative humidity (RH^{min} and RH^{max}), daily barometric pressure range (DPR), and daily emergency admissions (DEA) were organized in an input matrix (6 descriptors × 92 summer days). In this case, the approach made it possible to highlight the underlying correlation pattern among the six descriptors. Moreover, a Multiple Linear Regression analysis was performed. In particular, MLR generalizes the prediction methodology to allow for multiple weather predict variables. The MLR model used was:

$$Y = \beta_0 + \beta_1 w_1 + \beta_2 w_2 + \ldots\ldots + \beta_n w_n \quad (11)$$

where, Y, Dependent variable = DEA; β_0, Constant; $\beta_{(1\text{–}6)}$, Unstandardized coefficient for each predictor weather variable; w_1 to w_n, Predictor weather variables.

4. Results and Discussion

Regarding data analysis of temperature in the base period, the three threshold series used to identify extreme events of summer maximum temperature are presented in Figure 4. The use of an extension of the 3σ-rule allows us to take into account statistically significant events in terms of frequency occurrence in the range 0.68–0.99.

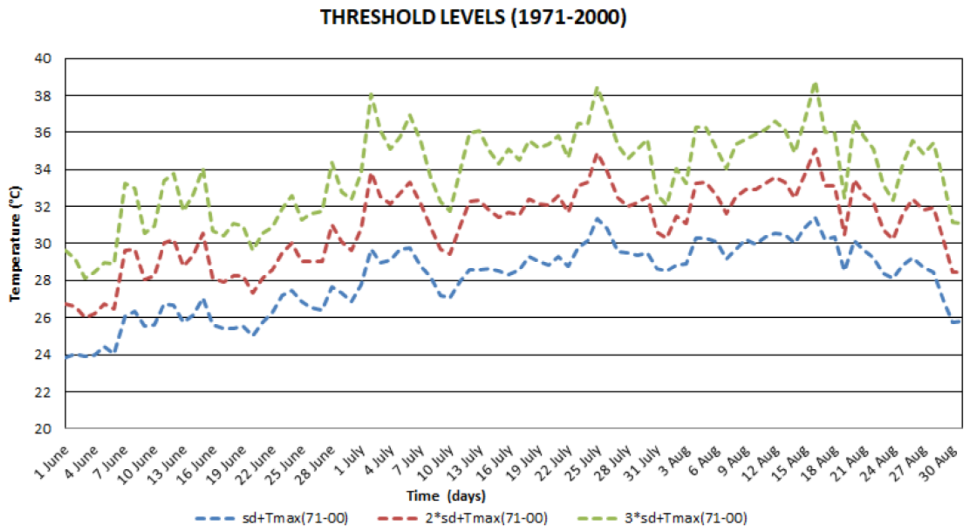


Figure 4. Maximum temperature threshold levels (base period 1971–2000).

Comparing these series with data measured in summers from 2000 to 2017, the *HDs* and *HWs* occurring in these years were counted and are summarized in Tables 1 and 2. For each year, the number of *HDs* according to the different levels of severity is specified in Table 1.

The number of *HWs* for each year, with corresponding intensities (expressed in number of days) according to the different levels of severity, are listed in Table 2.

It is possible to note that the highest number of *HDs* occurred in 2002, 2003, 2012, and 2017, while the highest HW_{L3} (combining number of events and intensity) was recorded in 2003 and 2012. Furthermore, Tables 1 and 2 reveal two years with atypical cases: in 2002, there was a maximum number of HD_{L1} (92 days) but no HW_{L3}; on the contrary, 2007 presented a low number of *HDs* and two extreme events with high intensity.

Therefore, we can say that three levels for *HW* classification made it possible to point out years characterized by a high percentage of *HDs* which do not necessarily determine situations of extreme severity at higher levels of HWs, especially in the third level.

Year 2012 was chosen to investigate a specific case among the four years in which there was an occurrence of HW_{L3}. In fact, for this year data were available from the public system of "Madonna delle Grazie" Hospital.

Table 1. Number of hot days (*HDs*) with the corresponding percentage calculated on all summer days ($M = 92$).

