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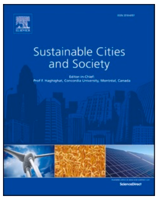

# Determining behavioural-based risk to SLODs of urban public open spaces: Key performance indicators definition and application on established built environment typological scenarios

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ABSTRACT

A behavioural-based approach can be used to assess how users' reactions to surrounding environmental conditions can alter the urban Built Environment (BE) risk to Slow Onset Disasters (SLODs). Public Open Spaces (POSs) in the BE are relevant scenarios, due to micro-climate-related stress, users' vulnerabilities (e.g., age, health frailty) and exposure time. Simulation methods can support behavioural-based risk-assessment, but results are generally site-specific. Performing analysis on BE Typologies (BETs) can improve robustness, since BETs represent archetypes from real-world scenarios. This work adopts a behavioural-based approach to evaluate time-dependant users' risks of POSs in different BETs due to SLODs-related stress (i.e., heat, air pollution). UTCI and AQI values are mapped within each BET. Users' distributions are then calculated depending on thermal acceptability correlations. Key Performance Indicators are developed associating users' distribution to SLODs effects on health (i.e., sweat rate, water loss; health affection rate probability). The approach is applied to Italian BETs, under one relevant climate, rating their heat and air pollution risks. Results suggest critical conditions for toddlers. In detail, about 2-hour high heat exposure could result in dehydration, while 1-hour exposure to low NO2 concentration could result in +1% mortality probability. This approach could potentially support decision-makers on BE risk-assessment.

## 1. Introduction

The resilience of our cities and society to different risks depends on the interactions between the urban Built Environment (BE), its environmental conditions, its users and institutions leading sustainable transitions to a safer BE (Amirzadeh et al., 2022; Jabareen, 2013; Sharifi, 2019b; B. Wang et al., 2020; Yang et al., 2021). Besides hazards and BE physical vulnerability, resilience-affecting factors also relate to the users and to the decision-makers' choices at local and global scales, which impact users' tasks and lifestyle (Baquedano et al., 2021; Kotharkar & Ghosh, 2022). The BE conditions can slowly or suddenly be modified by critical events, that imply different users' reactions and behaviours (Choi et al., 2019; Krüger et al., 2017), depending on the individual perception of BE and hazard stress, and on their individual features, such as health frailty, motion speed or fragilities in motion, (Bosina & Weidmann, 2017; Campos Ferreira et al., 2022; Guo & Loo, 2013; Luo et al., 2018; Villagràn De León, 2006). Thus, risk assessment and mitigation in urban BE should rely on users' exposure and vulnerability, moving towards a behavioural-based perspective (Bernardini et al., 2016).

BE resilience to SLow Onset Disasters (SLODs) has a paramount role given the way that SLODs unfold, because BE users do not always perceive the stress action that such continuous or prevalent effects have on them (Ho et al., 2021), reducing their actual responsivity to hazard arousal (Cori et al., 2020; Howe et al., 2019). Moreover, the effects of SLODs, such as heat stress due to increasing temperatures and air pollution stress, are strictly correlated to the way the users live in the BE and in Public Open Spaces (POSs) (Garau & Annunziata, 2022; Jens & Gregg, 2021; Jian et al., 2021; Sharifi, 2019a). In POSs, users are directly exposed to surrounding environmental conditions (i.e. solar radiation implying heat stress; pollutants implying air pollution stress), which thus affect their comfort, behaviours and health (Blanco Cadena et al., 2021; Erell et al., 2014; Nasrollahi et al., 2021; Nitidara et al., 2022; Pascal et al., 2013; Yıldız & Çağdaş, 2020). Risk in POSs could be

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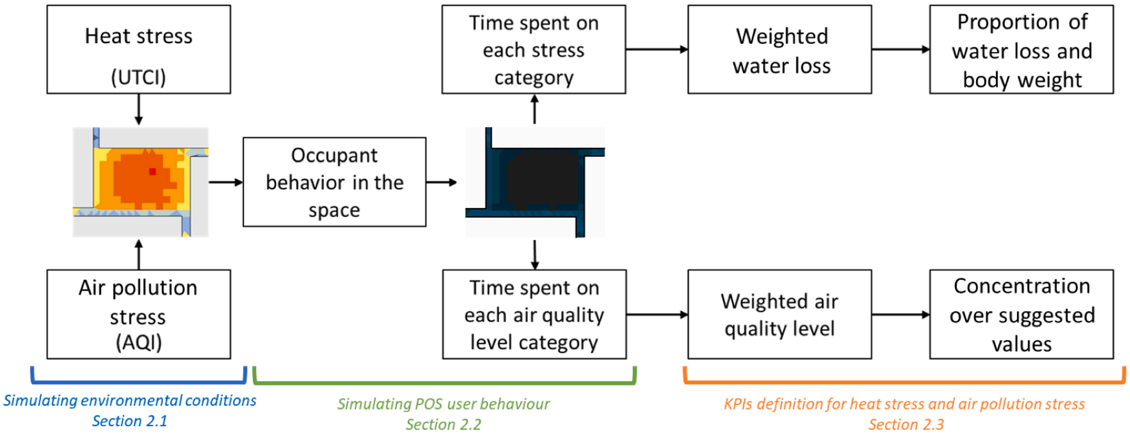

**Fig. 1.** Workflow of the proposed behavioural-based approach, including references to the methodological Sections. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

evaluated through key performance indicators (KPIs) describing stress levels on users, i.e. Universal Thermal Climate Index (UTCI) for thermal stress, and Air Quality Index (AQI) for pollutants danger (Bröde et al., 2009; Mintz, 2006). UTCI and AQI are essentially time and space dependant within the single POS.

UTCI has been linked to the hourly sweat rates (as a physiological response) for users exposed to a certain category of heat stress (Błażejczyk et al., 2010; Broede et al., 2013). UTCI allows estimating the potential amount of water loss in an hour [g/h] given the heat stress imposed on BE users, and so their risk levels depending on the individual features. For instance, previous works defined thresholds for initial symptoms of dehydration (water loss $>$ 4% of body weight) (Błażejczyk et al., 2014) and heat risk of mortality for users in urban BE (Sahani et al., 2022; Savić et al., 2018). Adaptation strategies to minimize morbidity and its determinants were also investigated by mainly focusing on large spatial scale and extreme events (Bakhsh et al., 2018).

Previous research works have also pointed out how heat stress affects users' behavioural patterns in the POS (Aghamohammadi et al., 2021; Göçer et al., 2019; Yıldız & Çağdaş, 2020; Yung et al., 2019). The users' preferences about the use of the POS areas depend on the combination of (a) their tasks and individual feature, including age, with (b) acceptability thresholds of the outdoor environment (e.g., UTCI) depending on their outdoor permanence time. General experimental-based correlations between heat stress and thermal acceptability probability values have been provided, including those concerning long-lasting permanence behaviours (e.g. 1-hour, such as for users performing tasks and spending time in the POS), and shortest permanence behaviours (called transient behaviours, such as for passersby who can be continuously exposed for up to 15 min) (Cheung & Jim, 2019).

Concerning air pollution, current methods are mainly orientated to estimating the relation between air pollution increments to recorded deaths, hospital entries, respiratory disease cases, and other general well-being issues on a large scale yearly (Li & Managi, 2022). Air pollution stress impacts are normally measured in terms of Disability-Adjusted Life Years (DALYs) and Years of Life Lost (YLLs) (Devleesschauwer et al., 2014). However, approaches using a more time-granular analysis could be more useful and have been recently utilized (Li & Managi, 2022). For example, increments in pollutants concentrations over time (hourly or daily) have been attributed to the probability of health affection, reporting symptoms, lung function decrease, asthma, hospital entry and mortality (Dockery & Pope, 1994). As for heat risks, the effects of BE features (mainly, the urban form, or the presence of greeneries and trees) and management strategies (e.g. traffic) have been combined with air pollution levels and so with stress for users (Liang et al., 2021; Liu et al., 2022; L. Wang et al., 2021). From a behavioural-based perspective, such an approach is important especially given the generally low level of awareness and preparedness of users to air pollution risks (Ho et al., 2021).

