Cities 133 (2023) 104160

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Users' vulnerability and exposure in Public Open Spaces (squares): A novel way for accounting them in multi-risk scenarios

Enrico Quagliarini, Gabriele Bernardini *, Guido Romano, Marco D'Orazio

DICEA Dept, Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy

ARTICLE INFO

Keywords:
Users' exposure
Users' vulnerability
Historic cities
Public Open Spaces
Typological scenarios

ABSTRACT

Public Open Spaces (POSs) such as streets and squares, in our cities are characterized by spatio-temporal variations of users' vulnerability and exposure in view of the hosted social, governmental, religious, and commercial functions. Single or multi-risks conditions in POSs can hence vary over time. This work proposes a methodology to perform local-scale analyses on use patterns in real-world POSs, pursuing a quick-to-apply approach based on remote analysis tools and easy-to-apply surveys, to be also used by non-expert technicians. Main literature-based factors concerning users' vulnerability/exposure and methods for their collection are identified. Rules to define typological (that is recurring) scenarios are provided through specific key performance indicators relating to overall POS use and daily/hourly temporalities. The methodology capabilities are preliminary assessed through a sample of 56 squares in historic Italian cities, considering working days and holidays. Results trace the overall typological characterization of the squares sample adopting a "robust-to-outliers" approach, and provide bases for expeditious assessment of users' vulnerability and exposure scenarios. The typological scenarios can be then used to support rapid risk assessment actions in POSs by safety designers and local authority technicians, and employed as input in simulation-based analyses to include the users' features in the related evaluations.

1. Introduction

The morphology and use of our cities are constantly shaped and affected by societal factors to which they should respond (Askarizad & Safari, 2020; Santos et al., 2021). Users populate, move, and behave in the urban built environment, which is a complex system composed of Public Open Spaces (POSs, such as streets and squares), the facing buildings, and urban infrastructures (Garau & Annunziata, 2022; Jian et al., 2021; Sharifi, 2019b). Thus, understanding the relationship between the built environment and the users is essential to evaluate the livability and the sustainability of cities and then provide insights on how to properly design them in view of current challenges, such as those of urbanization and densification growth, population increase, more safe and resilient societies also in view of climate change and resource depletion (Askarizad & Safari, 2020; Buzási et al., 2021; Fleischmann et al., 2021; Memluk, 2013; Santos et al., 2021).

In this overall context, historic cities are critical scenarios since they were not conceived to deal with sustainability, resilience, and contemporary technological issues that every day transform the way users think, experience, and inhabit cities (Apró et al., 2016; Cherfaoui & Djelal, 2018; Loda et al., 2020; Micelli & Pellegrini, 2018; Pasquinelli et al., 2022). Indeed, many historic cities managed to keep their original characteristics due to several factors such as their history and culture, heritage protection, lack of space, and need for investment (Angelidou, 2014; Apró et al., 2016). Nevertheless, the necessity to pursue (and realize) a smart vision is forcing them to adapt to changes in order to achieve a higher quality of life together with effectiveness and competitiveness on multiple socio-economic levels (Angelidou et al., 2017; Angelidou, 2014; ARUP, 2010; Loda et al., 2020).

Different scales of analysis (Sharifi, 2019a) can be considered to investigate these resilience-related issues by relying on the correlation between the built environment elements and the urban form in historic cities. Beyond the macro-scale approach, which traces the overall historic city structure, the mesoscale-level is one of the most interesting since it concerns the analysis of elements such as buildings, open spaces, blocks, neighborhoods, and streets (Sharifi, 2019b), whose importance is due to several reasons, such as: (1) this is the scale where a significant amount of users' daily activities (under normal and/or emergency conditions) that could have implications for the resilience of cities take place; (2) it allows achieving a more granular and context-specific

* Corresponding author.
E-mail address: g.bernardini@univpm.it (G. Bernardini).

https://doi.org/10.1016/j.cities.2022.104160
Received 30 March 2022; Received in revised form 12 November 2022; Accepted 15 December 2022
Available online 26 December 2022

understanding of the urban built environment; (3) it allows discussing interactions between users and the surrounding environment in a sufficiently detailed manner. POSs hence plays a pivotal role from a user-related perspective, and, mainly, squares are fundamental POSs to be investigated (Buzási et al., 2021; Cherfaoui & Djelal, 2019; Mehan, 2016), since their use affects risks for users in a dynamic manner (Bernabei et al., 2021). In fact, users gather in squares for various reasons, activities, and opportunities thanks to dynamic relationships between space, form, and functions (Carmona, 2021; Loda et al., 2020; Russo et al., 2021; Zakariya et al., 2014; Zucker, 2003). Such relationships can take place both in outdoor (e.g., urban voids as leisure areas, historic/artistic heritage, green areas, "blue" areas, shelters) and indoor areas (e.g., dwellings, government buildings, religious functions, commercial activities, services) (Memluk, 2013), especially in modern mixed-used environments designed to reduce travel time and carbon emissions, but where critical crowding conditions may arise (Choi et al., 2021).