Year	$n(HD_{L1})$	$n(HD_{L2})$	$n(HD_{L3})$
2000	70 (76%)	42 (46%)	25 (27%)
2001	77 (84%)	42 (46%)	14 (15%)
2002	**92 (100%)**	38 (41%)	0 (0%)
2003	**89 (97%)**	**65 (71%)**	**46 (50%)**
2004	68 (74%)	45 (49%)	20 (22%)
2005	68 (74%)	45 (49%)	27 (29%)
2006	55 (60%)	32 (35%)	23 (25%)
2007	74 (80%)	58 (63%)	32 (35%)
2008	78 (85%)	48 (52%)	28 (30%)
2009	69 (75%)	41 (45%)	15 (16%)
2010	68 (74%)	45 (49%)	18 (20%)
2011	74 (80%)	49 (53%)	25 (27%)
2012	**84 (91%)**	**74 (80%)**	**49 (53%)**
2013	65 (71%)	35 (38%)	16 (17%)
2014	59 (64%)	30 (33%)	8 (9%)
2015	75 (81%)	51 (55%)	25 (27%)
2016	66 (72%)	39 (42%)	14 (15%)
2017	76 (83%)	**65 (71%)**	38 (41%)

In bold are the cases in which the percentage of *HDs* for the three levels is greater than 90%, 70%, and 50%, respectively.

Table 2. Number of heat waves (*HW*) with the corresponding intensities expressed in number of days.

Year	$n(HW_{L1})$	$n(HW_{L2})$	$n(HW_{L3})$
2000	5 (9, 7, 15, 8, 21)	1 (9)	1 (7)
2001	5 (10, 15, 20, 7, 9)	1 (11)	0
2002	1 (92)	1 (13)	0
2003	2 (61, 24)	3 (14, 11, 15)	**2** (**11**, **11**)
2004	4 (8, 25, 10, 7)	1 (16)	0
2005	5 (7, 19, 7, 20, 7)	3 (15, 8, 8)	2 (10, 7)
2006	4 (18, 7, 10, 10)	1 (16)	1 (15)
2007	3 (25, 17, 19)	2 (22, 11)	**2** (**12**, **8**)
2008	4 (30, 15, 7, 13)	2 (16, 10)	0
2009	3 (17, 8, 12)	1 (8)	0
2010	3 (16, 16, 19)	2 (9, 14)	0
2011	4 (10, 16, 11, 20)	3 (9, 13, 15)	0
2012	3 (46, 16, 14)	**4** (**9**, **31**, **13**, **8**)	**2** (**11**, **8**)
2013	4 (12, 7, 23, 9)	2 (11, 8)	1 (8)
2014	4 (11, 7, 8, 12)	0	0
2015	3 (17, 40, 9)	1 (22)	1 (7)
2016	2 (25, 11)	1 (7)	0
2017	**6** (**7**, **13**, **11**, **8**, **15**, **9**)	**4** (**7**, **12**, **8**, **13**)	**2** (**7**, **12**)

In bold, the cases in which the greatest number of extreme events occurred.

The pattern of maximum temperatures in the summer of 2012 is compared in Figure 5 with the three threshold series to put in evidence the periods in which the extreme events occurred.

In particular, for each *HW*, it is possible to identify:

Three HW_{L1}: from 1 June to 16 July (46 days); from 27 July to 10 August (15 days); and from 13 August to 26 August, (19 days).

Four HW_{L2}: from 6 June to 14 June (9 days) and from 16 June to 16 July (31 days) included in the first HW_{L1}; from 28 July to 9 August (13 days) included in the second HW_{L1}; and from 19 August to 26 August (8 days) included in the third HW_{L1}.

Two HW_{L3}: from 16 June to 26 June (11 days) and from 8 July to 15 July (8 days) included both in the second HW_{L2} (Figure 5).

To investigate the correlation structure among weather conditions and *DEA* data in summer 2012, PCA was applied. All data (with no data missing) were organized in an input matrix [*6 descriptors* × *92 summer days*]. Table 3 summarizes the descriptive statistics.

