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ORIGINAL PAPER

A comparative sensitivity analysis of human thermal comfort indices with generalized additive models

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Abstract
This paper presents a comparative sensitivity analysis of six of the widely used human thermal comfort indices. The analysis consists of the evaluation of the effect of indices 'input parameters' variation and change rate on the output of human energy balance and simple thermohygrometric indices. For the implementation of the sensitivity analysis, the generalized additive model's methodology is applied on a long period and high temporal resolution dataset from Athens, Greece. The results indicate that the proposed methodology of generalized additive models is adequate for such an analysis. Moreover, this research revealed the differences in index behaviour. The thermohygrometric indices (i.e. Thermohygrometric Index and HUMIDEX) exhibit a clearly deferent sensitivity pattern in comparison to the human energy balance indices (i.e. physiologically equivalent temperature (PET), perceived temperature (PT), modified physiologically equivalent temperature (mPET) and Universal Thermal Comfort Index (UTCI)), and they are incapable to handle the complexity of the atmospheric stimuli on human thermal perception. On the other hand, human energy balance indices can follow the input parameters fluctuations but with different grades of sensitivity. PET and mPET present a moderate and gradual sensitivity both in terms of the input variation and input change rate. PT is the less sensitive index among the human energy balance investigated, but it is able to follow efficiently the input parameters variation during the measurements period. Moreover, UTCI is the most sensitive among all the selected indices for low values (and low change rate) of the input parameters but for high input parameter values (except the wind speed), UTCI exhibits a low sensitivity in comparison to the other human energy balance indices. In terms of sensitivity, the most influential input parameter is global radiation, and the less influential is vapour pressure.

1 Introduction

Thermal comfort and thermal stress are of the utmost importance for human health and well-being. The thermal environment directly affects the energy consumption for urban: (i) heating or cooling procedures (Yang et al. 2014; Nazarian et al. 2017; Ricciu et al. 2018), (ii) tourism (Didaskalou and Nastos 2003; Lin and Matzarakis 2008; Charalampopoulos et al. 2017), (iii) productivity levels (Epstein and Moran 2006; Akimoto et al. 2010; Damiati et al. 2016; Lipczynska et al. 2018) and (iv) human health (Nastos et al. 2010; Chen and Chang 2012; Parsons 2014; Salata et al. 2017). Resultantly, to assess and quantify the thermal conditions and their effect on human perception, a vast amount of thermal indices has been developed by the international scientific community. As de Freitas and Grigorieva (2015) indicate, the indices' schemes used differ in approach according to the number of variables taken into account, the rationale employed, the relative sophistication of the underlying body–atmosphere heat exchange theory and the particular design for the application. Some indices are used more frequently than others because of their output variable unit, their necessary input parameters, their accuracy on thermal perception assessment and their ability to be applied around a variety of different climatic conditions.

The most sophisticated indices which can be calculated only via computers due to their complexity are implementations of human thermophysiological models. The simplified approaches of the human thermal regulation are crucial for the accuracy and the precision of these indices. Since the thermal balance is influenced by local environmental conditions and individual physiological characteristics, the human body can be presented as a single or multi-part construction (Katić et al. 2016; Coccolo et al. 2016; Potchter et al.

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2018). Moreover, the complexity of the human thermal comfort assessment rises markedly when one takes into account the non-uniformity of the environmental conditions (Huizenga et al. 2001; Cheng et al. 2012). Hence, the key questions are how each index responds to a wide spectrum of atmospheric conditions. Is their response linear, steady or fluctuate under specific input parameter variation? How the variation and change rate of the input parameters can modify the output of the index? These are the typical questions which can be answered by the sensitivity analysis. Probably, the most direct way to evaluate the accuracy and their response to the environmental stimuli is the method of interviews with structured questionnaires accompanied by simultaneous micrometeorological measurements. But the cost of this method is high, and the ability to test the index under a broad variety of thermal conditions is restricted by the time which the research team can be present in the field. As a result, this raises the need to conduct computational methodologies such as sensitivity analysis.

This method of evaluation is common yet essential for wide variety of scientific research fields such as economic, social, environmental, engineering and physics studies (Frey and Patil 2002; Saltelli et al. 2007; Pianosi et al. 2016; Ferretti et al. 2016). For the discipline of human biometeorology and human thermal comfort, different approaches to sensitivity analysis were conducted. Fang et al. (2018) carried out a thermal comfort indices' sensitivity analysis investigation for a time period of 3 years at Guangzhou city (South subtropical China), a region with high air humidity and temperature. During their research, they investigated the fluctuation of physiologically equivalent temperature (PET) and Universal Thermal Comfort Index (UTCI) against combinations of parameters' difference such as operative temperature minus relative humidity, under different levels of wind speed, metabolic rate and clothing insulation. Under different climatic conditions, Provençal et al. (2016) investigated the sensitivity of PET, UTCI and HUMIDEX in Quebec, Canada. Their approach was based on scatter graphs of index values minus air temperature against the input parameters such as wind speed and vapour pressure. The data was collected from three meteorological stations inside and over Quebec City with an hourly time step for the period of March 2013 to February 2014. More recently, Fröhlich et al. (2019) conducted a sensitivity analysis on UTCI, PET and perceived temperature (PT) indices utilizing 10 years of hourly data from the city of Freiburg, Germany. Their analysis was focused on the influence of the vapour pressure, air temperature, wind speed and mean radiant temperature fluctuations to the UTCI, PET and PT outputs. The investigated changes on the original dataset were ± 2 °C, ± 2.5 hPa and ± 2 m/s and from the sun to shade for air temperature, vapour pressure, wind speed and radiation, respectively. Another similar sensitivity analysis was conducted by Fröhlich and Matzarakis (2016) in the hot and dry city of Doha, Qatar. This research was conducted using data for a time period from March 1999 to January 2014 with a 3-h time resolution. Similarly, to the research in Freiburg, the sensitivity analysis in Doha was made by the incremental changing of the original dataset. In the hot and humid Taiwan, Lin et al. (2018) conducted comparative research about the sensitivity of PET and modified physiologically equivalent temperature (mPET) utilising in situ micrometeorological measurements and questionnaires' survey from the year 2011 to 2014. This study was focused on the impact of vapour pressure on the variation of PET and mPET indices. Under different climatic conditions in the Victoria region in British Columbia, Canada Tuller (1997) conducted research to investigate the impact of onshore winds on human thermal sensation. Seen through this prism, the impact of air temperature, ground radiant temperature, sky radiant temperature and humidity changes to several indices such as wind chill, HUMIDEX and Fanger's model (among others) were calculated. Respectively, on one hand, there is a lack of research on the topic of human thermal comfort indices' sensitivity analysis, yet on the other, the most common way to face the sensitivity analysis of human thermal comfort indices is to modify the initial input dataset or to conduct short-term in situ measurements accompanied by interviews with structured questionnaires.

This study is the first step towards examining the applicability of generalized additive models (GAMs) on the sensitivity analysis of the human biometeorological indices. Additionally, this is an extensive yet comparative sensitivity analysis with original input dataset with high time resolution. Moreover, this study is an attempt to further comprehend the behaviour of the selected indices under a wide variety of meteorological conditions. Consequently, the objectives of this particular study were as follows, to:

1. Assess the applicability of GAMs on human biometeorological indices
2. Trace the sensitivity of the major human thermal comfort indices using a big and original dataset of a Mediterranean region
3. Compare the sensitivity of the selected indices on the same inputs' variation and change rate

2 Data and methods

2.1 Data

The selected data were processed from the meteorological station of the Agricultural University of Athens, Greece (lat 37° 59', long 23° 42′, alt 36 m a.s.l). According to the Köppen Geiger climate classification system, the area where the meteorological station is situated in belongs to the 'Csa' class (Kottek et al. 2006) with hot and dry summers and mild winters. The location of the station is in a planar, unobstructed area in the university campus. The measurements used for the implementation of the analysis, were air temperature (T_a, °C) and relative humidity (RH, %) at both 1.5 and 3.0 m levels, wind speed (WS, m/s) at 3.0 and 10 m level in addition to global radiation (GR, W/m^2) and sunshine duration (SD min per 10 min). The time interval for the above measurements was 10 min, and the measurements which were carried out by the equipment which is described in Table 1 lasted from the years 2002 to 2008.

In total, the raw data lines surpass 700.000 measurements. After the appropriate treatment (exception of technical faults and filters utilization), almost 338.000 lines of simultaneous measurements of the selected parameters were used. The descriptive statistics of the input parameters (Table 2) reveal the wide variety of the atmospheric conditions on the basis of which the research was conducted.

As shown, the input data are typical for the Mediterranean region with mild winter and hot summer with high radiation and medium humidity. As anticipated, the results of the sensitivity analysis were fairly restricted by the spectrum of the data, and their distribution since the uncertainty would be lower where the data measurements were denser. For the human energy balance indices, we assume that the hypothetical person is male, 35 years old, 1.75 m height with 75 kg weight, clothing insulation 0.9 clo and standing with activity equal to 80 W. All those parameters are constant and steady for every calculation of this study.

2.2 Selected thermal indices

To examine the sensitivity of the specified human thermal comfort indices, the Thermohygrometric Index (THI), HUMIDEX, PET, modified PET (mPET), UTCI and PT were selected. According to de Freitas et al. (2015), the first two indices belong to the algebraic or statistical model category (C), and the remaining indices belong to the energy balance stress category (G). The criteria of selection were associated to 'usage popularity', namely, the common degree Celsius output unit, and the different approach of each index to the human thermal environment. The first two are simple indices (Epstein and Moran 2006) which have been in use for more than five decades. The other four are more sophisticated because they incorporate complex human thermal regulation models (Coccolo et al. 2016; Potchter et al. 2018). Apart from the popularity and their common output unit, the selected indices are frequently utilized by architects, landscape designers, urban planners, physiologists and physicians (Lin 2009; Charalampopoulos et al. 2015; Martinelli et al. 2015; Algeciras and Matzarakis 2016; Nouri et al. 2018a); thus, the sensitivity analysis could be beneficial for a wide range of applications. Finally, according to the analysis of Potchter et al. (2018), one can estimate that almost 50% of human biometeorological studies were conducted using at least one of the six selected indices.

2.2.1 Thermohygrometric indices: Thermal Humidity Index (THI) and Humidex (H)

The THI and HUMIDEX indices define the human comfort as a function of the thermal environment as it is expressed by air temperature and humidity, neglecting the human body thermoregulation and behaviour (Tuller 1997; Unger 1999; Emmanuel 2005; Charalampopoulos et al. 2013). The required input parameters (air temperature and air humidity) are easy to be found because they are essential for every branch of atmospheric science and are measured by all meteorological stations. For the purposes of this research, the following Eqs. 1 and 2 were used to calculate THI (Unger 1999) and HUMIDEX (Conti et al. 2005) respectively:

$$\mathrm{THI} = T_a - (0.55 - 0.0055 \times \mathrm{RH}) \times (T_a - 14.5) \tag{1}$$

$$\mathrm{HUMIDEX} = T_a + \left(\frac{5}{9}\right) \times (e - 10) \tag{2}$$

where T_a is air temperature in degree Celsius, RH is relative humidity in percent and e is the vapour pressure in hectopascals.