Simulation methods can be adopted to determine the intensity and the extent to which the BE users are exposed to hazard-related stress and affected by it (Andersson-Sköld et al., 2015; de Nazelle et al., 2009; Yıldız & Çağdaş, 2020), thus also evaluating how users react to them, according to a behavioural-based approach (Bernardini et al., 2016). Such works are orientated towards the analysis of both risk assessment and risk-mitigation/adaptation strategies, although they are widely orientated to a territorial scale rather than the POS scale (Tang et al., 2020; Zhang et al., 2020). However, the interest for more granular resolution analysis, at the POS scale, is significantly increasing and works have been carried out by considering a neighbouring area, or even a single building block or POS, and the effects of environmental conditions on such micro-scale BEs composing the urban fabric (Abdallah & Mahmoud, 2022; Andersson-Sköld et al., 2015; Estacio et al., 2022; Mortezazadeh et al., 2021; Yıldız & Çağdaş, 2020). Such studies also included behavioural issues and users' probable trajectories and distribution over the POS, thus moving towards the inclusion of discomfort, stress perception, and thermal acceptability as bases of behavioural-based analysis. The approach capabilities in supporting designers and decision-makers at a local scale have been already confirmed (Estacio et al., 2022).

Nevertheless, two main issues still limit the development and application of such a SLOD-assessment process. First, behavioural KPIs considering the effects of heat and air pollution stress are still underdeveloped, especially concerning users' fruition issues in the POS. Second, most of the works are related to specific case studies, limiting their scalability. On the contrary, the use of urban unit archetypes could support preliminary assessment of main critical issues depending on the main BE features. The use of idealized scenarios has been widely adopted in other contexts (Dolce et al., 2020; Morganti, 2021), including those relating to simulation-based and behavioural-based assessment of BE performances, such as safety (Bernardini et al., 2021; Mignot et al., 2019). Concerning POSs, previous works developed BE Typologies (BETs) according to statistical-based analysis of a large sample of real-world urban squares (D'Amico et al., 2021). Each BET is hence described by statistical-based morphological, geometrical, and constructive features, which are quantified according to recurring, and so typological, values derived from real-world case studies (i.e. mean and quartile-based values). A cluster-based approach has been used to this end, and BETs were developed using Italian case studies, but the same approach could be replicated in different geographical contexts. .

In view of the above, this work is aimed at developing and testing a behavioural and simulation-based approach to evaluate risks for users due to heat and air pollution stress while they are hosted in the POS of

**Table 1**
Sweat rate allocation by UTCI heat stress category, re-elaborated from Błażejczyk et al. (2010 and 2014).

| UTCI [ °C] | Stress category | Sweat rate [g/ h] | Interpolation methods for simulation and estimation |
|---|---|---|---|
| >46 | Extreme heat stress | >650 | $\textit{sweate rate} = 650$ |
| 38 – 46 | Very strong heat stress | 200 – 650 [a] | $\textit{sweate rate} = \begin{cases} \frac{225 \cdot UTCI - 5800}{7}, & 46 \geq UTCI > 32 \\ \frac{100 \cdot UTCI - 2600}{3}, & 32 \geq UTCI > 26 \end{cases}$ |
| 32 – 38 | Strong heat stress | >200 [a] | |
| 26 – 32 | Moderate heat stress | 0–200 [a] | |
| 9 – 26 | No thermal stress | 0 | $\textit{sweate rate} = 0$ |

[a] Undefined values in the original study.

different BETs. The approach pursues quick-to-apply and generalization concepts, by: (a) adopting a granular approach over the POS space and over the users' exposure time (depending on behavioural patterns in POS fruition and by the thermal acceptability probability); (b) using simplified-but-reliable (i.e.: experimentally-based) assumptions on users' behaviours and stress effects on their health; (c) evaluating the POS as a whole, to weight SLODs effects of each POS sub-area, and to consider behavioural uncertainties; (d) testing idealized scenarios (i.e. the BETs) to derive general outcomes on similar input SLODs conditions. To this end, specific health-related, time and behavioural KPIs are developed, using simulations for estimating the hazard effects severity of the BE users using UTCI (for sweat rate) and AQI (for health affection rate).

## 2. Phases, materials, and methods

The work is organized into 3 main phases, as shown by the general workflow of the proposed behavioural-based approach in Fig. 1: (1) simulation-based estimation of environmental conditions within the POS in terms of heat (UTCI) and air pollution (AQI) stress as SLOD hazard levels (Section 2.1); (2) simulation of users' behaviours and distribution in the POS depending on the environment conditions (Section 2.2); (3) KPIs definition for heat stress and air pollution depending on users' vulnerability, behaviours and distribution in the POS (Section 2.3).

In view of the BE S$^2$ECURe project of which this work is part,[1] the proposed approach is applied to typological case studies in the Italian context (D'Amico et al., 2021; Rosso et al., 2018), and by considering the relevant conditions of Milan as significant heatwaves and air pollution-affected city (Salvalai et al., 2020), to demonstrate the capabilities of the overall method and rank the selected BETs for the considered SLODs risks levels (see Section 2.4).

### 2.1. Simulation-based estimation of POS environmental conditions

The simulation of POS environmental conditions is performed using Rhinoceros V6 + Ladybug Tools 1.3.0 and ENVIMET v.5 and allows retrieving heat stress and air pollution conditions depending on the general features of the 3D model of the POS. ENVI-met is a largely used and validated 3D urban climate modelling tool (Bastian et. al., 2016; Zhixin et al., 2021) for simulating the microclimatic effects of buildings, vegetation, and other objects in the built environment.

The following simplified assumptions are considered for the application to typological scenarios (D'Amico et al., 2021). Firstly, POS geometries are recreated as a 3D model on Rhinoceros, and generic optical properties are attributed to their volume surfaces. No specific information on the glazing portion is provided in this work, and reflectance values are mostly allocated to surfaces that represent roofs, facades, pavement, and greenery elements (i.e., grass and tree canopies). Secondly, concerning environmental conditions, standard weather data (i.e., .EPW and .STAT)[2] are herein used rather than specific case studies inputs, by assuming: (1) a large spatial resolution is set for the analysis grid (5 × 5 m); (2) no detailed calculation on mean radiant temperature; and (3) no detailed information on the wind speed distribution in the POS. Mean radiant temperature was considered equal to air temperature and wind direction and speed were considered equal to the ones provided in the weather data (.EPW file) (Mackey et al., 2017). Then, AQI is used to consider the effect of different air pollutants. To determine the analysis period for the studied climate, and its available standard .STAT weather file from open repositories is used as input for the LB IMPORT STAT component from Ladybug tools, which individuates the hottest week of the year. For air pollution, a shorter analysis period is assumed to avoid extremely lengthy simulations per case.

A time span of six hours, from 11:00 to 16:00, during the hottest week of the year, is set on the validated Radiance and EnergyPlus computing engine through Ladybug Tools to account for the potentially most critical heat stress. Meanwhile, for the same hours, but only during the hottest day within the hottest week is set for air pollution stress. Such a day is singled out by comparing the highest dry-bulb air temperature reported for each of the days of the hottest week. For air pollutant distribution simulations, background concentrations are set in ENVIMET as the median for each pollutant concentration over the considered period (for $NO_2$, $O_3$, PM10 and PM2.5) from site-specific measurements, considering at least 5-year records for the analysis period. Traffic is included as the only air pollutant source, being consistent with typical summer scenarios.

The obtained environmental conditions are averaged for the analysis period in each of the centre points of the automatically generated analysis squared grid (using the "LB GENERATE POINT GRID" component from Ladybug tools) based on the desired spatial resolution, and at a 0.9 m height, corresponding to the rounded-up half value of 1.75 m tall idealized user (ISO, 2004).

Specific details of the BETs application contexts are also provided in Section 2.4.

### 2.2. BE users' distribution

According to a quick application approach, users' behaviours in the POS are simulated in terms of their distribution within the POS depending on UTCI values. Eq. (1) provides the adopted experimental-based correlation between UTCI and users' thermal acceptability probability (PA) (Cheung & Jim, 2019) for: (a) 1-hour behaviour, relating to users who perform tasks in the POS; (b) transient behaviour, representing passersby's behaviours. Eq. (1) is not applied to obstacles, monuments and fenced areas in the POS where users cannot move or gather. Either PA calculation methods are applied to compare the approach sensitivity depending on such behavioural factors.

$$PA\ [\%] = \begin{cases} -0.2485\ UTCI^2 + 12.914\ UTCI - 85.681 \text{ for } 1-\text{hour behaviour} \\ -0.0859\ UTCI^2 + 4.019\ UTCI + 54.119 \text{ for transient behaviour} \end{cases} \tag{1}$$

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[1] https://www.bes2ecure.net/ (last access: 10/11/2022).