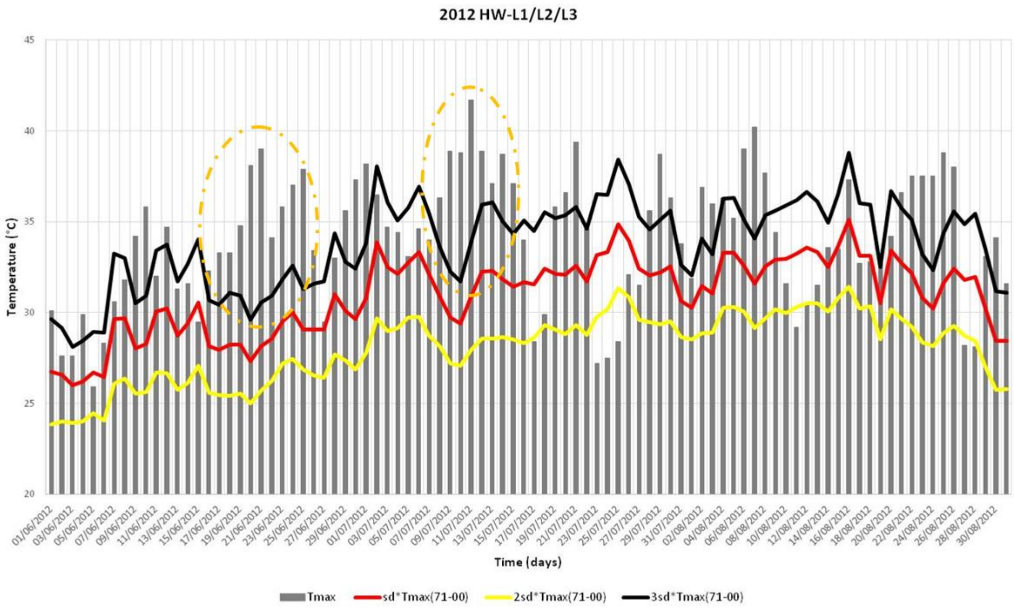


Figure 5. Trend of maximum temperatures of summer 2012 compared with the three threshold series of *HW*.

Table 3. Explorative statistical analysis of meteo-climatic database.

Variable	Units	*min*	*max*	*m*	*sd*
T_{max}	(°C)	25.9	41.7	34.1	3.5
T_{min}	(°C)	14.8	28.6	23.0	3.1
DPR	(hPa)	1.0	7.0	2.6	1.1
RH_{max}	(%)	37.0	100.0	68.0	19.0
RH_{min}	(%)	14.0	56.0	28.0	9.0
DEA	(n/day)	4.00	23.00	11.73	3.9

Legend: *m* = mean value; *sd* = standard deviation; *DPR* = daily barometric pressure range; *RH* = relative humidity.

The results of PCA are shown in Table 4. Combining the Kaiser's rule for the selection of significant eigenvalues and the empiric rule for the factor characterization (loadings >0.71 are regarded as excellent and <0.32 as very poor), only eigenvalues higher than 1 and loadings higher than 0.4 were taken into account [47,48]. In this investigated case, the first three eigenvalues explained 85% of the data variance. To interpret these three principal components (PCs), only the percentage contributions of original descriptors higher than 5% were considered (Table 4).

Table 4. PCA results.

	F_1	F_2	F_3
λ_i	3.16	1.14	1.00
$P(\lambda_i)$	52.7%	19.0%	13.4%
P_{tot}		71.7%	85.1%
	F_1	F_2	F_3
T_{max}	27%	-	-
T_{min}	24%	-	-
DPR	-	54%	35%
RH_{max}	21%	-	6%
RH_{min}	22%	-	13%
DEA	-	44%	44%

Legend: λ_i = eigenvalue; $P(\lambda_i)$ = percentage of variance explained by *i*-th eigenvalue; P_{tot} = cumulative percentage of variance; A_i = *i*-th eigenvector.