Table 1 Technical characteristics of the meteorological station's sensors

Parameter	Sensor type	Range	Accuracy	Update interval
Air temperature (T_a)—1.5 m, 3 m agl*	HD9008TR Delta—OHM	− 40… + 80 °C	± 0.1 °C	5 s without filter
Relative humidity (RH)—1.5 m, 3 m agl	HD9008TR Delta—OHM	5…98 %RH	± 2% (5…98% RH)	6 s without filter
Wind speed (WS)—3 m, 10 m agl	AN1 Delta-T Devices	0.2 to 75 m/s	± 0.1 m/s for 0.3–10 m/s	10 s
Global radiation (GR)	SKYE SKS 1110	0–5000 W/s	typ. < 3%, max 5%	10 s
Sunshine duration	BF3 Delta-T Devices	–	± 10% w.r.t. WMO definition	10 s

*Above ground level

Table 2 Input parameters descriptive statistics

	Air temperature 1.5 m (°C)	Vapour pressure (hPa)	Global radiation (W/m^2)	Wind speed (m/s)
Min	− 5.1	1.3	0.0	0.2
1st Qu	13.3	9.6	0.0	0.7
Median	19.3	12.9	72.0	1.3
Mean	19.6	13.1	240.0	1.5
3rd Qu	26.0	16.4	451.0	2.1
Max	44.3	31.7	1250.0	7.5

THI and HUMIDEX in their original and modified versions have been used by the scientific community to evaluate thermal discomfort over a wide variety of environments and climates (Unger 1999; Emmanuel 2005; Toy and Yilmaz 2010; Correa et al. 2012; Eludoyin et al. 2014; Desai and Dhorde 2018). Despite the simplicity of their equation and their 'age', they are a reasonable choice for urban bioclimate and human thermal comfort research (Eludoyin et al. 2014; Mekis et al. 2015; Zhang et al. 2016; Desai and Dhorde 2018).

The corresponding thermal comfort or sensation (Table 3) is not identical between THI and HUMIDEX as a consequence of their different equations and dissimilar expected sensitivity to air temperature and humidity levels. Both index calculations were conducted with an R-language script. Finally, the thermohygrometric indices were utilized as indicators for the sensitivity analysis method effectiveness due to their simple algebraic equation.

2.2.2 Human energy balance stress indices: PET, mPET, UTCI and PT

Seeing that the human body and its intrinsic thermal perception to climatic stimuli is the subject of human biometeorological conditions, it is of utmost importance to incorporate the human body's (and clothing) energy balance within the respective indices. Thus, the last generation of human thermal indices is more comprehensive and simultaneously also very complex in terms of their embedded calculations. Their biometeorological background is very wide, and their approach to thermophysiological models varies substantially. Given the plethora of the indices, this study selected four representative cases taking into account their different thermophysiological approach. These four consisted of the PET and mPET (mPET is calculated by the mPET model, an evolution from the Munich Energy-balance Model for Individuals (MEMI)) (Höppe 1999; Chen and Matzarakis 2017), PT which is based on PMV of the 'Klima–Michel model' (Staiger et al. 2012) and UTCI which is based on the Fiala multi-node model (Błażejczyk et al. 2010; Jendritzky et al. 2012). Their numeric classes are not identical, but it can be presented considering the physiological stress categories and the thermal perception classes as below (Table 4). The merge of mPET and PET classes was made after personal communication with Prof. A. Matzarakis who concluded that since there is no distinct classification for mPET, one can currently assume that it is identical those associated to PET. Taking into account that the outcomes of this research were specifically focused neither on thermal perception nor on stress categories Table 4 was constructed to enhance the indices comparability.

2.2.3 Physiologically equivalent temperature-PET

One of the most widely used human thermal comfort indices is PET, which is based on the Munich Energy balance Model for Individuals (MEMI). It has been defined as the air temperature at which, in a typical indoor setting (vapour pressure of 12 hPa or 50% at 20 °C and light air − 0.1 m/s), the human energy budget is maintained by the skin temperature, core temperature and perspiration rate, which are equivalent to those under the conditions to be assessed (Höppe 1999; Matzarakis et al. 1999; Nouri et al. 2018b). Although PET has been widely applied in human biometeorology (Chen and Matzarakis 2017; Potchter et al. 2018), it still has several limitations. The most prominent is that the two-node MEMI model is 30 years old and is therefore outdated. Additionally, the clothing parameter has weak influence due to the intrinsic model, and there is an underestimation of the influence of vapour pressure in warm and humid regions. This is an aftermath of the PET restriction to latent heat fluxes via respiration and via diffusion through the skin (Blazejczyk et al. 2012; Lin et al. 2018). However, PET continues being the most popular index

Table 3 The modified corresponding categories of thermal comfort according to THI and HUMIDEX indices (Tuller 1997; Conti et al. 2005; Mekis et al. 2015)

THI category	Celsius (°C)	HUMIDEX category	Celsius (°C)
Cold	− 1.7 to 12.9	Comfort	< 27
Cool	13 to 14.9	Partial discomfort	28 to 29
Comfortable	15 to 19.9	Noticeable discomfort	30 to 34
Hot	20 to 26.4	Evident discomfort	35 to 39
Very hot	26.5 to 29.9	Intense discomfort	40 to 44
Torrid	> 30	Dangerous	45 to 54
		High probability of heat exhaustion and heat stroke	> 55

Table 4 Modified PET, mPET, UTCI and PT equivalent temperature categories in terms of thermal stress (Matzarakis et al. 1999; Blazejczyk et al. 2012; Fang et al. 2018)

PET/mPET (°C)	UTCI (°C)	PT (°C)	Stress category	Thermal perception
> 41	≥ 46	≥ 38	Extreme heat stress	Very hot
–	38 ≤ to ≤ 46	–	Very strong heat stress	
35 to 41	32 to 38	32 to 38	Great heat stress	Hot
39 to 35	26 to 32	26 to 32	Moderate heat stress	Warm
23 to 29	–	20 to 26	Slight heat stress	Slightly warm
18 to 23	9 to 26	0 to 20	Comfort possible	Comfortable
13 to 18	0 to 9	− 13 to 0	Slight cold stress	Slightly cool
8 to 13	− 13 to 0	–	Moderate cold stress	Cool
4 to 8	− 27 to − 13	− 26 to − 13	Great cold stress	Cold
< 4	− 40 to − 27	–	Very strong cold stress	
–	− 40 ≤	− 39 ≤	Extreme cold stress	Very cold

for the human thermal comfort research studies in a wide geographic and climatic variety (Charalampopoulos et al. 2013, 2017; Salata et al. 2016; Nouri et al. 2018c; Moustris et al. 2018). The input parameters for the calculation of PET index are T_a, VP, WS at 1.5 m a.s.l. and global radiation (GR).

2.2.4 mPET

In order to address the aforementioned issues of the PET index, Chen and Matzarakis (2017) launched a modified version of PET, called mPET. The main modifications of the mPET are the integrated thermoregulation model (modified from a single double-node body model to a multiple-segment model) and the updated multiple-layer clothing model, which relays to a more accurate analysis of the human bio-heat transfer mechanism (Chen and Matzarakis 2017; Lin et al. 2018; Nouri et al. 2018b). In more detail, the introduced thermoregulation equations by the mPET have two major modifications, which are the multiple-segment body model and the human bio-heat transfer process. Depending on the number of the clothing layers (from single to triple) the body model's calculation nodes could vary from 15 to 25. The calculation of models' nodes in human thermal comfort indices (PMV, PET and mPET) represent the tissues of the body, such as two core nodes, fat and two skin nodes. Using this body model, it can more effectively consider the heat transfer from traveling from the inner body to the outer body, in comparison to the simpler two-node body used by the PET index. The input variables for the calculation of the mPET index are identical to the aforementioned parameters for the PET.

2.2.5 UTCI

The UTCI index was introduced by the COST Action 730 to assess the human reaction to the outdoor thermal environment (Bröde et al. 2012). It is based on the Fiala model that is an advanced multi-node thermophysiological model which can include the capability to predict both whole body thermal effects (hypothermia and hyperthermia; heat and cold discomfort) and local effects (facial, hands and feet cooling and frostbite). Briefly, the model consists of two interacting systems: (1) the controlling active system and (2) the controlled passive system (Błażejczyk et al. 2010; Havenith et al. 2012). It is appropriate for biometeorological assessments in all climatic zones according to Blazejczyk et al. (2012) and Jendritzky et al. (2012). Furthermore, UTCI involves the definition of a reference environment with 50% RH (but vapour pressure not exceeding 2 kPa), calm air and radiant temperature which are equal to air temperature (T_a) (Fang et al. 2018). For the facilitation of index usage, the operational procedure (Bröde et al. 2012) provided the simplified algorithms with which the UTCI values can be computed taking T_a, RH (or P_a—vapour pressure), WS and T_{mrt} as inputs. The WS measurements for this study have been taken at the level of 10 m above ground level, as index calculation procedure requires in order to avoid the uncertainties of the major wind speed estimation equations. Also, the input parameters were utilized for the calculation of index were T_a, VP, WS and GR.

2.2.6 PT

As mentioned by Staiger et al. (2012), perceived temperature (PT) index is a steady-state model allowing rapid calculation by avoiding integration over time and using an effective iteration. Therefore, it is perfectly suited for operational applications with high spatial and temporal resolution (e.g. meteorological forecasts). Also, this index has proved its suitability for numerous applications across a wide variety of scales, from micro to global, and is successfully used both in daily forecasts and climatological studies. Another interesting characteristic of this index is that it is designed for staying outdoors (Staiger et al. 2012). Similarly, to PET and mPET, PT is the air temperature (°C) of a reference environment in which the perception of heat and/or cold is the same as under the actual conditions. In the reference environment, the wind velocity is reduced to a light draught and mean radiant temperature is equal to T_a (such as inside a dense forest or a dark room). The water vapour pressure is identical to that of the actual environment as long as it is not reduced by condensation (Laschewski and Jendritzky 2002).

2.3 Methodology

The purpose of this study is to investigate the sensitivity of each selected index while accounting for its major inputs' fluctuation and their comparative sensitivity analysis in the same parameters' variation. Briefly, sensitivity analysis is the study of the relative importance of different input factors (parameters) on the model output, or the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input (Saltelli et al. 2004). The most popular yet simplistic and straightforward way to conduct sensitivity analysis is to retain a selected input parameter steady and calculate the index for a spectrum of values for the rest parameter (moving one factor). The results of this method are usually presented as shown in the following diagrams (Fig. 1).

There are more methodological approaches on the topic of the sensitivity analysis (and their related presentation), but the consensus among researchers is that models are indeed sensitive to input parameters in two distinct ways: (1) the variability, or uncertainty, associated with a sensitive input parameter is propagated through the model resulting in a large contribution to the overall output variability, and (2) model results can be highly correlated with an input parameter so that small changes in the input value result in significant changes in the resulting output (Hamby 1994). The methods of sensitivity analysis vary from differential analysis (direct method), one-at-a-time sensitivity measures, factorial design, local and global analysis to the well-known sensitivity indices or the subjective sensitivity analysis (Hamby 1994; Saltelli et al. 2007; Pianosi et al. 2016).