[2] .EPW: EnergyPlus Weather file data dictionary format - https://bigladdersoftware.com/epx/docs/8-3/auxiliary-programs/index.html; .STAT: EnergyPlus statistical report produced from the weather file conversion process - https://bigladdersoftware.com/epx/docs/8-3/auxiliary-programs/index.html (last access: 08/11/2022).

**Table 2**
Mean body weight [kg] by representative age classes, and related standard deviation values, according to USA statistics4.

| Age class (years) | Mean body weight – MALE (st. Dev) [kg] | Mean body weight – FEMALE (st. Dev) [kg] |
|---|---|---|
| Toddlers TU (0–4)* | 11 (4) | 11 (4) |
| Parent-assisted children PC (5–14)* | 40 (14) | 40 (14) |
| Young autonomous users YA(15–18) | 77 (4) | 65 (2) |
| Adult users AU (20–69) | 89 (3) | 76 (1) |
| Elderly EU (70+) | 83 (4) | 70 (5) |

* Data do not include the weight of the adult moving with the child.

**Table 3**
Collection of the population's average short-term exposure risk variance due to an increase in air pollutants concentration (Atkinson et al., 2013), or from [a] - Dockery and Pope (1994).

| | RR per 10 μg/m$^3$ | | | |
|---|---|---|---|---|
| Pollutant | Mortality | Hospital admissions (cardiovascular) | Hospital admissions (respiratory) | Symptoms |
| PM10 | 1.0100[a] | | 1.0080[a] | 1.028 |
| PM2.5 | 1.0123 | 1.0091 | 1.0190 | |
| O3 | 1.0029 | 1.0089 | 1.0089 | 1.0154 |
| NO2 | 1.0027 | 1.0015 | | |

## 2.3. Behavioural-based KPIs definition

### 2.3.1. Granular time-dependant heat stress affection on health

This work considers the potential sweating rate to represent granular time-dependant effects on users from heat stress. Thus, the amount of water loss can be computed depending on the sweat rate associated with a UTCI-heat stress category, for every time-step $t_i$ [h] defined according to the users' behavioural issues and distribution in Section 2.2. Table 1 summarises the assumed sweat rate allocation depending on the UTCI category, as provided by Błażejczyk et al. (2010 and 2014). Interpolated values are proposed to specify sweat rate depending on UTCI intervals, using start and end values of the range as boundary values.

Thus, Eq. (2) is applied considering both user's 1-hour and transient PA, thus deriving the users' possible averaged water loss in the POS of the BET depending on the UTCI conditions $WL_{POS,BET}$ [g/h], expressed by Eq. (2):

$$WL_{POS,BET} = \frac{\sum_{a=0}^{n}\left(Sweat\ rate_a\cdot\left(t_{crit,a}\cdot A_a\cdot\ PA_a\right)\right)}{\left(\sum_{a=0}^{n}A_a\right)\cdot t_{crit,\ tot}} \tag{2}$$

where $a$ is the area of the POS characterized by a given UTCI condition (and with a given sweat rate). Each $a$ is characterized by its dimension $A_a$ [m$^2$], while the related $PA_a$ considers UTCI effects on users' 1-hour or transient behaviours. The reference time is the $t_{crit,a}$ *and* $t_{crit,tot}$, considering the users' permanence in $a$ (as total exposure time) and the POS respectively. According to this work assumptions focused on the UTCI effects on users' behaviours, $t_{crit,a}$ is considered constant ($t_{crit,0} = t_{crit,1} = \ldots = t_{crit,n}$). Detailed analysis on users' path/presence over the total time within $a$ could be also performed to assess $t_{crit,a}$. Then, Eq. (3) calculates the total water loss of a single user for the hypothetical body weight. The larger the water loss/body weight rate, the larger the risk. Individual physiological conditions for the specific water loss risk ($WLR_{age}$) are assessed depending on age classes (Blanco Cadena, 2021): toddlers (TU), children (PC), young adults (YA), adults (AU), elderly (EU). Gender issues are linked with age-related issues (see Table 2).

$$WLR_{age} = \frac{WL_{POS,BET}}{body\ weight_{age}}\times\ 100 \tag{3}$$

In particular, *body weight*$_{age}$ [g] data can be associated with statistical anthropometric measurements depending on the specific country in which the analysis is performed. Due to the lack of completeness of available data for the Italian context related to the analysed BETs, data from USA statistics have been preliminarily adopted in this work[3] (Table 2).

### 2.3.2. Granular time-dependant pollution burden on health

Given the rationale of the work, a slightly different air pollutant burden strategy is proposed, motivated by: (1) the interest in making the methodology robust; (2) the lack of information on all air pollutant types; and (3) given that no literature-based agreement was found on the direct link between short-term exposures of air pollutants and health burden.

As shown by Table 3, the granular pollution burden on health is estimated as the absolute increased probability of health affections *short term pollution risk*$_i$ [%], by considering "mortality", "hospital admission" and "reporting symptoms", in respect of each relative risk (RR), according to Dockery and Pope (1994) for PM10 and Atkinson et al. (2013) for other pollutants (e.g. PM2.5, O3, NO2). Such a probability growth for RR is multiplied by the calculated increment of the pollutant concentration ($\Delta_{pollutant}$) to which a user is exposed compared with an ideal air-pollutant-free environment. No specificities of physiological vulnerabilities of users are considered to focus on the hourly scale of air pollutants variations, pursuing a quick-to-apply but reliable approach and focusing on users' behaviours in the POS of the BET.

$AQI_{POS,BET,crit}$ is estimated as the area-weighted average of AQI within the POS of the studied BET (Eq. (4)), thus pursuing the same approach of heat stress in Eq. (2). According to Section 2.3.1 assumptions focused on the UTCI effects on users' behaviours, it could be considered that $t_{crit,a}$ is constant ($t_{crit,0} = t_{crit,1} = \ldots = t_{crit,n}$), but the method is still valid by using a detailed analysis of the users' permanence in each of the areas $a$ of the POS in the BET. The reference time is $t_{crit,tot}$, considering the users' permanence in the POS as total exposure time, as for $WL_{POS,BET}$ in Section 2.3.1. Then, this value is reconverted to the concentration values of the pollutant of interest (Eq. (5) - which generated the displayed AQI) to directly obtain the percentual change in probability, or the total amount of RR, of health burden (see Eq. (6) and Eq. (7)) (Atkinson et al., 2013; Dockery & Pope, 1994; Martuzzi et al., 2006).

$$AQI_{POS,BET,crit} = \frac{\sum_{a=0}^{n}\left(A_a\cdot\ AQI_a\cdot t_{crit,a}\cdot\ PA_a\right)}{\left(\sum_{a=0}^{n}A_a\right)\cdot t_{crit,\ tot}} \tag{4}$$

$$Concentration_{AQI} = \frac{\left(AQI_{POS,BET,crit} - I_{Lo}\right)\cdot\left(BP_{Hi} - BP_{Lo}\right)}{I_{Hi} - I_{Lo}} + BP_{Lo} \tag{5}$$

$$\Delta_{pollutant} = Concentration_{AQI} - Concentration_{suggested} \tag{6}$$

$$short\ term\ pollution\ risk_i = \left(\frac{\Delta_{pollutant}}{10}\right)\cdot(RR_i - 1)\times\ 100 \tag{7}$$

In Eq. (5), according to the suggested values already presented by Mintz (2006), $I_{Hi}$ is the reference AQI value corresponding to $BP_{Hi}$; $I_{LO}$ is the reference AQI value corresponding to $BP_{Lo}$; $BP_{Hi}$ is the breakpoint that is greater than or equal to $Concentration_{AQI}$; and, $BP_{Lo}$ is the breakpoint that is less than or equal to $Concentration_{AQI}$. $Concentration_{suggested}$ may vary according to the goal of the study, which, in this study, is set as an ideal air-pollutant-free environment ($Concentration_{suggested} = 0$). In Eq. (7), $i$ refers to health affection types of Table 3, for each specific pollutant type studied.

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[3] https://www.cdc.gov/nchs/data/series/sr_11/sr11_252.pdf (last access: 19/07/2022).