It was possible to identify three new variables: the first variable is represented by a linear combination of T^{max}, T^{min}, RH^{max}, and RH^{min} (the percentage of explained variance was 52.7%); the second by a linear combination of *DPR* and *DEA* (the percentage of explained variance was 19%); and the third includes *DPR*, *DEA*, RH^{max}, and RH^{min} (explaining 13.4% of variance). In Figure 6, the original descriptors are shown in the principal component system: temperatures and relative humidity have opposite signs while temperatures and DEA data appear in the same quadrant.

PCA allowed for the reduction of the set of weather descriptors. In particular, the six original variables were separated into two different sets (T^{max}, T^{min}, RH^{max}, RH^{min}) and (*DPR, DEA*). To improve interpretation of the correlation structure, it is interesting to associate PCA results and *HD* identification. In the three score plots (F_1 versus F_2) depicted in Figure 7, the size of bubbles is proportional to the corresponding *DEA* value. It is possible to note that from threshold level 1 to level 3, the size of bubbles tends to increase. These results highlight the increase in severity level of *HDs*, decreasing the role of relative humidity. For the maximum level of threshold (HW_{L3}), the correlation between *DEA* and *HWs* is linked to a combination of *DPR* and temperatures.

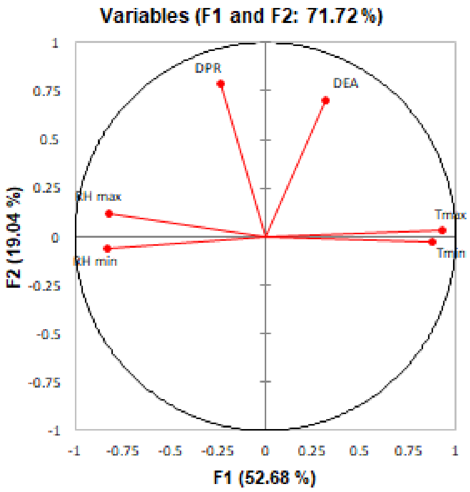
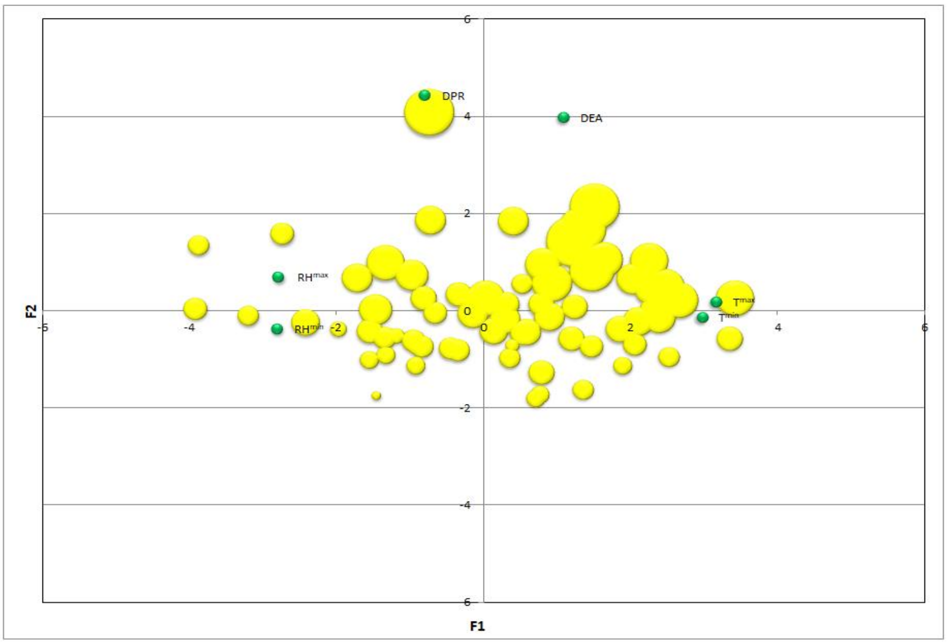
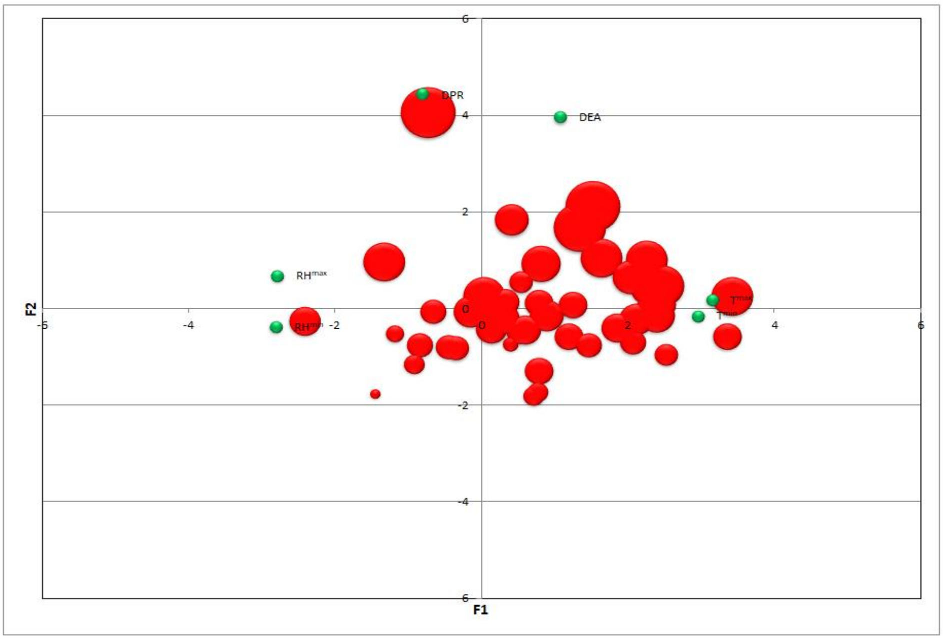