The major drawback of the 'moving one factor' direct methods is that the examined combinations of input parameters' values are very few and in most cases are fictional. On the other hand, if one has to examine the impact of the measured inputs' values variation to the model's output values, the cases are finite. As Ferretti et al. (2016) suggests moving one factor at a time away from a fixed baseline in a multidimensional space of uncertain factors leaves the majority of that space unexplored. This is one of the consequences of the so-called curse of dimensionality, whereby the mass of a hyper-cube tends to concentrate on its edges and corners at increasing dimensionality—corners which are not visited if one moves factors away from their baseline one at a time. Further, moving one factor at a time leaves all interactions dormant, because in order to activate them, one needs to move more than one factor at a time, as known in the statistical theory of the design of experiments. Experimental designs are in fact designed to efficiently uncover the effects of various order, e.g. main effects and second-order interactions. Surprisingly, many reported numerical experiments do not include a design at all. For this research, it was chosen to use a high amount of real measurements to avoid the aforementioned uncertainties.

This approach is easy in terms of biometeorological research, but Fanger (1970) in classic 'Thermal comfort. Analysis and applications in environmental engineering' indicated that 'Meteorologists normally give individual parameters independently of each other: air temperature, wind velocity, number of hours sunshine etc. However, for outdoor work and from a recreational point of view, it is the combined effect of the variables which is of interest'. As a result, this research was conducted by the implementation of a methodology which is able to reveal the impact of an input parameter on the index sensitivity under real atmospheric conditions.

The novelty of the presented methodology was the utilisation of generalized additive models (GAMs) as a technique to reveal and analyse the sensitivity patterns of the selected indices on their major inputs' variation. The choice of the GAMs was catalysed by the chaotic figure of the scatterplots of input parameters vs output results (Fig. 2).

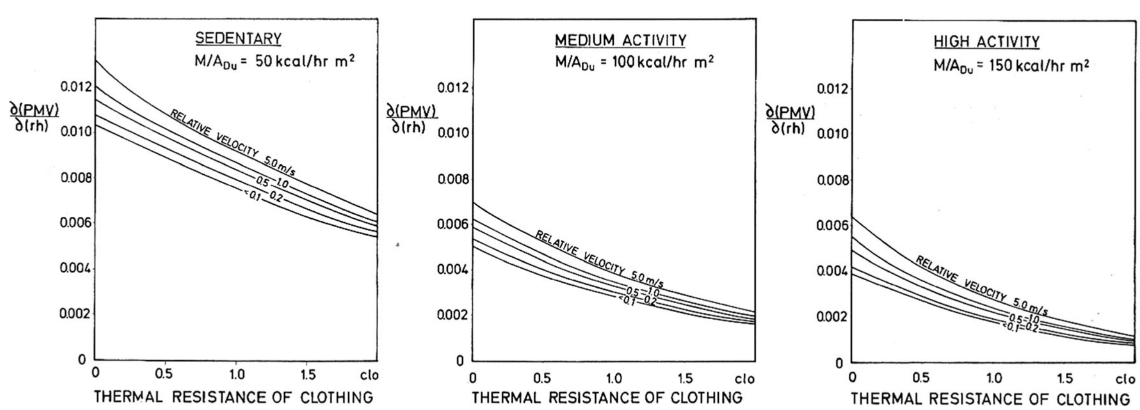


Fig. 1 Typical diagrams depicting the sensitivity of PMV to RH fluctuation under selected wind speed and clothing insulation values by Fanger (1970)

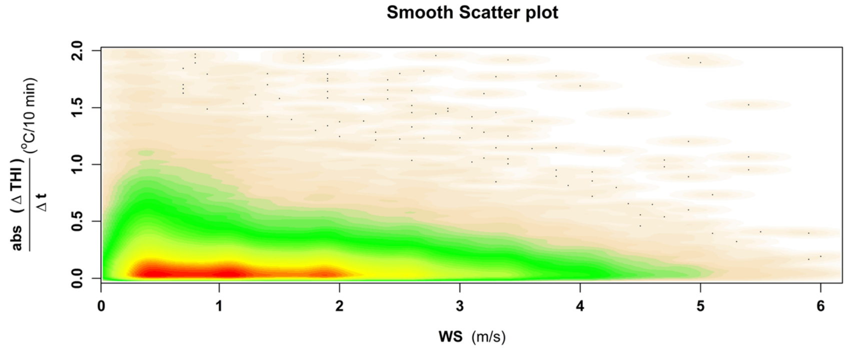


Fig. 2 Smoothed scatterplot of THI index sensitivity to wind speed

As illustrated in Fig. 2, it was obvious that there is no ‘regular way’ to interpret the scattered pattern of the illustrated data. For this reason, GAMs were used to evaluate the influence of the major atmospheric parameters (inputs) on the selected human thermal comfort indices.

2.3.1 Data manipulation and indices calculation

The data treatment procedures which include checks for extreme values, outliers and ‘no data’ records were conducted. At the same time, for the purposes of the research, the normal sequence of the data was secured. To ensure that the collected data was accurate, some absolute and comparative filters were employed. The absolute filters were constructed taking into account the meteorological equipment’s specifications (Table 1), these being wind speed measurements lower than 0.2 m/s were rejected, as well as relative humidity measurements higher than 98% and lower than 5%. The comparative filters were constructed taking into consideration the simultaneous measurements of the same parameter at two different heights. More specifically, if the absolute differences between the simultaneous measurements of T_a at the level of 1.5 m and 3 m a.g.l. respectively were higher than 3 °C, both measurements were rejected. The threshold for the relative humidity difference between the two levels was 15%, and in the case of wind speed, it was 2 m/s. After the absolute and the comparative filters were applied, the filter rejected values were higher than four times the standard deviation (SD) of the sample. All the aforementioned data analyses were conducted using the R language ‘dplyr’ package (Wickham et al. 2016). Some additional calculations were conducted for the wind speed data which were measured at 3 and 10 m above ground level. For the estimation of UTCI, the 10-m wind speed measurements were used. In order to estimate PET, mPET and PT the wind speed data collected at the level of 3 m and were transformed at the level of 1.5 m according to Eq. 3 (Grimmond et al. 1998; Oke et al. 2017; Nouri et al. 2017).

$$WS_{h_z} = WS_{h_0}\left(\frac{h_z}{h_0}\right)^a \tag{3}$$

where WS_{h_z} is the WS at the preferred level, WS_{h_0} is the WS at the measurements level and $a = 0.18$ (bushland, orchards). After the cleansing (outliers and the false measurements), the data was formatted by an R script to became suitable as input text files for the RayMan model. As mentioned, the PT, PET, mPET and UTCI indices were calculated with the RayMan and an R script calculated the THI and HUMIDEX. After that, all the results were homogenized and intergraded in matrices for the sensitivity analysis.

Generally, the measurements of the sensitivity analysis vary according to the focus of the research. The most widely used sensitivity analysis is the change of the output to the variation of an input parameter and the change of the output to the change of an input parameter (Provençal et al. 2016; Fröhlich and Matzarakis 2016; Fang et al. 2018; Ricciu et al. 2018). Hence, the sensitivity of the selected indices was calculated via two different measurements. The first one was the change of the index with the variation of the input parameter. And the second sensitivity’s analysis measurement was the index’s sensitivity to input change rate (difference of two sequential input measurements). The reason the absolute values were calculated was because when the sensitivity analysis was conducted, the changes of the index values are the important issue and not specific values of the index themselves. In turn, this implies that the sensitivity cannot be negative.

2.3.2 Generalized additive models

The GAMs are semi-parametric extensions of generalized linear models that specify smoothing functions to fit non-linear response curves to the data. This approach has been found particularly effective at handling the complex non-linearity of atmospheric procedures (Dominici et al. 2002; Hu et al. 2008; Pearce et al. 2011; Goggins et al. 2012). The general structure of the GAM containing smooth functions is defined as follows:

$$g(\mu) = \beta_0 + s_1(x_1) + s_2(x_2) + \cdots + s_i(x_i) \tag{4}$$

where $g(\mu)$ is the link function connecting the estimated mean to the distribution of the response variable, β_0 is the model intercept and s_i is the smoothing function to be estimated and x_i is a predictor (Hastie and Tibshirani 1987; Aalto et al. 2017). Generally, the model allows for flexible specification of the dependence of the response on the covariates, but by specifying the model only in terms of 'smooth functions' (Wood 2017). The primary purpose of GAMs utilisation is the examination of the variation pattern of each selected input parameter in relation to the change rate of the indices.

For the implementation of GAMs' in this study, in penalized thin plate regression splines, the 'mgcv' (Wood 2018) and 'gam' (Hastie 2013) R language packages were used. More specifically, several routines and functions of those packages (e.g. gam.check, vis.gam) were used to evaluate and choose the appropriate model which drives to the most accurate explanation of the data. Finally, the general form of the model used was a family of cubic splines:

$$y \sim s(x, bs = \mathrm{cs}) \tag{5}$$

where y is the estimated sensitivity, x is the input parameter and bs is the basis penalty smoother, cubic spline (cs) for our case.

The GAMs are widely used in ecology, biophysics, economics and other branches of science which deal with big or chaotic data where linear or classic polynomial methods cannot give adequate solutions. So far, the GAM method is not utilized widely for biometeorological studies, but recently, Ruuhela et al. (2017) used it to describe the relationships between the relative mortality and the thermal indices (PET, T_a). Moreover, with the aid of computers' coding, some publications with GAMs in the branch of the atmosphere sciences have been published (Ren and Tong 2006; Hu et al. 2008; Goggins et al. 2012; Morabito et al. 2012; Santidrián Tomillo et al. 2015; Hjort et al. 2016; Aalto et al. 2017).

3 Results and discussion

The distribution of the indices' sensitivity is shown in Figs. 3, 4, 5, 6 for input parameters variation and by Fig. 7, 8, 9, 10 for input parameters change rate. Every figure is accompanied by a table containing the summary statistics calculated with normally distributed input parameters which enhance the results interpretation procedure. The figures are graphed utilizing the ggplot2 R-language package (Wickham 2016), and the grey band around the coloured lines is the confidence interval at the level of 95%.

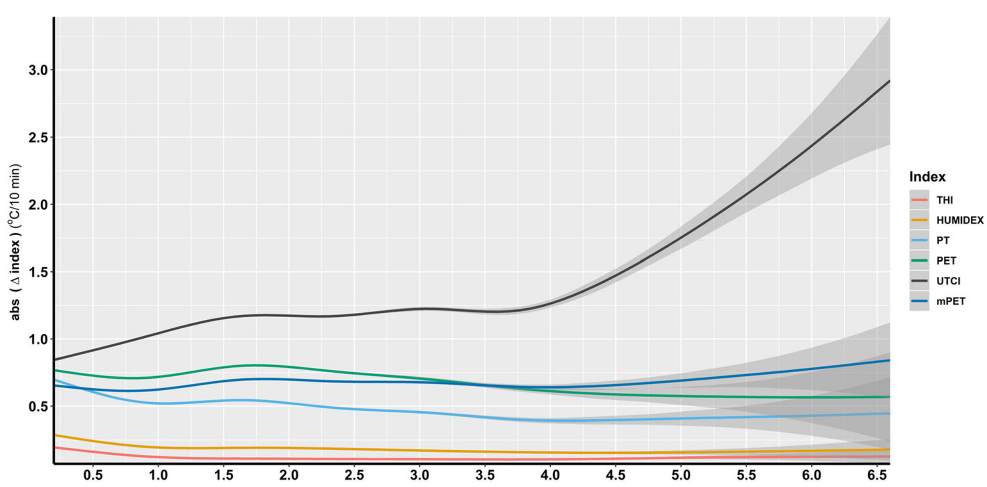
3.1 Indices sensitivity to parameters' variation

The following graphs (Figs. 3, 4, 5, 6) illustrate the sensitivity of the selected indices to the input parameters' variation. The sensitivity of the index is expressed as the first derivative (the absolute difference between two sequential index values over time—consisting of 10 min interval).