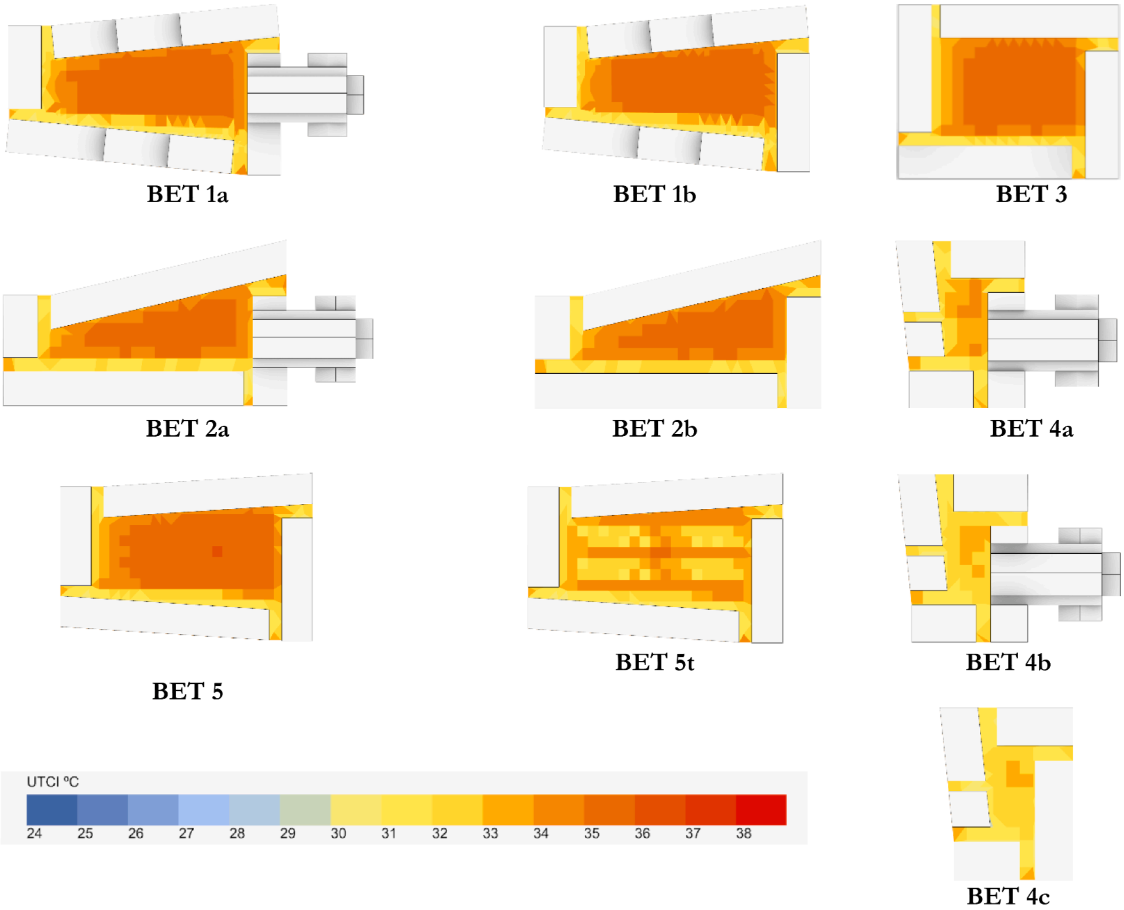

**Fig. 2.** Results of the computed UTCI representing people's thermal stress outdoors within the constructed BETs for the Italian context subjected to Milan's Climatic conditions (North side at the top of each figure). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 2.4. *Application scenarios: BETs and climate*

The main morphological, geometrical and radiative features (albedo and transmittance) of the BETs considered in this work are derived according to the classification of D'Amico et al. (2021), relating to Italian squares within historical city centres. BETs data are shown in Appendix A, including both morphology and geometry (Fig. A.1 which vary depending on the BET) and radiative features (Table A.1 which are considered constant in all the scenarios). BETs are assessed considering one unique climate scenario to test the methodological approach and to compare effects on SLODs stress due to the POS features effects on UTCI, AQI, and users' behaviours. In detail, the climate of Milan, Italy (Cfa - Köppen-Geiger climate type (Beck et al., 2018) and climate zone E – Italian decree D.p.r 412[4]) is analysed for both UTCI and AQI as it can suffer critical simultaneous SLODs (ranked on top 3 amongst European countries at risk on an overheated planet by UNEP(2021)). As described by Salvalai et al. (2020), these area is characterized by high vulnerability given the high average population age in Italy; high hazard intensity on air pollutant concentrations and high air temperatures during summer; and, high exposure being within the most populated region and amongst the most densely populated municipality in Italy. According to Milan's weather data, the simulated period involves the hottest week for the UTCI (06/07 to 12/07) and the hottest day for the AQI (11/07) set with .STAT file, between 11:00 and 16:00. Different periods are set, given the computational burden for estimating pollutant dispersions with the validated CFD simulator in ENVIMET. In addition, for air pollutants distribution, the background concentrations pollution is set as the median experimental concentration value for each pollutant during the hottest week, based on 5 years from open regional repositories[5]: $NO_2 = 15\ \mu g/m^3$, $O_3 = 83\ \mu g/m^3$, $PM10 = 20\ \mu g/m^3$ and $PM2.5 = 15\ \mu g/m^3$ (considering the time from 2015 to 2019). Fixed wind speed and direction (i.e., 1.9 m/s and 310° from the North) were considered in ENVIMET, reducing computational costs. Considering only the most critical air quality condition, vehicle roads are set to be on the perimeter of the POS (air pollutants are emitted closer to users), considering the typical POS in historic urban BEs as a pedestrian area. Its intensity is set as medium/high (i.e., 8000 vehicles distributed during the day) from ENVIMET default settings. Finally, a fixed $t_{crit,tot}$ equal to 1 h is used for heat and air pollution stress, in both PA calculations.

## 3. Results

### 3.1. *POS environmental conditions that affect users' distribution and health*

Fig. 2 shows the distribution of UTCI value within the POS in the BET according to the adopted 5mx5m simulation grid as defined in Section 2.1, considering the selected period of analysis (i.e., 11–16 between 06/

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[4] https://www.gazzettaufficiale.it/eli/id/1993/10/14/093G0451/sg (las access 19/07/2022).

[5] https://www.arpalombardia.it/Pages/ARPA_Home_Page.aspx (last access: 19/07/2022).

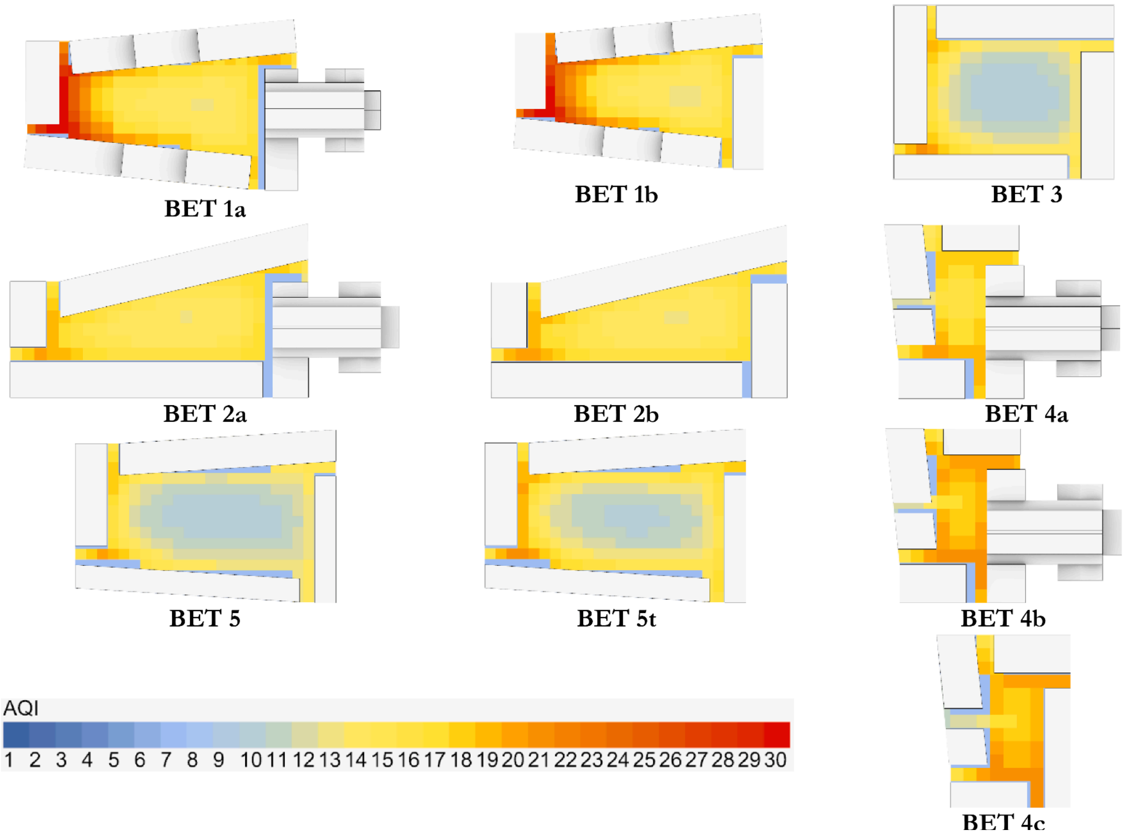


**Fig. 3.** Results of the computed AQI displaying the air pollution conditions to which people would be exposed when present in the outdoor area within the constructed BETs for the Italian context subjected to Milan's Climatic conditions. (North side at the top of each figure). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

07 to 12/07) according to the description in Section 2.4.