Moreover, POSs are also the fundamental stages in which users react to different kinds of disasters and emergency conditions (Bernabei et al., 2021; Buzási et al., 2021; Kapucu, 2012; Santos et al., 2021). SLow Onset Disasters – SLODs (e.g. pollution, heatwaves, pandemics (UNDRR, 2016)) can vary the presence of users indoor and outdoor, thus also affecting the attractiveness of specific parts of the POS also depending on their features (Choi et al., 2019; Garau & Annunziata, 2022; Yıldız & Çağdaş, 2020). On the other hand, SUdden Onset Disasters – SUODs (e.g. terrorist acts, earthquakes, floods, fires (UNDRR, 2016)) could add critical conditions to users in POSs and especially in the squares, depending on the specificities of the emergency response. For instance, in terrorist acts affecting the square, users should evacuate the POS to distance themselves from the attack source, while, in earthquakes, users could gather in the square to minimize interferences with debris while waiting for rescuers' arrival, in respect to the rest of the compact historical urban fabric (Bernardini et al., 2016). Considering the general resilience challenges, the specificities of the POSs, and their rule towards users before and during an emergency, the assessment and reduction of risk for users in the POSs is then a fundamental goal and should be carried on by using a sustainable and holistic approach (Bernabei et al., 2021; Buzási et al., 2021; Kapucu, 2012; Santos et al., 2021).

To support such actions, this work aims at defining a novel, quick-to-apply methodology to collect and quantify data on users' *vulnerability* and *exposure* in POSs, which are base factors in risk assessment actions (PreventionWeb - UNDRR, 2021). The proposed methodology assesses such data depending on the dimensions and typologies of the spaces (and their users). Starting from previous literature definitions of users' vulnerability and exposure (discussed in the following Section 2), new specific Key Performance Indicators (KPIs) are herein innovatively provided (1) to depict specific POSs conditions, when the method is applied to a single case, and (2) to derive typological conditions, that is statistically recurring, when applied to a sample of case studies in the same relevant context. In this work, we focused on the characterization of squares as relevant urban POSs, also considering the following common base assumptions (Cherfaoui & Djelal, 2018, 2019; Paukaeva et al., 2021): (1) both outdoor and indoor areas directly face the POS and are connected to the POS itself; (2) data and temporalities are assessed in pre-emergency conditions, to allow using collected data on users' vulnerability and exposure as general inputs for different kinds of SLODs and SUODs; (3) the POS is the only attractor of users. The work investigates an homogeneous sample of POSs (56 squares, resumed in Appendix B), which: (1) shares similar morphological and constructive characteristics (regular shape, i.e. convex); (2) are placed in historic cities sharing common features (historic Italian cities among provincial capitals, cities with over 20,000 inhabitants, and cities as attractor poles in the surrounding territories); (3) are prone to at least one of the following risks: earthquake, terrorist attack (SUODs); heatwave, pollution (SLODs) (D'Amico et al., 2021).

2. Users' vulnerability and exposure: literature background and current gaps

Users' *vulnerability* and *exposure* to any particular hazard should be assessed to estimate the potential risks in a certain POS and so the effectiveness of risk-reduction strategies (Afriyanie et al., 2020; Miranda & Ferreira, 2019; Osman, 2021; UNDRR, 2021).

The *vulnerability* is defined as the set of physical, social, economic, and environmental factors which increase the susceptibility of a community to the impacts of hazards (UNDRR, 2016), and includes:

A. the vulnerability due to the built environment, which depends on physical (e.g., the area [m^2] (Li et al., 2019; Quagliarini, Lucesoli, & Bernardini, 2021)) and non-physical parameters (e.g., urban layout and intended use of structure and infrastructures (De Angeli et al., 2022; Ebrahimian Ghajari et al., 2018)) of indoor and outdoor areas that can affect the presence of users;
B. the vulnerability due to the users, which depends on physical and social features (e.g., age, gender, disabilities, culture, socioeconomic status, disaster preparedness, familiarity with the areas) that can alter users' behaviors in terms of motion capabilities, utilization, and perception of the surrounding environments (Bernardini et al., 2016; Booth et al., 2020; Cardona et al., 2012; Koks et al., 2015; Villagràn De León, 2006).