Despite the fact that wind speed and the global radiation are not input parameters for THI and HUMIDEX equations, the study examined the sensitivity of these parameters for two reasons. Firstly, because they indirectly affect the values of the rest of the input parameters and secondly, due to these parameter's influences upon the indice's sensitivity (WS and GR), hence being a simple but accurate measure for the effectiveness of the implemented method (GAMs).

As anticipated, the increment of WS did not affect the sensitivity of HUMIDEX and THI (Fig. 3). As a result, both lines were almost parallel without any significant gradient. The slight slope from the beginning of their course to 0.75 m/s was caused by the implemented smoothing process of the GAMs. The mean sensitivity of THI and HUMIDEX was negligible (0.12 and 0.14 °C/10 min). In comparison to the thermohygrometric, the rest of the indices, which were based upon a human energy budget model, shape different patterns(?) to the WS variation. The most sensitive index

Fig. 3 The indices sensitivity to wind speed (cl = 95%)



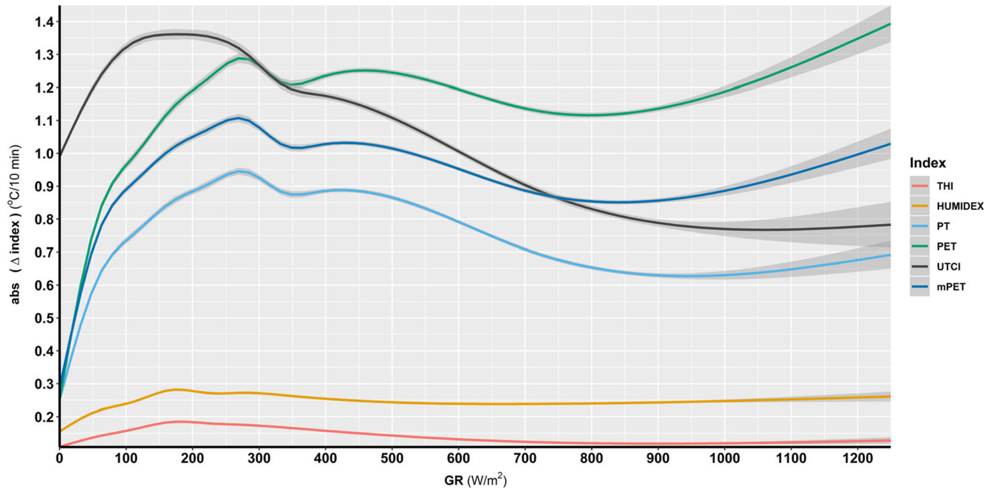


Fig. 4 The indices sensitivity to global radiation (cl = 95%)

was UTCI, and its sensitivity increased rapidly for WS values from 0.5 to 1.5 m/s, and above this value becomes level to 3.75 m/s. After this point, UTCI sensitivity to WS increased rapidly reaching 2.92 at the wind speed of 6.7 m/s. PET and mPET indices had a similar course, but PET was more sensitive to WS variation than mPET from the beginning to 3.25 m/s. The difference between them was almost steady (~ 0.1 °C/10 min). After this point, mPET gained sensitivity and surpasses PET. Generally, both indices had an almost steady sensitivity to WS. Perceived temperature (PT) started with 0.7 °C/10 min, but the sensitivity dropped rapidly to 0.55 °C/10 min and then slowly became 0.35 °C/10 min. The mean value of PT sensitivity was calculated as 0.47 °C/10 min (Table 5), and it was the lowest among the human energy balance indices. It is noteworthy that PT was more sensible than PET at very low wind speeds (0.2 to 0.35 m/s), and after that, its sensibility was lowering and remained lower than PET and mPET for the wind speeds from 0.35 to 6.7 m/s.

According to the descriptive statistics in Table 5, the most sensitive index to wind speed variation was UTCI, which was more than two times higher than the next index which is mPET.

Considering the graphical representation and the descriptive statistics (Fig. 3; Table 5), one can see three distinctive cases regarding the indices' sensitivity to WS variation. The first one was the case of THI and HUMIDEX; the second was the case of PT, PET and mPET; and the third one was the UTCI index. This grouping is in accordance with the modelling approach of each index since the THI and HUMIDEX consist of a linear thermohygrometric equation (Zhang et al. 2016; Desai and Dhorde 2018), and mPET is an improved evolution of PET in terms of a multiple-segment body model and the human bio-heat transfer system (Chen and Matzarakis 2017; Nouri et al. 2018d; Lin et al. 2018). Also, UTCI had a distinct behaviour given WS variations and was very sensitive to this parameter in comparison to the rest of the investigated indices as founded by Blazejczyk et al. (2012). Additionally, the UTCI's higher sensitivity to wind speed was also found by Provençal et al. (2016), hence once more suggesting that the index is in turn more sensitive to this parameter in comparison

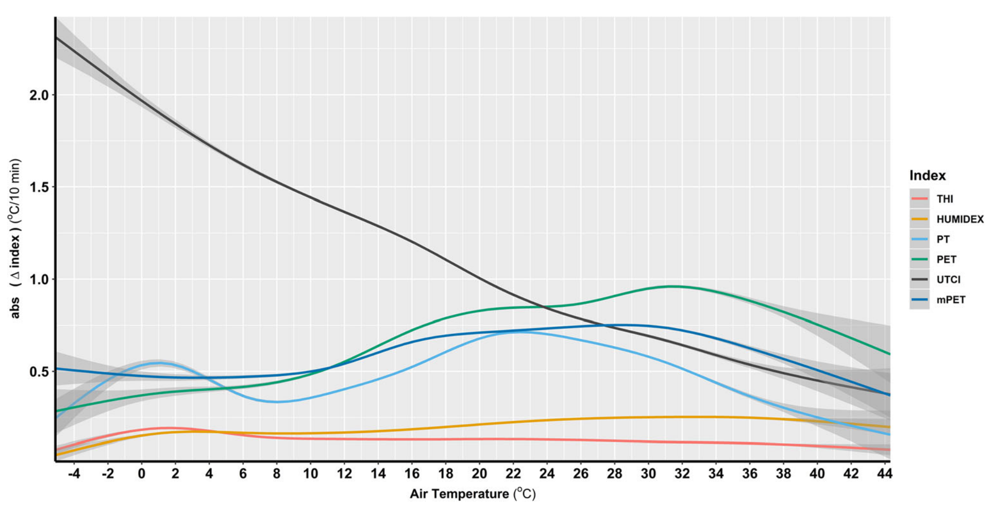


Fig. 5 The indices sensitivity to air temperature (cl = 95%)

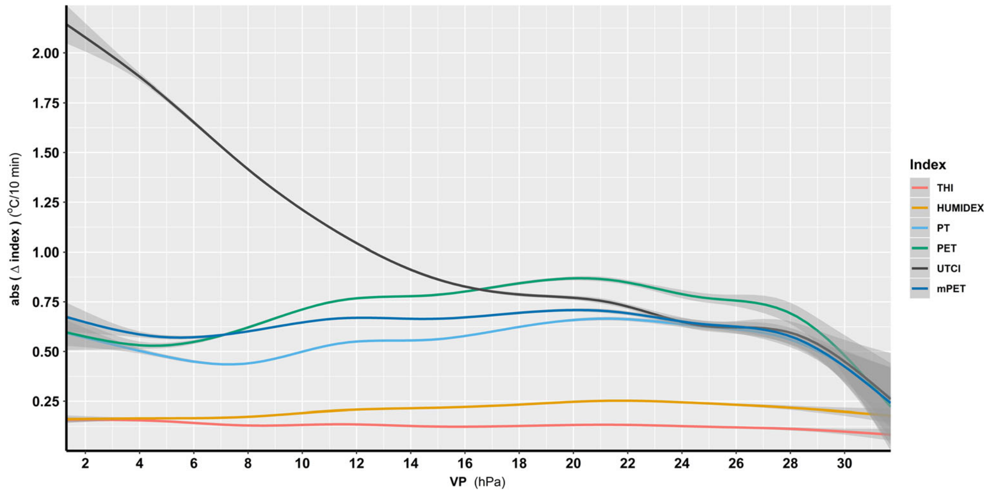


Fig. 6 The indices sensitivity to vapour pressure (cl = 95%)

to PET and HUMIDEX. We have to note that there is a strong yet interesting debate about the WS input and the UTCI results (Urban and Kyselý 2014), so we have to take into account these distinctive process characteristics.

Figure 4 and Table 6 present the sensitivity of the indices to the global radiation (GR) variance. The statistically filtered GR fluctuated from 0 to 1250 W/m^2 representing the spectrum from the absolute absence of solar radiation (nocturnal period) to the sunshine and unobscured sky above the meteorological station. As anticipated, the sensitivity of HUMIDEX and THI does not vary significantly with the GR fluctuation, drawing almost linear and horizontal courses. Among the two indices, HUMIDEX remains more sensitive with a mean sensitivity of 0.25 °C/10 min when the mean THI's sensitivity was 0.14 °C/10 min. There was a narrow part of a slight increasing sensitivity from 0 to 180 W/m^2 which was probably caused by the GAMs smoothing procedure and by the indirect effect of GR on air temperature and humidity. In contrast to the thermohygrometric indices, the other selected indices had a considerable fluctuation of their sensitivity to the GR variance. More specifically, PT, PET and mPET had an identical pattern form which diverges acutely as GR values got higher. Their sensitivity was as low as 0.25 to 0.29 °C/10 min when GR was close to 0 W/m^2, and it increased sharply to the point of 270 W/m^2 which was a very low value of GR in the geographic position of the measurements site. Almost 75 W/m^2 was recorded 70–80 min and 90–100 min after dawn during the summer and winter period respectively when the sky was cloudless.

The divergence of the PT, PET and mPET courses got wider as GR reached 200 W/m^2, and after that, the sensitivity's differences was almost stable. During whole GR values' spectrum, the sensitivity of PET was higher than mPET and PT. Regarding the former, it was also noted that the PT presented the lower sensitivity among the human energy budget indices.