As expected, the greatest heat stress was found in the least shaded areas, thus depending on the interactions between buildings height and the POS sides dimensions. In fact, more compact POSs, such as the ones of BET 4, show lower UTCI values than the ones of wider BETs. In particular, BET 4c, which is characterized by higher building fronts in respect of the other BETs, is affected by the less hazardous conditions of the whole sample. Also as expected, the introduction of trees generates a positive impact to enlarge the areas with a lower UTCI value (~31 vs. ~35), as remarked by the comparison between BET 5t (which includes trees on the POS) with BET 5 (same POS sizes and building fronts height, but no trees). Concerning air pollution stress, normally AQI considers the main threatening air pollutant. Nevertheless, PMs were found to vary only slightly within the BETs (e.g., std = 0.07 $\mu g/m^3$ for the total area of a BET). Thus, AQI only considers the distribution of $NO_2$ since traffic was set as the only source of pollution (found mostly responsible for $NO_x$ (US EPA, 2018)).

Then, pollutants' concentration and distribution were estimated, transformed into AQI and mapped within the BETs following the steps mentioned in Section 2.3. Fig. 3 shows the AQI values on the same 5 × 5 m grid adopted in the BET, for the different BETs considered in this work. The AQI was found to be larger on BET1a, BET1b, BET4b and BET4c. BET1a and BET1b are characterized by a larger concentration on the closest leeward side of the buildings to the fixed wind direction (South-West). BET4b and BET4c have very narrow POS, streets and high facing buildings. It is worth noting that AQI follows the edges of the POS, according to boundary traffic conditions. Thus, POS exits hence are more affected by AQI and less by UTCI than the POS centre.

### 3.2. BETs users' distribution based on environmental conditions

Following Section 2.2, users' distributions are affected by UTCI values shown in Figs. 4 and 5, which respectively reflect the thermal acceptability probability (PA) for users' 1-hour behaviours and transient behaviours in the POS, for each considered BET. In both these conditions, calculated PA values range from about 60% to 100%, thus the colour scale reports the same values range.

Considering 1-hour behaviours shown in Fig. 4, in large POSs, users would rather stay on the edges of the POSs, avoiding the potential and direct exposure to solar radiation. The presence of trees in BET 5t increases the probability of people remaining in the centre of the POS, since their localization provides a more shaded and cooler space to stay on. Likewise, smaller POSs seem to attract users to remain nearby the centre of the POS, as buildings can also shield them from adverse solar radiation.

In contrast, considering the transient behaviour, and referring to typical passersby conditions, PA values are generally higher than the ones on the 1-hour behaviours (see Fig. 5). In fact, users can better accept less UTCI-affected favourable conditions since they are passersby, and absolute differences in the PA values are smaller across the POS (and so of the simulation grids). Nevertheless, the users' distribution has the same trend as the 1-hour behaviour acceptability results. For transient behaviour, PA values are always > 75% for all the BETs, implying that the probable users' distribution is more homogeneous and differences between the centre of the POS and its edges are less noticeable than for PO. The presence of trees in BET 5t affecting users' distribution is once again noticed, by increasing the probability of users' permanence in the central areas of the POS.

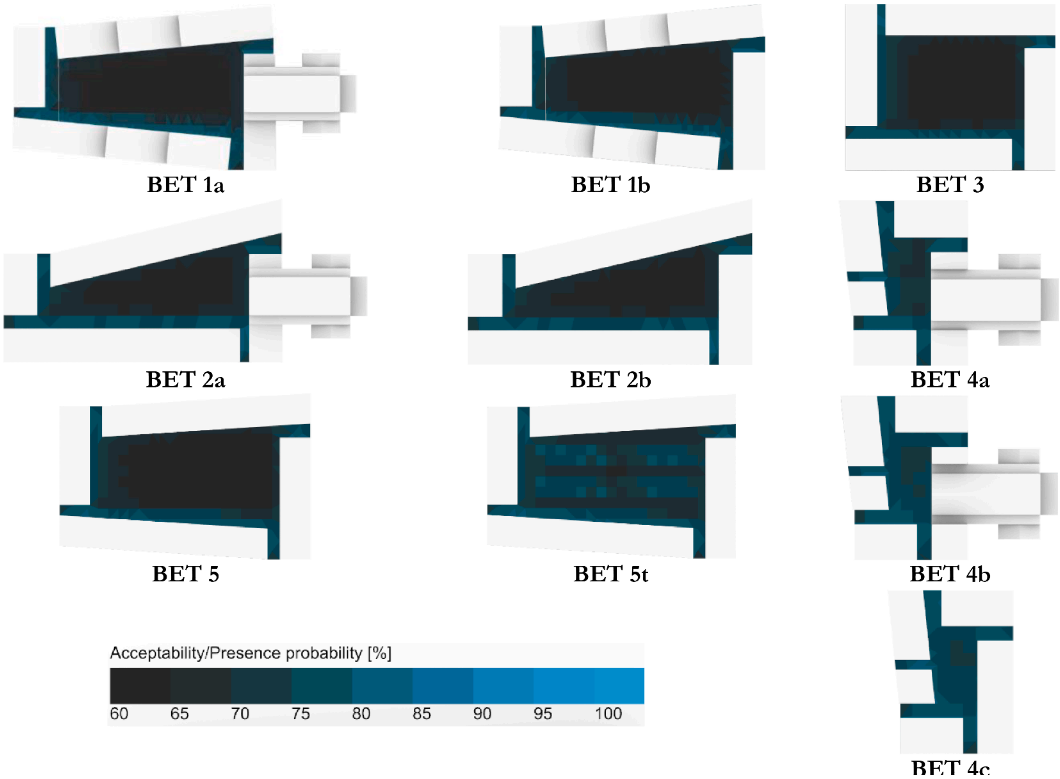

BET 1a BET 1b BET 3 BET 2a BET 2b BET 4a BET 5 BET 5t BET 4b BET 4c

**Fig. 4.** Results of the computed 1-hour behaviour acceptability and assumed probability of people's presence in the outdoor area based on the UTCI within the constructed BETs for the Italian context subjected to Milan's Climatic conditions (North side at the top of each figure). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