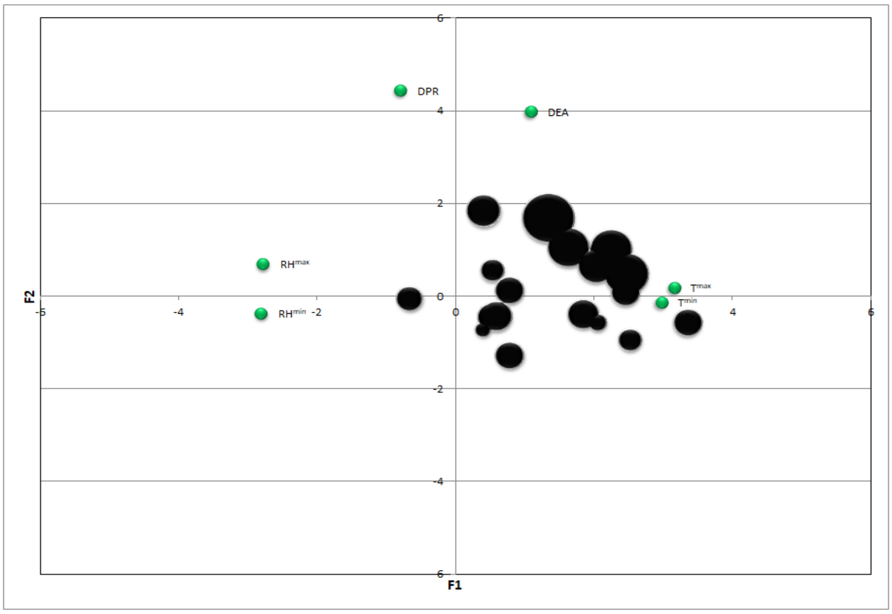
Figure 6. Correlations between variables and factors.



(**a**) HW_{L1}



(**b**) HW_{L2}



(**c**) HW_{L3}

Figure 7. Bubble chart with correlations of *DEA* and meteo-climatic variables, on the principal components, for the three threshold levels.

In order to analyze the relationship between *DEA* values and weather variables in summer 2012 and according to multivariate statistical analysis, a multiple linear regression model was developed. In this context, the following variables were considered: *ln*(*DEA*) (natural logarithm of Daily Emergency Admissions), T^{max}, T^{min}, and *DPR*. To take into account the influence of holidays (including Saturdays) in daily admission in the emergency room, the DOW (day of week) variable was also considered (Figure 8).