The variation of UTCI's sensitivity to GR was totally different in comparison to the corresponding variations of PET, mPET and PT. Analytically, the sensitivity of UTCI was very high, even for values of GR close to 0 W/m^2, and it was almost four times higher than the other human energy balance indices. The UTCI sensitivity increased at the point of 100 W/m^2, and then the sensitivity got constantly lower to the GR point of

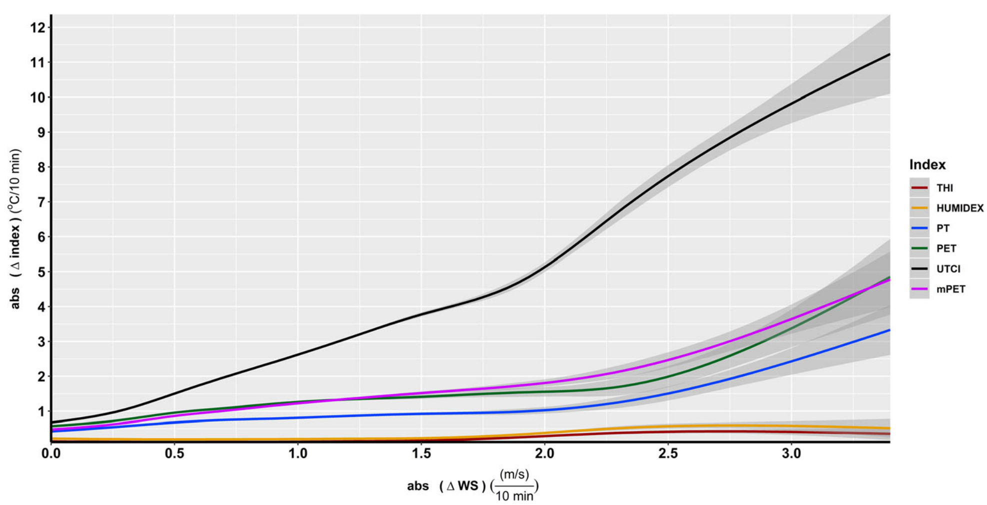


Fig. 7 The indices' sensitivity to wind speed change rate (cl = 95%)

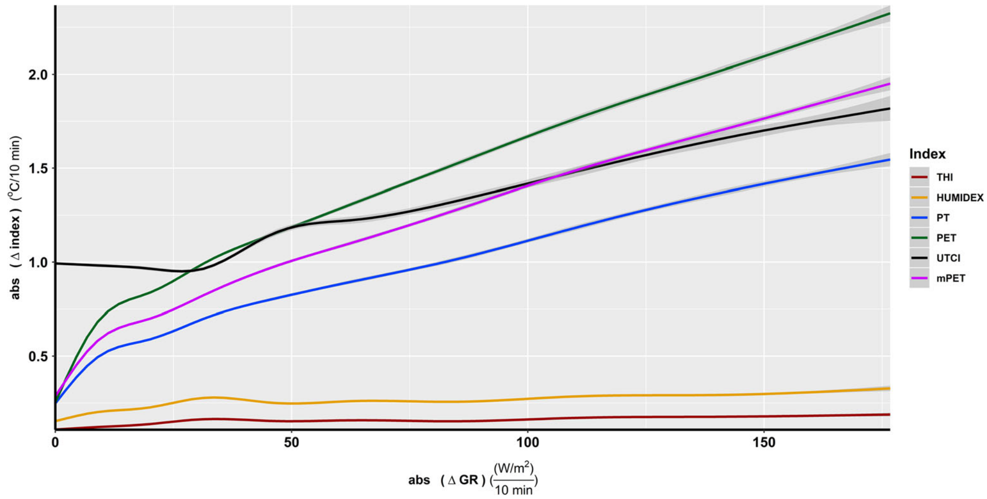


Fig. 8 The indices' sensitivity to global radiation change rate (cl = 95%)

1000 W/m^2. A very interesting finding was that the sensitivity of UTCI was lower for GR close to 900 than for GR close to 0 W/m^2. Also, the sensitivity of this index to GR was lower than the corresponding sensitivity of PET for GR higher than 300 W/m^2 and lower than the sensitivity of mPET for GR higher than 750 W/m^2.

Notwithstanding, the mean sensitivity of UTCI (1.01 °C/10 min) was higher than mPET and PT indices, it was lower for the crucial values of GR (> 300 W/m^2). This finding was in complete agreement with the research of Provençal et al. (2016) who concluded that 'When the weather was prone to inflict hot stress, the PET was in fact more sensitive to T_{mrt}, making it more likely to reach dangerous levels' knowing that the effect of GR on T_{mrt} is straightforward and well documented (Lin 2009; Matzarakis et al. 2010; Kántor and Unger 2011; Martinelli et al. 2015). Clearly, the behaviour of UTCI under low GR conditions was difficult to be interpreted in terms of human physiology and thermal perception.

In Fig. 5, the sensitivity of the indices to air temperature (T_a) variation was graphed. Overall, it was possible to identify that the uncertainty of GAMs was high for T_a lower than 0 °C and higher than 38 °C due to the low amount of inputs. The sensitivity of THI and HUMIDEX was low (mean THI 0.13, mean HUMIDEX 0.20), and both courses were linear and almost horizontal. This was the aftermath of the indices' first order of algebraic equations. But the shape and the position of their sensitivity's lines was evidence of the efficient functionality of GAMs.

The grouping of the four indices was graphed likewise for the T_a effect on their sensitivity. It was possible to verify that PET, mPET and PT had an almost similar course for T_a higher than 30 °C. For T_a close to 0 °C the higher sensitivity was calculated for PT when mPET and PET were following. Right after 4 °C, the sensitivity of PT went lower than PET and mPET and remained at this position until the end of the T_a spectrum. Also, mPET's sensitivity to T_a was higher than PET's to the point of 10 °C, and after this point, there was a slight gradient, and the sensitivity of PET went higher than mPET's sensitivity. Both indices are very close in a descriptive statistics' point of view (Table 7).

Once more, the UTCI index formed a substantially different course in comparison to the rest of the selected indices. Its

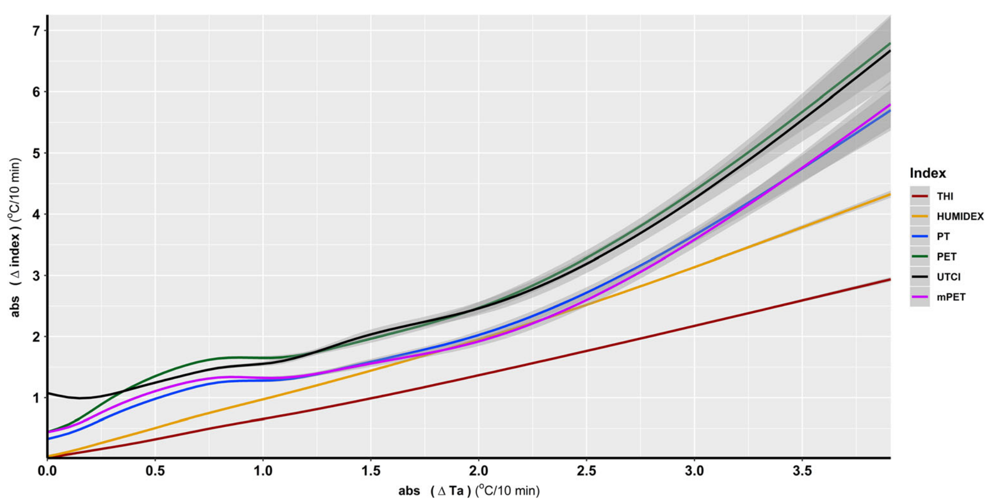


Fig. 9 The indices' sensitivity to air temperature change rate (cl = 95%)

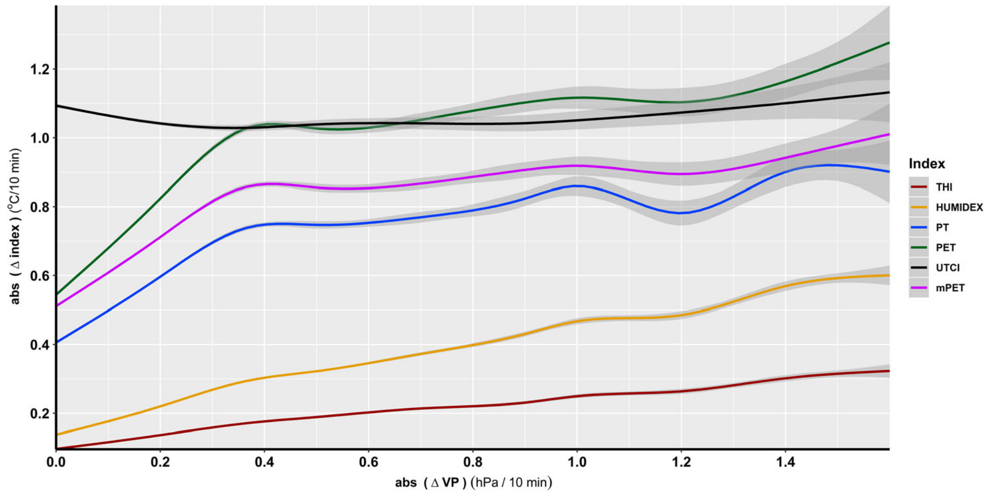


Fig. 10 The indices' sensitivity to vapour pressure change rate (cl = 95%)

sensitivity to T_a was almost linear with a negative gradient, having very high sensitivity (2.31 °C/10 min) under cold conditions which got lower as T_a increased. Close to 24 °C, the UTCI's sensitivity to T_a got as low as mPET and PET and after this point was getting lower in comparison to PET. The gradient of the UTCI sensitivity to T_a corroborated the finding of Blazejczyk et al. (2012), who identified that UTCI was more sensitive than the other indices to changes in ambient stimuli T_a since it was more closely related to the air temperature. The key question addressed by the analysis was if this high sensitivity to low temperatures and the low sensitivity to high temperatures were advantages from a human biometeorological point of view.

Figure 6 illustrates the sensitivity of the selected indices to the atmospheric VP (hPa). As shown, the sensitivity of thermohygrometric indices (THI and HUMIDEX) to VP was very low, linear and stable with a mean sensitivity of 0.13 and 0.21 °C/10 min, respectively (Table 8). The group of PET, mPET and PT indices formed an almost linear increasing section from 4 to almost 20 hPa. The higher sensitivity among them was calculated for PET and mPET.

Up to 4 hPa in Fig. 6, the uncertainty was higher, and the sensitivity of this indices' group decreased. For the same VP values, UTCI sensitivity decreased rapidly, and after 14 hPa, the gradient of the decrement was lower. It was also notable that after 16 hPA the UTCI sensitivity was getting lower than PET's sensitivity. It is worth mentioning that the UTCI was restricted by default under the 20 hPa (Jendritzky et al. 2012), so a quite large amount of atmospheric conditions was out of range for this index.

The disclosed results partially contradict the findings of Lin et al. (2018) since the authors found that mPET was more sensible than PET to vapour pressure. Probably, those findings' discrepancies are a consequence of the more warm and humid conditions of Taiwan in comparison to the atmospheric conditions in Greece. Generally, the results of the sensitivity to inputs variations indicate that the human energy balance indices were more sensitive to GR variations when the lower sensitivity was calculated for the T_a variations.

3.2 Indices sensitivity to parameters' change rate

As mentioned in the methodology section, the study additionally investigated each index's sensitivity to the input parameters' change rate. This is also a familiar sensitivity measurement which can reveal the index response to input parameters changes.