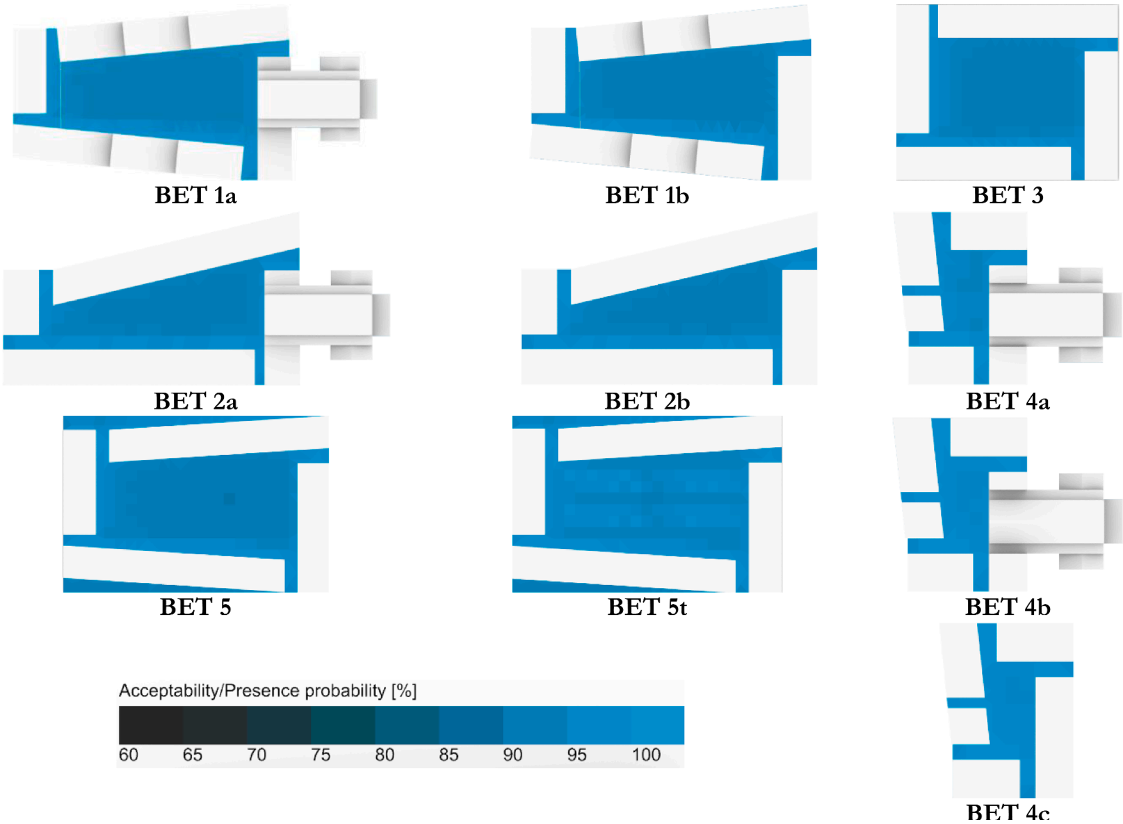

BET 1a BET 1b BET 3 BET 2a BET 2b BET 4a BET 5 BET 5t BET 4b BET 4c

**Fig. 5.** Results of the computed transient behaviour acceptability and assumed probability of people's presence in the outdoor area based on the UTCI within the constructed BETs for the Italian context subjected to Milan's Climatic conditions (North side at the top of each figure). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 4**
Percentage [%] of water loss on body weight ($WLR_{age}$) given the potential 1-hour exposure of the users performing 1-hour behaviour, and perceived thermal stress within the BET, given a certain age class. Codes relating to age classes, as reported in Table 2, are: toddlers (TU), children (PC), young adults (YA), adults (AU), elderly (EU).

| Gender & age class | BET1a | BET1b | BET2a | BET2b | BET3 | BET4a | BET4b | BET4c | BET5 | BET5t |
|---|---|---|---|---|---|---|---|---|---|---|
| Male/Female TU | 0.79 | 1.15 | 0.65 | 0.95 | 1.54 | 0.49 | 0.47 | 1.05 | 1.31 | 1.19 |
| Male/Female PC | 0.22 | 0.32 | 0.18 | 0.26 | 0.42 | 0.14 | 0.13 | 0.29 | 0.36 | 0.33 |
| Male YA | 0.11 | 0.16 | 0.09 | 0.14 | 0.22 | 0.07 | 0.07 | 0.15 | 0.19 | 0.17 |
| Female YA | 0.13 | 0.19 | 0.11 | 0.16 | 0.26 | 0.08 | 0.08 | 0.18 | 0.22 | 0.20 |
| Male AU | 0.1 | 0.14 | 0.08 | 0.12 | 0.19 | 0.06 | 0.06 | 0.13 | 0.16 | 0.15 |
| Female AU | 0.11 | 0.17 | 0.09 | 0.14 | 0.22 | 0.07 | 0.07 | 0.15 | 0.19 | 0.17 |
| Male EU | 0.10 | 0.15 | 0.09 | 0.13 | 0.20 | 0.07 | 0.06 | 0.14 | 0.17 | 0.16 |
| Female EU | 0.12 | 0.18 | 0.10 | 0.15 | 0.24 | 0.08 | 0.07 | 0.16 | 0.21 | 0.19 |

**Table 5**
Percentage [%] of water loss on body weight ($WLR_{age}$) given the potential 1-hour exposure of the users performing transient behaviour, and perceived thermal stress within the BET, given a certain age class. Codes relating to age classes, as reported in Table 2, are: toddlers (TU), children (PC), young adults (YA), adults (AU), elderly (EU).

| Gender & age class | BET1a | BET1b | BET2a | BET2b | BET3 | BET4a | BET4b | BET4c | BET5 | BET5t |
|---|---|---|---|---|---|---|---|---|---|---|
| Male/Female TU | 1.10 | 1.6 | 0.9 | 1.31 | 2.16 | 0.65 | 0.61 | 1.35 | 1.83 | 1.59 |
| Male/Female PC | 0.30 | 0.44 | 0.25 | 0.36 | 0.59 | 0.18 | 0.17 | 0.37 | 0.50 | 0.44 |
| Male YA | 0.16 | 0.23 | 0.13 | 0.19 | 0.31 | 0.09 | 0.09 | 0.19 | 0.26 | 0.23 |
| Female YA | 0.19 | 0.27 | 0.15 | 0.22 | 0.37 | 0.11 | 0.10 | 0.23 | 0.31 | 0.27 |
| Male AU | 0.14 | 0.20 | 0.11 | 0.16 | 0.27 | 0.08 | 0.08 | 0.17 | 0.23 | 0.20 |
| Female AU | 0.16 | 0.23 | 0.13 | 0.19 | 0.31 | 0.09 | 0.09 | 0.20 | 0.26 | 0.23 |
| Male EU | 0.15 | 0.21 | 0.12 | 0.17 | 0.29 | 0.09 | 0.08 | 0.18 | 0.24 | 0.21 |
| Female EU | 0.17 | 0.25 | 0.14 | 0.21 | 0.34 | 0.10 | 0.10 | 0.21 | 0.29 | 0.25 |

### *3.3. SLODs affection on health: behavioural-based KPIs comparison in the BETs*

Regarding heat stress, the sweat rate was calculated at each point of the analysis grid using Eq. (2) and Eq. (3), considering a $t_{crit,tot}$ of 1 hour as exposure time to obtain a unique and normalized heat stress health affection impact risk value for every BET and age class. Such results have been summarized and compared in Table 4 for 1-hour behaviour and in Table 5 for transient behaviour. As expected, differences between the BETs exist. The worst performing BETs were found to be BET3, 5 and 5t, followed closely by 1b and 4c, probably because of their high sky vault exposure (1b, 3, 5 and 5t), which implies more direct solar radiation perceived in the POS. The best-performing BET was BET4b followed by BET4a, in view of the high building fronts height in respect of the POS sizes Meanwhile, the performance of BET4c could be attributed to the diffuse acceptability within the POS.

Concerning age-related issues, results show that toddlers are those who are more at risk of dehydration (maximum of 2.16% and 1.54% for transient and 1-hour behaviour respectively), given their lower weight and their lower capacity to rehydrate. Regardless of the BET in which they are placed, for 1-hour exposure, toddlers are approximately at 1/4 and 1/3 of the dehydration limit value having a 1-hour and transient behaviour respectively (i.e., average $WLR_{TU}$~0.96% and 1.31%). On the worst-case scenario (BET 3 – transient behaviour), a toddler exposed to the obtained environmental conditions for less than 2 h, or just above 3 h (BET 3 – 1-hour behaviour), could potentially reach a dehydration risk state (~4% water loss on body weight). These results are above the values suggested by literature (below 1-hour for an adult (Vanos et al., 2018)) and consolidated international guidelines (below 2-hours for an average adult (WHO, 2004)). Nevertheless, they can be considered feasible as the results are weighted for the whole open space, contemplating people's presence and different thermal stress, thus reducing the obtained risk value. Finally, concerning joint gender and age issues, the different behavioural responses (transient or 1-hour) of users in the POS of the BET can generate an average absolute $WLR_{TU}$ difference that ranges from 0.02% to 0.62% from elders to toddlers.