The *exposure* is defined as the situation of people, infrastructures, and other tangible human assets located in hazard-prone areas, combined with their capacity to cope with specific vulnerabilities to particular hazards (De Angeli et al., 2022; UNDRR, 2016). Exposure-related issues on historic/artistic heritage, services, and economic activities are usually considered only with respect to disastrous events which can provoke damages or destruction, such as earthquakes or bombing attacks (Mouroux & Brun, 2006). Nevertheless, factors like the number [pp] or density [pp/m^2] of users over space and time (Bernabei et al., 2021; De Lotto et al., 2019; Li et al., 2019; Yang et al., 2018) and/or the presence of special buildings, sensitive targets, or high-density areas (Engel et al., 2018; Langenheim et al., 2020; Paukaeva et al., 2021; Ponce-Lopez & Ferreira, 2021) could significantly affect the users' safety, health, and wellbeing (Ebrahimian Ghajari et al., 2018): a) negatively, since they can be exposed to SLODs (Luo et al., 2018; Mouratidis & Yiannakou, 2021; WHO, 2016) and/or SUODs (Giuliani et al., 2020; Song et al., 2019; Woo, 2015); or b) positively, in case they are placed in areas characterized by features or solutions that can mitigate risks, such as green areas, wide square in compact urban layout, POSs implementing structural and non-structural risk reduction solutions (Afriyanie et al., 2020; Coaffee, 2018; Pietilä et al., 2015; Yao et al., 2021).

In view of the above, it is clear how measuring users' *vulnerability* and *exposure* should involve different levels of analysis according to holistic approaches (Cherfaoui & Djelal, 2018; Dai et al., 2020; Li et al., 2019; UNDRR, 2016) that allow considering together different quantities and parameters that dynamically change over time and space (including factors like seasonality, weather conditions, hours of sun, and shadow shapes (Haynes et al., 2017; Lindberg & Grimmond, 2011; Nemeškal et al., 2020; Paukaeva et al., 2021)). As such, spatiotemporal analyses (known also as "urban temporalities") are fundamental to evaluate how and when things are taking place and estimate the relationships between time and urban spatial dimensions (therefore between uses and users) (Cherfaoui & Djelal, 2018; García-Palomares et al., 2018; Quagliarini, Lucesoli, & Bernardini, 2021).

Nevertheless, temporalities are still limitedly considered for user-related analyses, especially while dealing with risk quantification and assessment, and should be evaluated through KPIs not only at the macroscale (that is at the whole urban scale (da Silva et al., 2022; Nemeškal et al., 2020)), but also at the mesoscale (Sharifi, 2019b). Possible applications to POSs, and, in particular, to urban squares (Cherfaoui & Djelal, 2018), are then needed, mainly because they can

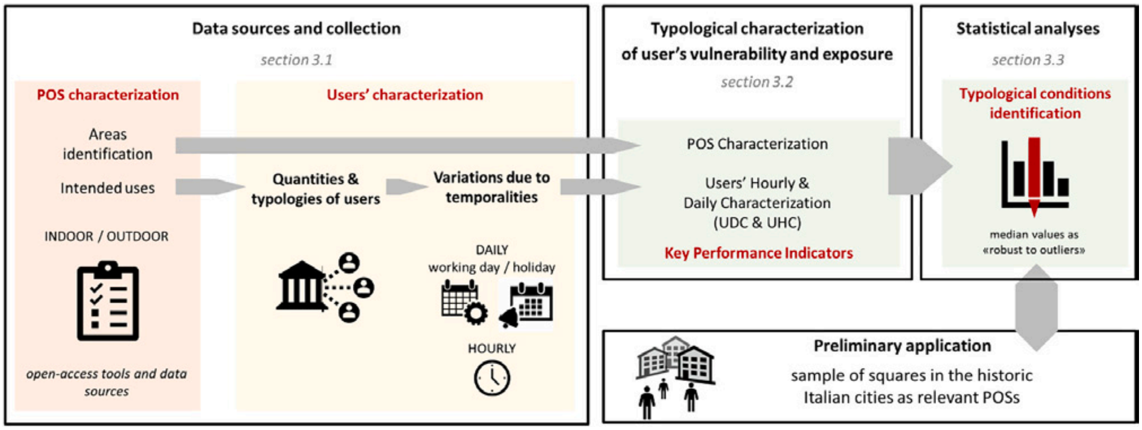

Fig. 1. Phases and methods framework.