The sensitivity to the WS change rate is presented in Fig. 7, and as anticipated, the thermohygrometric indices had a very low sensitivity to WS changes. In addition, their courses were linear and horizontal with a mean value of 0.25 and 0.36 °C/ 10 min for THI and HUMIDEX, respectively. Such an

Table 5 Descriptive statistics of indices sensitivity (°C/10 min) to WS (m/s) variation

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.12	0.18	0.47	0.67	1.48	0.69
Min	0.11	0.15	0.39	0.57	0.84	0.61
Pctl(25)	0.11	0.16	0.41	0.58	1.17	0.65
Median	0.11	0.17	0.44	0.67	1.22	0.68
Pctl(75)	0.12	0.19	0.52	0.74	1.75	0.70
Max	0.20	0.29	0.70	0.80	2.92	0.84

Table 6 Descriptive statistics of indices sensitivity (°C/10 min) to GR variation (W/m^2)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.14	0.25	0.74	1.16	1.01	0.93
Min	0.11	0.16	0.25	0.26	0.77	0.29
Pctl(25)	0.12	0.24	0.64	1.13	0.78	0.87
Median	0.13	0.25	0.70	1.20	0.98	0.94
Pctl(75)	0.16	0.26	0.87	1.25	1.19	1.02
Max	0.19	0.28	0.95	1.39	1.36	1.11

occurrence can be attributed to their algebraic first order equation. Moreover, the THI and HUMIDEX lines were fluctuating locally beyond 2 m/s/10 min when the uncertainty was increasing.

Additionally, Fig. 7 demonstrates that the sensitivity of PET, mPET and PT to wind speed (WS) changes was almost linear with a higher gradient for PET and mPET and a lower gradient for PT. The shape of those three indices was almost identical, but the higher sensitivity was calculated for PET for low wind speed (WS) change rate. After 1.25 m/s/10 min, the sensitivity of mPET was overpassing the PET's corresponding sensitivity.

According to Fig. 7 and Table 9, UTCI once more presented a distinguished behaviour in terms of sensitivity to wind speed (WS) change. All in all, this index was the most sensitive among the selected four, starting from 0.68 °C/10 min during wind speed (WS) stable conditions and overcoming 11 °C/10 min when the wind speed change rate was 3.4 m/s per 10 min. The above findings were in general agreement with Fröhlich and Matzarakis (2016) which pointed that 'PT is found to be less sensitive to the changes in wind speed than the other two indices' when the other two indices were UTCI and PET. After that, the authors mentioned that 'UTCI is the most sensitive to wind speed among the three indices'. Once more, we have to take into account the debate about the uncertainties of UTCI index calculation and the WS measurements height level.

The sensitivity to the global radiation's (GR) change rate, as shown in Fig. 8, formed a grouping of the indices. The sensitivity of the thermohygrometric indices was low, and their courses were almost parallel and horizontal. Since the GR is not an input parameter for THI and HUMIDEX equations, the shape of the courses was, as anticipated, horizontal, linear and close to 0. The rest indices tended to increase their sensitivity with the GR change rate almost linearly.

More precisely, for small change rates (0 to 25 W/m/10 min), UTCI sensitivity was almost horizontal and equal to 0.90 °C/10 min. However, right after this point, it increased rapidly to the point of 300 W/m^2/10 min change rate. After that, the increment decreased with a gradient almost half of its previous gradient. It was noteworthy that UTCI sensitivity was almost four times higher than the other human energy balance indices for stable conditions (~ 0 W/m/10 min) in terms of GR changes. This finding indicated that the UTCI index can change almost 1 °C/10 min as a consequence of air temperature, humidity and wind speed variation under stable radiation conditions. On the other hand, PET, mPET and PT were more sensitive to GR variation, since under stable GR conditions, it can change only by 0.25–0.29 °C/10 min, but they increased rapidly by the end of the change rate spectrum.

As shown in Fig. 8 and Table 10, the sensitivity of human energy balance indices was increasing with the global radiation change rate. PET was the most sensitive among them as it revealed change rates higher than 30 W/m/10 min, PT takes the third place in terms of sensitivity. Comparing mPET and UTCI, it was possible to identify that that UTCI was more sensible for changes rates from 30 to 100 W/m/10 min. When the change rate was higher than 450 W/m/10 min, UTCI sensitivity was the lowest among the energy balance indices.

The indices' sensitivity to air temperature change rate (Fig. 9) formed a linearity for thermohygrometric indices (THI and HUMIDEX) with a positive gradient. According to Table 11, the sensitivity was very low under stable air temperature (T_a) conditions, revealing values of 0.04 and 0.02 for HUMIDEX and THI, respectively. For the maximum air

Table 7 Descriptive statistics of indices sensitivity (°C/10 min) to T_a variation (°C)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.13	0.20	0.47	0.67	1.13	0.59
Min	0.07	0.05	0.16	0.28	0.37	0.37
Pctl(25)	0.11	0.17	0.35	0.43	0.64	0.48
Median	0.13	0.20	0.46	0.73	1.03	0.57
Pctl(75)	0.13	0.24	0.58	0.85	1.56	0.71
Max	0.19	0.25	0.71	0.96	2.31	0.75

Table 8 Descriptive statistics of indices sensitivity to VP (hPa) variation (°C/10 min)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.13	0.21	0.55	0.70	1.01	0.62
Min	0.08	0.16	0.27	0.22	0.26	0.24
Pctl(25)	0.12	0.18	0.49	0.58	0.65	0.59
Median	0.13	0.21	0.56	0.75	0.81	0.64
Pctl(75)	0.13	0.23	0.62	0.80	1.32	0.67
Max	0.16	0.25	0.67	0.87	2.14	0.71

temperature (T_a), change range HUMIDEX reached 4.33 °C/min and THI 2.94 °C/min.

Moreover, PET and mPET began from the same sensitivity point (0.44 °C/10 min), but PET quickly increased resultant of with a higher gradient than mPET and reached a maximum of 6.80 when the corresponding maximum of mPET was 6.68 °C/10 min. UTCI presented one of the highest sensitivity in comparison to the rest of the indices, with exception to PET which surpassed UTCI for T_a change rates higher than 0.35 °C/10 min.

Figure 10 and Table 12 present the indices' sensitivity to VP's changes rate. The course of THI and HUMIDEX was almost linear due to their linear algebraic equation. In terms of gradient, the HUMIDEX tended to raise the sensitivity more rapid than THI when the VP change rates were getting higher.

The mean sensitivity of these indices remained low with a mean value of 0.22 and 0.40 °C/10 min for THI and HUMIDEX, respectively. Moreover, the sensitivity got steadily higher with the change rates' increment. On the other hand, the group of PET, mPET and PT indices was shaping an almost homogenous form with a higher gradient from steady conditions to 0.3 hPa/10 min. After this point, the sensitivity of the aforementioned indices remained quite steady for each index having almost zero gradient. Among those indices, the higher sensitivity was calculated for PET followed by mPET and PT. Specifically, PET increased its difference from PT and mPET for all the spectrum of VP rate change values. It was noteworthy to pinpoint that mPET and PT seemed to have an identical course shape. In terms of VP change rate, UTCI sensitivity was almost steady with a negligible decrement from 0 to 0.25 °C/10 min. After this point, the sensitivity remained steadily at 1.1 °C/10 min which were equal to PET's sensitivity.

The above results are in contrary to the findings of Fröhlich and Matzarakis (2016) because according to their findings, the UTCI had less sensitivity to VP changes than PT, and the PET did not appear to be as affected as PT. Such a discrepancy was probably caused by the difference of VP's changes spectrum between studies. More concretely, Fröhlich and Matzarakis (2016) tested the sensitivity for changes of ±5 hPa when the presented research calculated the sensitivity for changes to 1.6 hPa. However, this being identified, it is also worth noting that the human energy balance indices present an almost steady sensitivity, no matter if the VP change rate is increasing.

Overall, and regarding the high sensitivity of UTCI compared to the rest indices, one has to consider if this high sensitivity is desirable, explainable and useful for the approach to the real human thermal environmental perception. Moreover, the results indicate that the twofold analysis of the sensitivity (inputs variation and change rates) may lead to a thorough understanding of the index behaviour under a wide variety of conditions.

4 Conclusions

This article has aimed to calculate and analyse the sensitivity of the most widely used thermal comfort indices against their major input variables. Additionally, a comparative analysis between the indices was performed to investigate their performance under the prevailing thermal conditions. Meanwhile, the sensitivity has been studied according to two approaches. The first one focuses on the sensitivity of each index to the input parameter's variance. The second focuses on the sensitivity of the index to the change rate of the input parameter. The results were delivered by utilizing a long period input

Table 9 Descriptive statistics of indices sensitivity (°C/10 min) to WS change rate ($m \cdot s^{-1}$/10 min)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.25	0.36	1.26	1.81	5.05	1.94
Min	0.12	0.20	0.42	0.57	0.68	0.48
Pctl(25)	0.13	0.21	0.78	1.18	2.29	1.12
Median	0.20	0.27	0.94	1.48	4.16	1.62
Pctl(75)	0.39	0.55	1.58	2.10	7.98	2.57
Max	0.43	0.59	3.33	4.85	11.24	4.78

Table 10 Descriptive statistics of indices sensitivity (°C/10 min) to GR change rate ($W{\bullet}m^{-2}$/10 min)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.19	0.35	2.29	3.60	2.38	2.93
Min	0.11	0.16	0.25	0.26	0.95	0.29
Pctl(25)	0.18	0.31	1.47	2.18	1.74	1.84
Median	0.20	0.36	2.24	3.48	2.37	2.87
Pctl(75)	0.21	0.39	3.09	4.96	3.00	3.99
Max	0.22	0.42	4.19	6.86	3.83	5.42

dataset that includes every season of the year, with a comprehensive measurements' analysis. To achieve the real sensitivity analysis without 'fictional' input data, the generalized additive models (GAM) methodology was implemented. In summary, the following conclusions obtained from the study are here reemphasized:

1) Generalized additive models (GAMs) can provide an adequate solution for the investigation of sensitivity analysis of big, yet chaotic datasets.
2) The results indicate that GAMs are able to provide reasonable results for this type of analysis.
3) The sensitivity of the thermohygrometric indices (THI and HUMIDEX) is very low in terms of input parameters' variation or input parameters' change rate. Even in the case of T_a and VP which are affecting directly the output of the thermohygrometric indices, their sensitivity is much lower than human energy balance indices' sensitivity. Generally, HUMIDEX is more sensitive to inputs' variation and change rate in comparison to THI. This being said, THI and HUMIDEX are unable to deal effectively with the variation and change of the input parameters.
4) In general, it is clear that the most sensitive index is UTCI in terms of mean and maximum sensitivity values, concerning the variation of the input parameters (with the exception of T_a). In more detail, UTCI exhibits a distinctive behaviour under low values of the input parameters or low change rate of them. The behaviour of UTCI during WS variation and changes indicates an excessive sensitivity to this parameter. Also, UTCI is the most sensitive for very low GR, low to medium T_a and low VP values. In terms of parameter change rates, the sensitivity of UTCI is higher than the rest indices for low change rates. So, UTCI is the most sensitive among the human energy balance indices to the investigated atmospheric parameters, but it is losing sensitivity under typical meteorological conditions.
5) PET is very sensitive to GR's variation and to GR's change rate in comparison to the rest indices. This index has the higher sensitivity for high T_a, VP and GR conditions. Overall, it is the most sensitive index of the human energy balance group when T_a and GR change rapidly. Probably, this is evidence of a good response of the index to the related biometeorological stimuli.
6) According to the results, mPET is improved on WS's sensitivity in terms of parameter's variation and on GR in terms of change rate. For the examined spectrum of VP values, mPET is more sensitive under high VP conditions.
7) PT is forming a similar sensitivity's behaviour in comparison to the other human energy balance indices for the parameters of WS and GR. The overall sensitivity of the index is the lowest among the indices of its group.
8) Among the selected indices, three distinct categories were revealed in terms of sensitivity. The first is the group of thermohygrometric indices (THI, HUMIDEX); the second consists of human biometeorological indices PET, mPET and PT; and the last category is UTCI. This finding is in full accordance with their thermophysiological background.
9) The most influential stimulus in terms of sensitivity is the GR (variation and change rate). After this, the WS is the most effective parameter if one is to examine its variation and T_a when examining the change rate of the inputs. On the contrary, VP seems to have an insignificant effect on

Table 11 Descriptive statistics of indices sensitivity (°C/10 min) to T_a change rate (°C/10 min)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	1.39	2.01	2.43	2.97	2.93	2.43
Min	0.02	0.04	0.33	0.44	0.99	0.44
Pctl(25)	0.64	0.95	1.28	1.65	1.55	1.33
Median	1.33	1.90	1.98	2.42	2.42	1.88
Pctl(75)	2.12	3.05	3.51	4.23	4.10	3.44
Max	2.94	4.33	5.70	6.80	6.68	5.80

Table 12 Descriptive statistics of indices sensitivity (°C/10 min) to VP change rate (hPa/10 min)

	THI	HUMIDEX	PT	PET	UTCI	mPET
Mean	0.22	0.40	0.76	1.03	1.06	0.86
Min	0.10	0.14	0.41	0.54	1.03	0.51
Pctl(25)	0.18	0.30	0.75	1.02	1.04	0.85
Median	0.22	0.40	0.78	1.08	1.05	0.89
Pctl(75)	0.26	0.49	0.84	1.12	1.08	0.91
Max	0.32	0.60	0.92	1.28	1.13	1.01

the sensitivity of the selected indices under the investigated atmospheric conditions.

The next steps forward should drive to the answer of the key question of what the preferred sensitivity in terms of magnitude and variation is. In addition, one may also investigate the precise need and role for thermal indices which vary from high or low sensitivity. Finally, does the community need thermal indices with constant sensitivity, or is the fluctuated sensitivity preferred?—To answer this question, one must inevitably explore to which extent scientists require a specific amount of sensitivity and, moreover, under specific weather conditions. In addition to the presented research, we plan to investigate the sensitivity analysis to the input parameters variation and change rates under classified atmospheric conditions in order to involve more than one atmospheric parameter per time. Moreover, it is interesting to analyse the sensitivity of the indices to personal data (height, age, weight, clothing insulation, etc.) variations.

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References

Aalto J, Riihimäki H, Meineri E, Hylander K, Luoto M (2017) Revealing topoclimatic heterogeneity using meteorological station data. Int J Climatol 37:544–556. https://doi.org/10.1002/joc.5020

Akimoto T, ichi TS, Yanai T, Sasaki M (2010) Thermal comfort and productivity - evaluation of workplace environment in a task conditioned office. Build Environ 45:45–50. https://doi.org/10.1016/J.BUILDENV.2009.06.022

Algeciras JAR, Matzarakis A (2016) Quantification of thermal bioclimate for the management of urban design in Mediterranean climate of Barcelona, Spain. Int J Biometeorol 60:1261–1270. https://doi.org/10.1007/s00484-015-1121-8

Błażejczyk K, Broede P, Fiala D, et al (2010) Principles of the new Universal Thermal Climate Index (UTCI) and its application to bioclimatic research in European scale. Misc Geogr 14:91–102

Blazejczyk K, Epstein Y, Jendritzky G, Staiger H, Tinz B (2012) Comparison of UTCI to selected thermal indices. Int J Biometeorol 56:515–535. https://doi.org/10.1007/s00484-011-0453-2

Bröde P, Fiala D, Błażejczyk K, Holmér I, Jendritzky G, Kampmann B, Tinz B, Havenith G (2012) Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). Int J Biometeorol 56: 481–494. https://doi.org/10.1007/s00484-011-0454-1

Charalampopoulos I, Tsiros I, Chronopoulou-Sereli A, Matzarakis A (2013) Analysis of thermal bioclimate in various urban configurations in Athens, Greece. Urban Ecosyst 16:217–233. https://doi.org/10.1007/s11252-012-0252-5

Charalampopoulos I, Tsiros I, Chronopoulou-Sereli A, Matzarakis A (2015) A note on the evolution of the daily pattern of thermal comfort-related micrometeorological parameters in small urban sites in Athens. Int J Biometeorol 59:1223–1236. https://doi.org/10.1007/s00484-014-0934-1

Charalampopoulos I, Nastos PT, Didaskalou E (2017) Human thermal conditions and north Europeans' web searching behavior (Google Trends) on mediterranean touristic destinations. Urban Sci 1:8. https://doi.org/10.3390/urbansci1010008

Chen A, Chang VW-C (2012) Human health and thermal comfort of office workers in Singapore. Build Environ 58:172–178. https://doi.org/10.1016/J.BUILDENV.2012.07.004

Chen Y-C, Matzarakis A (2017) Modified physiologically equivalent temperature—basics and applications for western European climate. Theor Appl Climatol 132:1–15. https://doi.org/10.1007/s00704-017-2158-x

Cheng Y, Niu J, Gao N (2012) Thermal comfort models: a review and numerical investigation. Build Environ 47:13–22. https://doi.org/10.1016/j.buildenv.2011.05.011

Coccolo S, Kämpf J, Scartezzini J-L, Pearlmutter D (2016) Outdoor human comfort and thermal stress: a comprehensive review on models and standards. Urban Clim 18:33–57. https://doi.org/10.1016/j.uclim.2016.08.004

Conti S, Meli P, Minelli G, Solimini R, Toccaceli V, Vichi M, Beltrano C, Perini L (2005) Epidemiologic study of mortality during the Summer 2003 heat wave in Italy. Environ Res 98:390–399. https://doi.org/10.1016/j.envres.2004.10.009

Correa E, Ruiz MA, Canton A, Lesino G (2012) Thermal comfort in forested urban canyons of low building density. An assessment for the city of Mendoza, Argentina. Build Environ 58:219–230. https://doi.org/10.1016/j.buildenv.2012.06.007

Damiati SA, Zaki SA, Rijal HB, Wonorahardjo S (2016) Field study on adaptive thermal comfort in office buildings in Malaysia, Indonesia, Singapore, and Japan during hot and humid season. Build Environ 109:208–223. https://doi.org/10.1016/J.BUILDENV.2016.09.024

de Freitas CR, Grigorieva EA (2015) A comprehensive catalogue and classification of human thermal climate indices. Int J Biometeorol 59:109–120. https://doi.org/10.1007/s00484-014-0819-3
Desai MS, Dhorde AG (2018) Trends in thermal discomfort indices over western coastal cities of India. Theor Appl Climatol 131:1305–1321. https://doi.org/10.1007/s00704-017-2042-8
Didaskalou E, Nastos PT (2003) The role of climatic and bioclimatic conditions in the development of health tourism product. Anatolia 14:107–126. https://doi.org/10.1080/13032917.2003.9687020
Dominici F, McDermott A, Zeger SL, Samet JM (2002) On the use of generalized additive models in time-series studies of air pollution and health. Am J Epidemiol 156:193–203. https://doi.org/10.1093/aje/kwf062
Eludoyin OM, Adelekan IO, Webster R, Eludoyin AO (2014) Air temperature, relative humidity, climate regionalization and thermal comfort of Nigeria. Int J Climatol 34:2000–2018. https://doi.org/10.1002/joc.3817
Emmanuel R (2005) Thermal comfort implications of urbanization in a warm-humid city: the Colombo Metropolitan Region (CMR), Sri Lanka. Build Environ 40:1591–1601. https://doi.org/10.1016/j.buildenv.2004.12.004
Epstein Y, Moran DS (2006) Thermal comfort and the heat stress indices. Ind Health 44:388–398. https://doi.org/10.2486/indhealth.44.388
Fang Z, Lin Z, Mak CM, Niu J, Tse KT (2018) Investigation into sensitivities of factors in outdoor thermal comfort indices. Build Environ 128:129–142. https://doi.org/10.1016/j.buildenv.2017.11.028
Fanger PO (1970) Thermal comfort. Analysis and applications in environmental engineering. McGraw-Hill Book Company
Ferretti F, Saltelli A, Tarantola S (2016) Trends in sensitivity analysis practice in the last decade. Sci Total Environ 568:666–670. https://doi.org/10.1016/j.scitotenv.2016.02.133
Frey CH, Patil SR (2002) Identification and review of sensitivity analysis methods. Risk Anal 22:553–578. https://doi.org/10.1111/0272-4332.00039
Fröhlich D, Matzarakis A (2016) A quantitative sensitivity analysis on the behaviour of common thermal indices under hot and windy conditions in Doha, Qatar. Theor Appl Climatol 124:179–187. https://doi.org/10.1007/s00704-015-1410-5
Fröhlich D, Gangwisch M, Matzarakis A (2019) Effect of radiation and wind on thermal comfort in urban environments - application of the RayMan and SkyHelios model. Urban Clim 27:1–7. https://doi.org/10.1016/j.uclim.2018.10.006
Goggins WB, Chan EYY, Ng E, Ren C, Chen L (2012) Effect modification of the association between short-term meteorological factors and mortality by urban heat islands in Hong Kong. PLoS One 7:9–14. https://doi.org/10.1371/journal.pone.0038551
Grimmond CSB, King TS, Roth M, Oke TR (1998) Aerodynamic roughness of urban areas derived from wind observations. Bound-Layer Meteorol 89:1–24. https://doi.org/10.1023/A:1001525622213
Hamby DM (1994) A review of techniques for parameter sensitivity analysis of environmental models. Environ Monit Assess 32:135–154. https://doi.org/10.1007/BF00547132
Hastie T (2013) gam: generalized additive models, R package, version 0.98. R Found Stat Comput, Vienna
Hastie T, Tibshirani R (1987) Generalized additive models: some applications. J Am Stat Assoc 82:371–386. https://doi.org/10.1080/01621459.1987.10478440
Havenith G, Fiala D, Błazejczyk K, Richards M, Bröde P, Holmér I, Rintamaki H, Benshabat Y, Jendritzky G (2012) The UTCI-clothing model. Int J Biometeorol 56:461–470. https://doi.org/10.1007/s00484-011-0451-4
Hjort J, Suomi J, Käyhkö J (2016) Extreme urban–rural temperatures in the coastal city of Turku, Finland: quantification and visualization based on a generalized additive model. Sci Total Environ 569–570:507–517. https://doi.org/10.1016/j.scitotenv.2016.06.136
Höppe P (1999) The physiological equivalent temperature - a universal index for the biometeorological assessment of the thermal environment. Springer-Verlag
Hu W, Mengersen K, McMichael A, Tong S (2008) Temperature, air pollution and total mortality during summers in Sydney, 1994–2004. Int J Biometeorol 52:689–696. https://doi.org/10.1007/s00484-008-0161-8
Huizenga C, Hui Z, Arens E (2001) A model of human physiology and comfort for assessing complex thermal environments. Build Environ 36:691–699. https://doi.org/10.1016/S0360-1323(00)00061-5
Jendritzky G, de Dear R, Havenith G (2012) UTCI—why another thermal index? Int J Biometeorol 56:421–428. https://doi.org/10.1007/s00484-011-0513-7
Kántor N, Unger J (2011) The most problematic variable in the course of human-biometeorological comfort assessment — the mean radiant temperature. Open Geosci 3:90–100. https://doi.org/10.2478/s13533-011-0010-x
Katić K, Li R, Zeiler W (2016) Thermophysiological models and their applications: a review. Build Environ 106:286–300. https://doi.org/10.1016/J.BUILDENV.2016.06.031
Kottek M, Grieser J, Beck C, Rudolf B, Rubel F (2006) World map of the Köppen-Geiger climate classification updated. Meteorol Z 15:259–263. https://doi.org/10.1127/0941-2948/2006/0130
Laschewski G, Jendritzky G (2002) Effects of the thermal environment on human health: an investigation of 30 years of daily mortality data from SW Germany. Clim Res 21:91–103. https://doi.org/10.3354/cr021091
Lin T-P (2009) Thermal perception, adaptation and attendance in a public square in hot and humid regions. Build Environ 44:2017–2026. https://doi.org/10.1016/j.buildenv.2009.02.004
Lin T-P, Matzarakis A (2008) Tourism climate and thermal comfort in Sun Moon Lake, Taiwan. Int J Biometeorol 52:281–290. https://doi.org/10.1007/s00484-007-0122-7
Lin T-P, Yang S-R, Chen Y-C, Matzarakis A (2018) The potential of a modified physiologically equivalent temperature (mPET) based on local thermal comfort perception in hot and humid regions. Theor Appl Climatol 135:1–4. https://doi.org/10.1007/s00704-018-2419-3
Lipczynska A, Schiavon S, Graham LT (2018) Thermal comfort and self-reported productivity in an office with ceiling fans in the tropics. Build Environ 135:202–212. https://doi.org/10.1016/J.BUILDENV.2018.03.013
Martinelli L, Lin TP, Matzarakis A (2015) Assessment of the influence of daily shadings pattern on human thermal comfort and attendance in Rome during summer period. Build Environ 92:30–38. https://doi.org/10.1016/j.buildenv.2015.04.013
Matzarakis A, Mayer H, Iziomon MG (1999) Applications of a universal thermal index: physiological equivalent temperature. Int J Biometeorol 43:76–84. https://doi.org/10.1007/s004840050119
Matzarakis A, Rutz F, Mayer H (2010) Modelling radiation fluxes in simple and complex environments: basics of the RayMan model. Int J Biometeorol 54:131–139. https://doi.org/10.1007/s00484-009-0261-0
Mekis É, Vincent LA, Shephard MW, Zhang X (2015) Observed trends in severe weather conditions based on humidex, wind chill, and heavy rainfall events in Canada for 1953–2012. Atmosphere-Ocean 53:383–397. https://doi.org/10.1080/07055900.2015.1086970
Morabito M, Profili F, Crisci A, Francesconi P, Gensini GF, Orlandini S (2012) Heat-related mortality in the Florentine area (Italy) before and after the exceptional 2003 heat wave in Europe: an improved public health response? Int J Biometeorol 56:801–810. https://doi.org/10.1007/s00484-011-0481-y
Moustris K, Tsiros IX, Tseliou A, Nastos P (2018) Development and application of artificial neural network models to estimate values of a complex human thermal comfort index associated with urban heat and cool island patterns using air temperature data from a