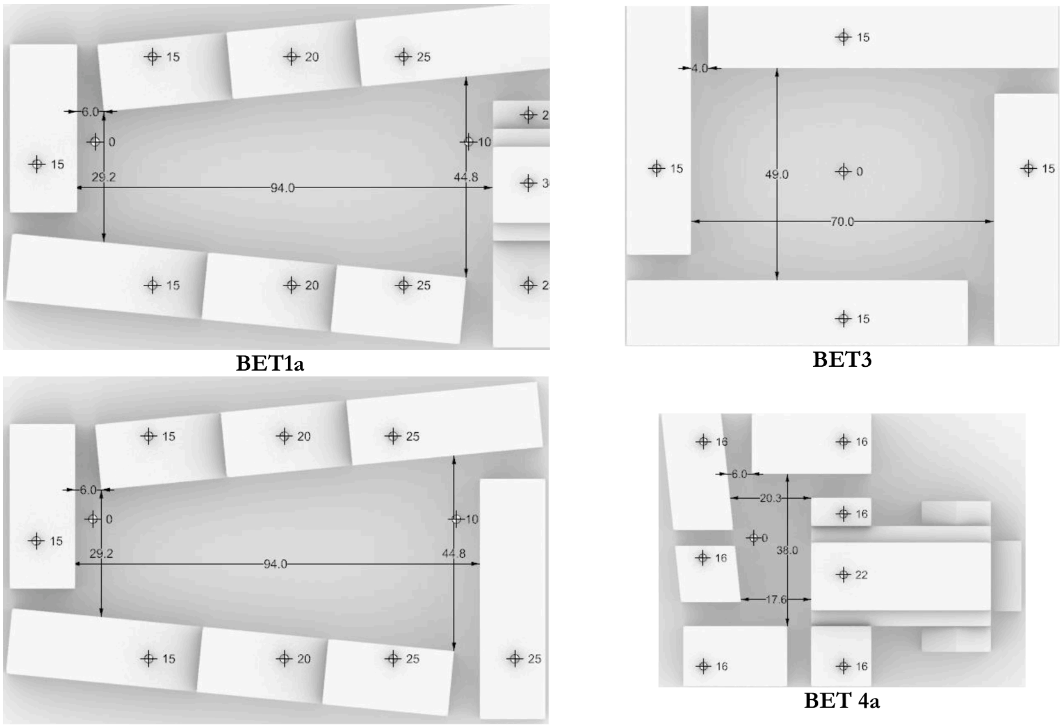
The absolute percentual health risk increment represented on the *short term pollution risk* [%] is summarized in Tables 6 and 7, according to Section 2.3.2 methods. The percentual health risk increment found for the different BETs is found to be larger on BET1b and BET4c. In fact, these two BETs are characterized by a larger concentration on the closest leeward side of the buildings to the wind direction (South-West). For $NO_2$ and considering either behaviour for 1-hour exposure in such POS, the probability of casualty increases on average by 1% compared to an

**Table 6**
Short term pollution risk [%] given the potential 1-hour exposure of the users performing 1-hour behaviour to NO2 within the BET compared to a control group in an air-pollutant-free environment.

| Affections | BET 1a | BET1b | BET2a | BET2b | BET3 | BET4a | BET4b | BET4c | BET5 | BET5t |
|---|---|---|---|---|---|---|---|---|---|---|
| Hospital admission with cardiovascular issues | 0.18 | 0.27 | 0.15 | 0.21 | 0.24 | 0.15 | 0.18 | 0.33 | 0.21 | 0.24 |
| Mortality | 0.32 | 0.48 | 0.27 | 0.38 | 0.43 | 0.27 | 0.32 | 0.59 | 0.38 | 0.43 |

**Table 7**
Short term pollution risk [%] given the potential 1-hour exposure of the users performing transient behaviour to NO2 within the BET compared to a control group in an air-pollutant-free environment.

| Affections | BET 1a | BET1b | BET2a | BET2b | BET3 | BET4a | BET4b | BET4c | BET5 | BET5t |
|---|---|---|---|---|---|---|---|---|---|---|
| Hospital admission with cardiovascular issues | 0.09 | 0.09 | 0.06 | 0.06 | 0.09 | 0.06 | 0.03 | 0.09 | 0.09 | 0.09 |
| Mortality | 0.16 | 0.17 | 0.11 | 0.1 | 0.16 | 0.11 | 0.06 | 0.16 | 0.16 | 0.16 |



BET1a

BET3

BET 1b

BET 4a

**Fig. A.1.** Schematic diagrams of the BETs in the Italian historical context (D'Amico et al., 2021). All measures are in meters [m]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

air-pollution-free environment. Meanwhile, the lowest risk conditions relate to BET 2a and BET4a, which are affected by the poorer air quality in the narrow POS areas, but a rather better quality where people have a greater PA. In general terms, the behavioural response of both users adopting 1-hour and transient behaviours can generate an average absolute difference of 0.17% and 0.03%, respectively, for hospital admission with cardiovascular issues and mortality probability increase.

## 4. Discussion

The work successfully defines a behavioural-based approach to assess risks due to heat and air pollution stress for users in POS, by rapidly quantifying and estimate of the potential impact of the built environment configuration and users' behaviours by means of water loss risk for heat stress, and short-term pollution risk for air pollution. The approach is based on computer-aided simulations to derive environmental conditions for users' risks. The overall capabilities of the approach and the KPIs are demonstrated by applying them on a specific set of BETs derived from the historical Italian context (D'Amico et al., 2021), and framed within the context of the city of Milan (a critical scenario for climatic and air quality conditions (Salvalai et al., 2020)). These BETs can be considered archetypes of real-world squares, and they are described by main reliable (but simplified) morphological, geometrical, and constructive features without representing real case studies Thus, it should be noted that the results hereby presented are an abstraction of reality and should be treated as so. In line with this the data validation has not been performed in absolute way but using a comparative approach amongst the different simulation runs (only one factor is changed at time) reducing thus the uncertainty due to the lack of real-world data.

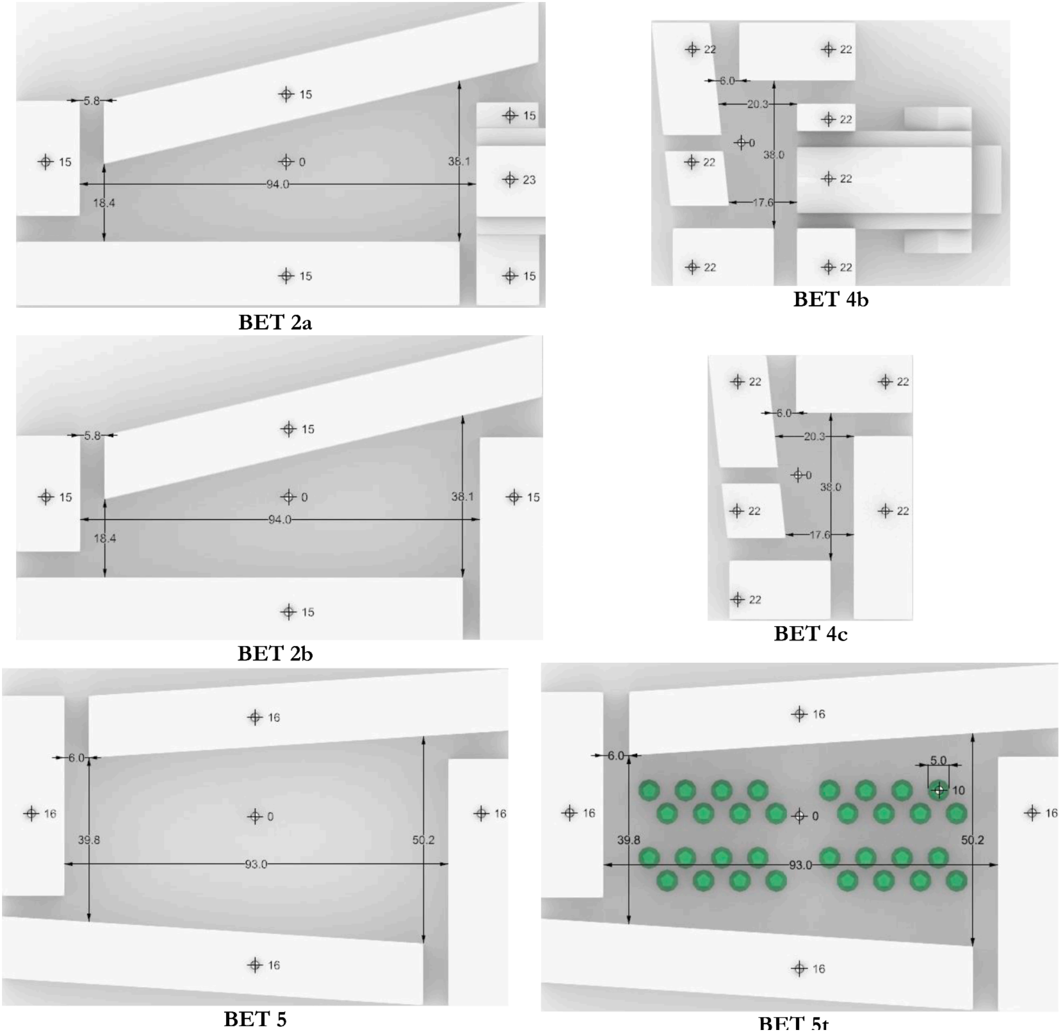
Considering the analysed BETs as a whole, the heat stress-related risk for the analysed BETs seems to be generally high especially for toddlers, while the air pollution-related risk found for the period studied did not show significant effects on users, although the critical air quality conditions of Milan. However, this could be explained by the fact that the hottest week of the year does not necessarily overlap with the most, or significantly polluted, week of the year. Moreover, the heat stress on the users was found to steer users into areas of poor air quality, especially when traffic is present within the BETs. As expected, the presence of trees can reduce heat stress by providing shade (Tables 4 and 5) (Estacio et al., 2022) but be detrimental to air pollution exposure (Tables 6 and 7) by altering or even limiting wind flow (L. Wang et al., 2021).