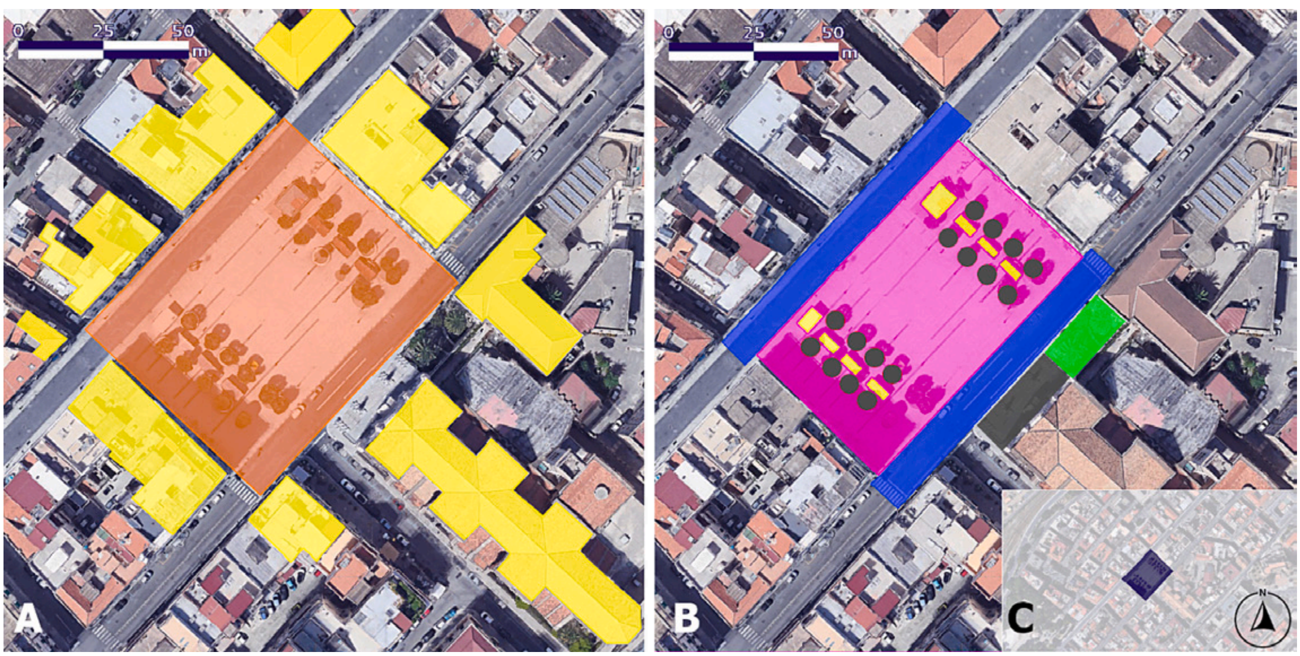

Fig. 2. Identification of Public Open Space areas for the case study of Piazza Duomo in Reggio Calabria (see Appendix B) by: A) distinguishing between outdoor (in orange) and indoor (in yellow) areas; B) recognizing outdoor areas types as carriageable - CA (in blue), walkable - WA (in magenta), unwalkable - UA (in grey), dehors - D (in yellow), and private courtyard – CY (in green); C) identifying the POS in the urban fabric. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

contribute to reliable scenarios creation for single and multi-risk analysis, including those using simulation tools (Bernabei et al., 2021; Curt, 2021; Natanian et al., 2019).

To cope with these needs, quick and easy-to-apply approaches relying on rapid tools and open-access, standardized data sources are necessary, so as to: a) speed up the evaluation of the users' *vulnerability* and *exposure*, and provide timely results towards the reduction of the risks for the whole community (Bernabei et al., 2021); b) reduce application complexity and efforts also by non-expert technicians, such as those of local administrations (Quagliarini, Lucesoli, & Bernardini, 2021); c) improve replicability and take advantage of typological approaches for the definition of recurring conditions that can also lead to common operational frameworks for assessing, identifying, and designing interventions for improving POSs in real-world contexts (D'Amico et al., 2021; Dibble et al., 2019; He et al., 2021; Miranda & Ferreira, 2019; Santos et al., 2013; Sharifi, 2019b).