standard meteorological station. Int J Biometeorol 62:1265–1274. https://doi.org/10.1007/s00484-018-1531-5
Nastos PT, Paliatsos AG, Anthracopoulos MB, Roma ES, Priftis KN (2010) Outdoor particulate matter and childhood asthma admissions in Athens, Greece: a time-series study. Environ Health 9:45. https://doi.org/10.1186/1476-069X-9-45
Nazarian N, Fan J, Sin T, et al (2017) Predicting outdoor thermal comfort in urban environments: a 3D numerical model for standard effective temperature. Urban Clim https://doi.org/10.1016/j.uclim.2017.04.011
Nouri AS, Costa JP, Matzarakis A (2017) Examining default urban-aspect-ratios and sky-view-factors to identify priorities for thermal-sensitive public space design in hot-summer Mediterranean climates: the Lisbon case. Build Environ 126:442–456. https://doi.org/10.1016/J.BUILDENV.2017.10.027
Nouri AS, Charalampopoulos I, Matzarakis A (2018a) Beyond singular climatic variables – identifying the dynamics of wholesome thermo-physiological factors for existing/future human thermal comfort during hot-dry Mediterranean summers. Int J Environ Res Public Health 15:1–25. https://doi.org/10.3390/ijerph15112362
Nouri AS, Costa JP, Santamouris M, Matzarakis A (2018b) Approaches to Outdoor thermal comfort thresholds through public space design: a review. Atmosphere 9:108. https://doi.org/10.3390/atmos9030108
Nouri AS, Fröhlich D, Matos Silva M, Matzarakis A (2018) The impact of Tipuana tipu species on local human thermal comfort thresholds in different Urban canyon cases in Mediterranean climates: Lisbon, Portugal. Atmosphere 9:12https://doi.org/10.3390/atmos9010012
Nouri AS, Lopes A, Costa JP, Matzarakis A (2018d) Confronting potential future augmentations of the physiologically equivalent temperature through public space design: the case of Rossio, Lisbon. Sustain Cities Soc 37:7–25. https://doi.org/10.1016/J.SCS.2017.10.031
Oke TR, Mills G, Christen A, Voogt J (2017) Urban climates. Cambridge University Press
Parsons K (2014) Human thermal environments. CRC Press
Pearce JL, Beringer J, Nicholls N, Hyndman RJ, Tapper NJ (2011) Quantifying the influence of local meteorology on air quality using generalized additive models. Atmos Environ 45:1328–1336. https://doi.org/10.1016/j.atmosenv.2010.11.051
Pianosi F, Beven K, Freer J, Hall JW, Rougier J, Stephenson DB, Wagener T (2016) Sensitivity analysis of environmental models: a systematic review with practical workflow. Environ Model Softw 79:214–232. https://doi.org/10.1016/j.envsoft.2016.02.008
Potchter O, Cohen P, Lin T-PP, Matzarakis A (2018) Outdoor human thermal perception in various climates: a comprehensive review of approaches, methods and quantification. Sci Total Environ 631–632:390–406. https://doi.org/10.1016/j.scitotenv.2018.02.276
Provençal S, Bergeron O, Leduc R, Barrette N (2016) Thermal comfort in Quebec City, Canada: sensitivity analysis of the UTCI and other popular thermal comfort indices in a mid-latitude continental city. Int J Biometeorol 60:591–603. https://doi.org/10.1007/s00484-015-1054-2
Ren C, Tong S (2006) Temperature modifies the health effects of particulate matter in Brisbane, Australia. Int J Biometeorol 51:87–96. https://doi.org/10.1007/s00484-006-0054-7
Ricciu R, Galatioto A, Desogus G, Besalduch LA (2018) Uncertainty in the evaluation of the Predicted Mean Vote index using Monte Carlo analysis. J Environ Manag 223:16–22. https://doi.org/10.1016/J.JENVMAN.2018.06.005
Ruuhela R, Jylhä K, Lanki T, Tiittanen P, Matzarakis A (2017) Biometeorological assessment of mortality related to extreme temperatures in Helsinki region, Finland, 1972–2014. Int J Environ Res Public Health 14:944. https://doi.org/10.3390/ijerph14080944
Salata F, Golasi I, de Lieto Vollaro R, de Lieto Vollaro A (2016) Outdoor thermal comfort in the Mediterranean area. A transversal study in Rome, Italy. Build Environ 96:46–61. https://doi.org/10.1016/J.BUILDENV.2015.11.023
Salata F, Golasi I, Petitti D, de Lieto Vollaro E, Coppi M, de Lieto Vollaro A (2017) Relating microclimate, human thermal comfort and health during heat waves: an analysis of heat island mitigation strategies through a case study in an urban outdoor environment. Sustain Cities Soc 30:79–96. https://doi.org/10.1016/J.SCS.2017.01.006
Saltelli A, Tarantola S, Campolongo F, Ratto M (2004) Sensitivity analysis in practice: a guide to assessing scientific models. John Wiley & Sons
Saltelli A, Ratto M, Andres T, et al (2007) Global sensitivity analysis. The primer. John Wiley & Sons
Santidrián Tomillo P, Saba VS, Lombard CD, Valiulis JM, Robinson NJ, Paladino FV, Spotila JR, Fernández C, Rivas ML, Tucek J, Nel R, Oro D (2015) Global analysis of the effect of local climate on the hatchling output of leatherback turtles. Sci Rep 5:1–12. https://doi.org/10.1038/srep16789
Staiger H, Laschewski G, Grätz A (2012) The perceived temperature – a versatile index for the assessment of the human thermal environment. Part A: scientific basics. Int J Biometeorol 56:165–176. https://doi.org/10.1007/s00484-011-0409-6
Toy S, Yilmaz S (2010) Evaluation of urban–rural bioclimatic comfort differences over a ten–year period in the sample of Erzincan city reconstructed after a heavy earthquake. Atmósfera 23:387–402
Tuller SE (1997) Climatic controls of the cool human thermal sensation in a summertime onshore wind. Int J Biometeorol 41:26–33. https://doi.org/10.1007/s004840050050
Unger J (1999) Comparisons of urban and rural bioclimatological conditions in the case of a Central-European city. Int J Biometeorol 43:139–144. https://doi.org/10.1007/s004840050129
Urban A, Kyselý J (2014) Comparison of UTCI with other thermal indices in the assessment of heat and cold effects on cardiovascular mortality in the Czech Republic. Int J Environ Res Public Health 11:952–967. https://doi.org/10.3390/ijerph110100952
Wickham H (2016) ggplot2: elegant graphics for data analysis. Springer
Wickham H, Francois R, Henry L, Müller K (2016) dplyr: a grammar of data manipulation. R package version 0.5. 0
Wood SN (2017) Generalized additive models, 2nd edn. Chapman and Hall/CRC
Wood S (2018) The mgcv package. www. r-project. org
Yang L, Yan H, Lam JC (2014) Thermal comfort and building energy consumption implications – a review. Appl Energy 115:164–173. https://doi.org/10.1016/J.APENERGY.2013.10.062
Zhang W, Du Z, Zhang D et al (2016) Assessing the impact of humidex on HFMD in Guangdong Province and its variability across social-economic status and age groups. Sci Rep 6:1–8. https://doi.org/10.1038/srep18965