Considering the differences amongst the analyses BETs, it can be noticed that BETs with large exposure to the sky vault (BET2a, BET2b, BET3 and BET5) seem to performed better for dispersing/transporting air pollutants, thus ensuring better air quality. However, they lack direct solar radiation protection to reduce their heat-related risk. Meanwhile, BETs with narrow outdoor spaces or areas (BET4a, BET4b, BET4c) and BETs with a pronounced slope (BET1a, BET1b) seem to promote air pollutants staggering. Narrows BETs also perform better blocking direct solar radiation, as expected.

This work represents the first tentative to derive how typological conditions of the built environment can affect users' risks to the considered SLODs. Thus, the authors are also aware of possible limitations of this work, which mainly concern (1) the definition of the analysed BETs and the related climate conditions, and (2) the further development in the KPIs calculation.

Concerning point (1), the BET application relating to the assumed simulation conditions might be very specific for the Italian context and for Milan's climate, or for Milan's climate category (Cfa).

The BETs analysed were recreated from screened outdoor areas in the context of interest, that relates to the Italian historical city centres, and this could affect the extension of the results for different countries, but not the KPIs application. Also, other specific BETs modelling details could affect the obtained risk results. The azimuth orientation of the outdoor space was not considered when the BETs geometries were defined (D'Amico et al., 2021); the archetypes do not include



BET 2a

BET 4b

BET 2b

BET 4c

BET 5

BET 5t

**Fig. A.1.** (*continued*).

**Table A.1**
Albedo coefficient for the selected materials in the BETs.

| Surface type | Surface reflectance [-] | Surface transmittance [-] |
|---|---|---|
| Roof | 0.7 | – |
| Façade | 0.5 | – |
| Asphalt | 0.08 | – |
| Greenery | 0.2 | 0.3 |
| Tree canopy | 0.18 | 0.3 |

transparent surfaces and the surface roughness was not modelled, which could modify locally the solar radiation and air dynamics behaviour. The same methodology could be applied to other climate contexts, using the same BETs or improving their description, to compare how the climate alters the POS risks. In this sense, some limitations for the work application to the Milan climate exist given the adopted modelling approach. Warm temperatures were found mostly present with low wind velocities (modifying greatly heat stress and air pollutant distribution) which can easily vary from one location to another. The values obtained were calculated with a standardized ".EPW" weather file, which is an efficient and quick-to-apply solution, but the authors are aware that it could be considered partially outdated[6] also because it misses key information on the most recent temperature increase (European Environment Agency (EEA), 2020). In this perspective, the authors are aware that further efforts to improve the reliability of UTCI and AQI should be performed. In particular, the employed UTCI calculation method (Section 2.1) does not consider the Mean radiant temperature variations due to surrounding surface radiative heat exchange on the analysed area (assumed as equal to air temperature), nor for the wind speed (proportionally diminished from the 10 m measure for urban areas). Furthermore, the tree trunk shading potential was ignored in the preliminary BETs application of this work. On the other hand, concerning the AQI computing, fixed wind speed and direction were assumed, and all pollutant emission sources were not included as it was considered beyond the scope of this work.

Concerning previous point (2), more reliable KPIs values could be derived, considering both the given BETs and a more aboard application perspective, because of the aforementioned UTCI and AQI-related assumptions. Moreover, results obtained for heat-related risk could have been affected by the selection of body weight data concerning the US population was used, which tends to have the largest prevalence of overweight (Chooi et al., 2019). Further efforts based on reliable Italian statistics could be performed by applying the proposed methodology, to verify possible underestimation in respect of the Italian context. Further individual features could be included within the modelling approach (i.e. including additional attractors for users related to specific intended uses in the POS), thus moving towards a more detailed description of the users' behaviours and existing morbidity affecting final risk at the

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[6] https://docs.ladybug.tools/ladybug-tools-academy/v/climate-analysis/ (Accessed on 27/07/2022).

individual level. A combined KPI merging UTCI and AQI-related stress levels could be finally defined to move towards a holistic risk-assessment approach for the considered BETs.

Nevertheless, future works correlated to the proposed methods provide interesting perspectives. The adoption of typological scenarios seems to remark general SLOD-related issues affecting risks for the users in POSs. These issues can be quickly assessed thanks to the adopted archetypes of BEs, and then they can guide designers in the preliminary assessment of real-world scenarios, by deepening analysis and tailoring solutions on the case study specificities. In this sense, further research should move from risk-assessment to risk-mitigation strategies analysis according to the pursued typological quick-to-apply approach and using the proposed KPIs. Different values of the abovementioned parameters affecting heat stress, air quality and users' vulnerabilities (including the presence of specific mitigation elements, such as canopies, green surfaces, and so on) can be considered for further simulations and KPIs assessment in the same BETs, thus still deriving typological conditions and their variations under different simulation inputs, which can also correspond to several risk-awareness and mitigation scenarios. The adoption of a typological approach could still guarantee the rapid assessment of SLODs risk conditions for decision-makers while performing preliminary risk analysis tasks. At the same time, the proposed approach and KPIs could be used for the application to a specific case study, moving towards an ad-hoc analysis concerning the users' risks and the effectiveness of risk-mitigation solutions. Such future efforts will also reduce modelling uncertainties and provide insights into complete real-world conditions, including those about users' specificities (i.e. typologies), as well as function and attraction rules of certain POS areas. Finally, the current application to a square could be hence also replied for other kinds of POSs, such as streets and other open spaces in the urban fabric (e.g., parks, leisure areas, complexes of buildings).

## 5. Conclusions

Most of the risk assessment analyses concerning SLow Onset Disasters (SLODs) such as heatwaves and air pollution are concentrated on correlating yearly casualties or damages to the frequency and intensity of severe events arousal. More granular analysis, either in terms of time and/or Built Environment (BE) scale, is needed, and it should consider the users' behaviours in the BE. This work provides a potential solution to resolve this shortcoming by providing a quick-to-apply methodology for behavioural-based risk assessment in the Public Open Space (POS) in the BE, where users are more affected by the direct effects of repetitive short-term exposures to either increasing temperatures and/or air pollution. A preliminary application of the methodology is performed by considering BE Typologies (BETs) representing idealized scenarios of Italian squares in historical urban areas. BETs are described according to typological, that is recurring, main geometrical, morphological and constructive features derived from statistical-based analysis of real-world squares, thus representing simplified but reliable scenarios.

Considering the Italian context represented by the selected BETs, depending on the considered users' behaviours (i.e. passersby versus users remaining in the POS for completing some tasks) and under the considered environmental circumstances (i.e. Milan climate conditions), results show that a toddler: (1) exposed for just less than 2 h (~4% water loss on body weight) can reach a dehydration risk state; and, (2) an exposure for 1-hour to very low concentrations of $NO_2$ can increase the mortality probability on the long run by approximately 1%. However, users' behaviours affecting their thermal acceptability of POS conditions can generate a relative increase of risk outcomes between 35 and 40% for both heat and air pollution-related risks when passing from a 1-hour to transient behaviour. Passersby's related behaviours seem to have increased risks given their higher thermal acceptability probability affecting their position in the POS.

The method hereby presented has the advantage of being sufficiently robust and flexible to be applied in any BE context, including other parts of the World, as long as the information required is generally available (geometry, weather, air pollution concentrations and demographics), by also using remote and freeware data sources. The BET application ensures preliminary effectiveness evaluations, but it can be also replicated to real-world BEs, thus being of great use for public and private entities. In fact, the behavioural-based assessment of risks of the POS in the BE can lead to the timely proposal of physical, social or educational risk mitigation measures. The use of such KPIs enables the monitoring and comparison of the BE resilience performance comprising users' behaviour (also, in pre and post-mitigation intervention scenarios).

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Appendix A: BETs description

The schematic diagram (plan views) of the BETs is provided by Fig. A.1, while the albedo coefficients are shown in Table A.1.

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