3. Phases, data sources and collection, and analysis methods

The work is structured in three main phases (Fig. 1). In Section 3.1, the users' *vulnerability* and *exposure* factors are assessed through open-access tools and data sources to characterize the POS, taking advantage of current approaches and gaps exposed in Section 2. In Section 3.2, such data are organized in quantitative parameters (KPIs), to finally perform statistical analysis towards the definition of possible related typological conditions in Section 3.3.

3.1. Data sources and collection

All the sources used for the present analysis are remote-based, open-access (e.g., local maps, census databases, free online tools (Hassanzadeh, 2019; Polese et al., 2020)), and available for whatever POS, city, and country. It is worth noticing that the current methodology considers the intended uses of the squares in similar, standardized, pre-emergency conditions, therefore it represents a first step towards the users'

Table 1
Summary of the users' temporalities according to the types of areas. W is for Working days, H is for Holidays (full list of abbreviations in Appendix A).

Type of areas [m^2]	Type of users (position, familiarity)	{Daily timetable when applied}: Occupant Load OL_i (hourly timetable when applied)
Carriageable areas (CA)	*- the use of carriageways is only assigned to vehicles with no distinction with the daytime and type (Hahm et al., 2019).*	{W and H}: 0.0 pp/m^2 (1–24)
Walkable areas (WA)	Only Outdoor Users **OO** (outdoor, unfamiliar)	{W and H}[a]: 0.1 pp/m^2 (7–24) 0.0 pp/m^2 (1–6)
Unwalkable areas (UA)	*- these areas are not available for users as they represent an obstacle in the POS*	{W and H}: 0.0 pp/m^2 (1–24)
Dehors (D)	Prevalent Outdoor Users **PO** (outdoor, unfamiliar)	{W and H}: 0.4 pp/m^2 (intended uses opening time) 0.0 pp/m^2 (intended uses closing time)
Private courtyards (CY)	*- these areas are occupied by the same users of the indoor areas linked to them*	{W and H}: 0.0 pp/m^2 (1–24)
Indoor areas as Non-residential areas (IO_1)	Non-Resident Users **NR** (indoor, unfamiliar)	{W and H}: Depending on the intended use (intended use opening time)[b]
Indoor areas as Residential areas (IO_2)	Residents Users **R** (indoor, familiar)	{W and H}: 0.05 pp/m^2 (0–24)

[a] Considering a low level of crowding in ordinary conditions (under the level of service A threshold (Bloomberg & Burden, 2006)) only during the daily hours (i.e., from 7 to 24 every day) (Cheliotis, 2020; Yıldız & Çağdaş, 2020).
[b] See Appendices C and D. The main values are: 0.4 pp/m^2 for intended uses open to the public (e.g., restaurants, bars, shops, public offices); 0.7 pp/m^2 for churches; 0.1 pp/m^2 for intended uses close to the public. Churches' opening times refer to Sunday service timetables.

vulnerability and *exposure* assessment by pursuing a conservative, quick- and easy-to-apply approach, connected with related tools and sources (that can however be easily replaced in presence of specific tools/data provided by single municipalities for more up-to-date/in-depth analyses). In particular, data sources and collection are set up to quantify the maximum number of users to consider within the POS through the breakdown analysis of (1) the *type of areas* occupied by the users (Li et al., 2019), (2) the organization of demographic data into *age ranges* (Quagliarini, Lucesoli, & Bernardini, 2021), and (3) the impact of temporalities evaluated by the daytime (day or night) and day type (working day or holidays) (Cherfaoui & Djelal, 2018).

The *type of areas* occupied by the users have been distinguished as *outdoor* and *indoor* (Fig. 2). In particular, five different types of *outdoor areas* are distinguished in terms of their intended uses: (1) *carriageable areas* CA are primarily used/occupied by vehicles, e.g. carriageway, parking lots; (2) *walkable areas* WA are accessible by pedestrians, e.g. sidewalks, accessible/non-fenced green areas and gardens; (3) *unwalkable areas* UA are occupied by monuments, fountains, greeneries, other fenced areas and stairs; (4) *dehors* D are open-air terraces of restaurants, open markets and other outdoor areas hosting a specific intended use or connected to a specific building, placed at the ground levels, and they include both temporary (removable) and permanent structures; (5) *private courtyards* CY are generally inaccessible to the public, e.g. fenced courtyards of dwellings. Although porticos can be mainly classified within these areas depending on their use, they are not considered in this work as *outdoor areas* since their dimension identification via quick analysis tools of aerial views are difficult to be performed.