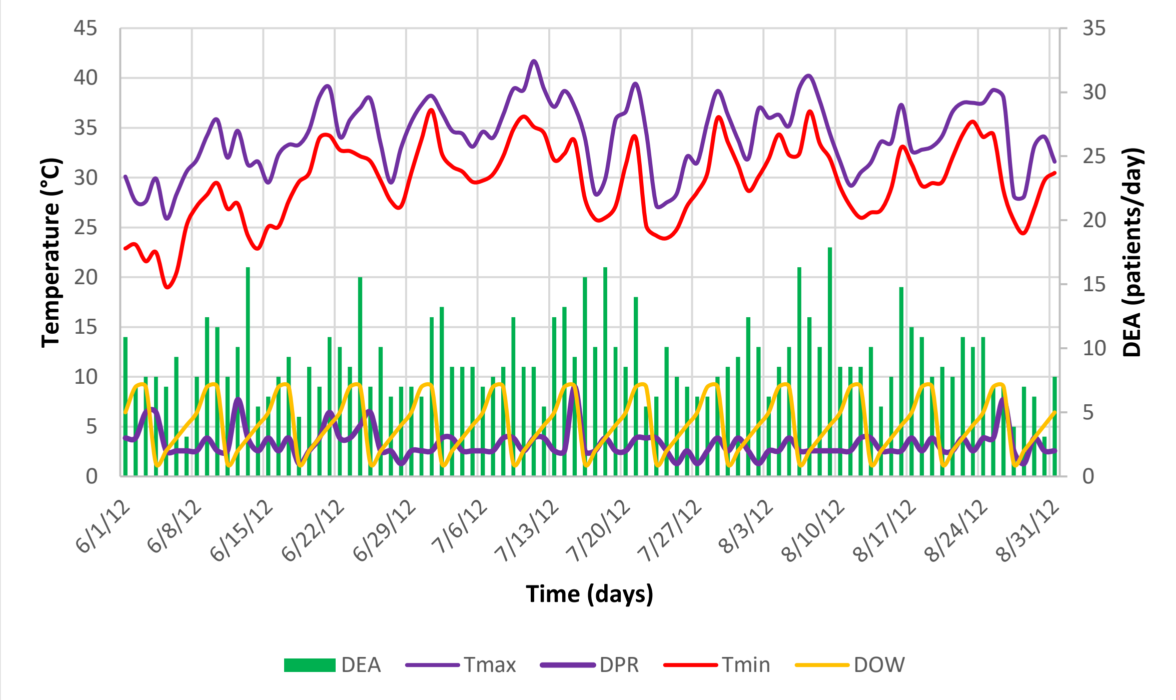


Figure 8. Trend of DOW (day of week) variable compared to temperatures, *DPR*, and *DEA*.

Furthermore, an autocorrelation test of temperatures and *DPR* data series was carried out, allowing for consideration of the two-day lagged series in the regression model. The multiple linear regression model parameters are reported in Table 5.

Table 5. Multiple Linear Regression model parameters.

Variables	Coefficient	t Statistics
Intercept	1.472	14.023
X1 T_{max}(lag$_2$)	0.018	3.323
X2 T_{min}(lag$_2$)	0.016	3.126
X3 *DPR*(lag$_2$)	0.014	2.890
X4 DOW	0.002	2.616

In particular, the parameter values reported in Table 5 show the marginal role of DOW in the process ($\beta = 0.002$, $p < 0.01$). On the contrary, the effect of temperature (maximum and minimum) and *DPR*(lag$_2$) is greater (β = 0.018 and $p < 0.001$, β = 0.016 and $p < 0.001$, β = 0.014 and $p < 0.001$, respectively), representing *DEA* precursors and consequently of potential use in surveillance of hospital admission risk factors.

Figure 9 shows the trend of DEA for high threshold levels (HW_{L2} and HW_{L3}) and the obtained multiple linear regression model. From the figure, it is possible to observe that even if the model is unable to reproduce *DEA* (R^2adj = 0.33) peak values (probably due to the short observation period), the model estimates the *DEA* trend very well for nearly the entire period of analysis and for each HW threshold level. This confirms the results obtained also by multivariate analysis, which indicate that, especially for extreme events (HW_{L2} and HW_{L3}), the *DEA* was strongly related to temperatures (maximum and minimum) and *DPR*.

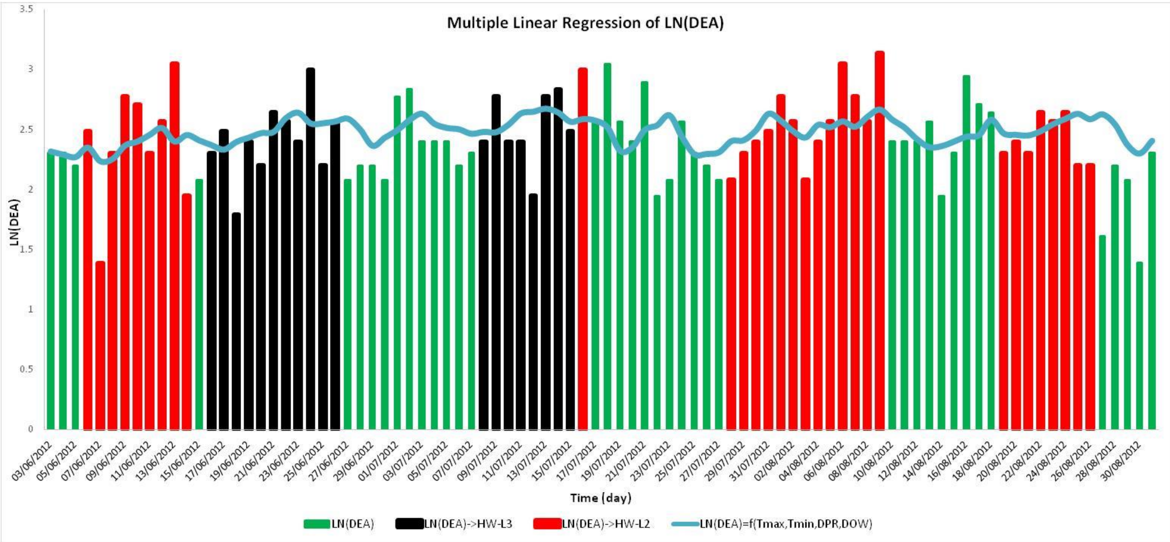


Figure 9. Trend of *DEA* for HW_{L2} and HW_{L3} threshold levels and the multiple regression model result.

5. Conclusions

Based on common scientific knowledge, under which temporal weather variations have an impact on satisfaction with life (in particular on individuals with poor health condition), this study assessed the impact of high temperatures, typically related to heat waves, on daily hospital admissions between 1 June 2012 and 31 August 2012 at the emergency room of a hospital in Matera, Italy. In particular, a methodology composed of several methods was applied: a procedure to identify the heat waves in a 2000–2017 dataset compared to the base period (1970–1999) and, subsequently, a PCA technique and MLR model to examine the association between *DEA* and weather data for summer 2012.

The analysis of daily mean values and standard deviations of maximum temperatures in the 2000–2017 period made it possible to detect three threshold series, which reflect the occurrence of *HWs*. The years 2003, 2012, and 2017 presented the maximum frequency of hot days and heat waves (with a third-level HW-days percentage greater than 20%). In 2012, HW_{L3} occurred between the third and fourth weeks of June and the first two weeks of July.

The results of PCA show that the role of relative humidity decreases when the severity level of *HWs* increases. Moreover, the results of the PCA and MLR model highlight the combination of temperatures (T_{max} and T_{min}) and *DPR* as precursors for a surveillance system of risk factors in hospital admissions.

The paper first highlights some important strengths of the methodology as the total replicability in other similar contexts. On the contrary, the weakness point of this work is the length of the available dataset, which did not allow for a verification of the predictive capabilities of the model. For these reasons, future developments will address the prediction of the values of *DEA* (e.g., analysis of a dataset that also includes the 2017 year in order to verify the predictive capabilities of the model) and the development of other techniques both for the identification of the heatwaves (anomalies detection) and for the predictive model (machine learning).

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