The *indoor areas* considered are those of the buildings directly connected to the *outdoor areas* through elements such as doors, passages, gates, and their identification has been supported by Google Maps and Street Maps[1] tools, which allow checking the number of buildings floors, and their intended uses. *Indoor areas* non-directly connected to the *outdoor area* are herein excluded. According to the adopted quick-to-apply approach (De Lotto et al., 2019; Quagliarini, Lucesoli, & Bernardini, 2021), *indoor areas* are classified depending on their intended use, such as residential buildings, commercial activities, and private/public services and institutions. Furthermore, strategic buildings and special uses that can be subject to terrorist attacks have been classified into homogeneous groups depending on the combination of the intended uses, temporalities, crowd conditions, and emergency-related issues (D'Amico et al., 2021; Federal Emergency Management Agency, 2009; Ministry of Interior (Italy), 2015; Quagliarini, Fatiguso, et al., 2021):

- "Theatres, Museums, Religious buildings", as buildings freely open to the public and generally characterized by the most significant occupant loads, up to overcrowding;
- "Government buildings" (such as city halls, courts, police stations), as public buildings which are generally used as offices, can have a role in disaster conditions, and can ideally be hard targets for terrorist acts;
- "Metro - Rail stations", as public buildings where users are in transit;
- "Hospitals, Schools, Universities" as specific public buildings with a strategic rule in the city, also hosting vulnerable users.

Table 1 resumes the aforementioned *types of areas* together with the type of users occupying each of them, and the relative occupant load OL_i [pp/m^2] and temporalities defined by Italian regulation (see Appendix C (Ministry of Interior (Italy), 2015)) evaluated considering daily and hourly timetables. In particular, Only Outdoor users (OO) and Residents (R) are non-variable components, while Prevalent Outdoor users (PO) and Non-Residents (NR) strictly depend on the opening time of the intended uses. Daily temporalities are provided by distinguishing between Working days (as the most recurring conditions during the year) and Holidays (representing Sundays and other national holidays), while hourly temporalities of the POS are evaluated for each hour of the day (1–24) (Li et al., 2019). In this work, mass gathering events or one-off events (such as local fairs or festivals) are ignored as exceptional situations for crowding conditions. Furthermore, areas with variable temporalities (e.g., open-market in the morning/working days as D, pedestrian area as WA, or parking lots in the afternoon/night/holidays as CA) are characterized by time-dependent *OL* values according to those in Table 1. Finally, the familiarity of the users with the POS (and the evacuation procedures) has been also indicated, and only R are conservatively considered as familiar (Bernabei et al., 2021).

The effective surface SU_i [m^2] of each *outdoor area* (CA; WA; UA; D; CY) and *indoor area* (IO_i) has been calculated through the freeware online tools Calcmaps, which allows measurement analysis on aerial views. In detail, in this process, the gross areas are considered rather than the net internal ones, thus slightly overestimating the following maximum users' number evaluation moving towards a conservative approach in the users' vulnerability and exposure quantification (De Lotto et al., 2019; Quagliarini, Lucesoli, & Bernardini, 2021). Google Street Maps views and photos are used to support the areas and buildings characterization (i.e., to check intended uses and opening times during the different days of the week, number of floors, presence of porticos, and presence of doors, passages, or gates connecting indoor and outdoor areas) (Li et al., 2019; Quagliarini, Lucesoli, & Bernardini, 2021). In case of missing data, the opening time has been assessed through databases containing information on companies[2], social network pages, or

[1] Available at https://www.google.it/maps/?hl=it (last access: 25/07/2021).
[2] Main considered free-access databases on timetables of companies and activities open to the public: https://www.paginegialle.it/, https://www.orarìdiapertura24.it/ (last access: 09/02/2021 – in Italian).

Table 2
Summary of the users' temporalities according to the age range and familiarity with the POS. W is for Working days, H is for Holidays (full list of abbreviations in Appendix A).

Type of users [age range, motion conditions]	Familiar users - R {Daily timetable} (Hourly timetable // Presence coefficient *cp* [−])	Unfamiliar users – OO, PO, NR {Daily timetable when applied} (Hourly timetable when applied // Presence coefficient *cp* [−])
Toddlers (TU) – [0–4, assisted: *directly dependent on their parents*]	{W and H}: (1–24 // 1) – at home	{W and H}: (intended use opening time // 1); (intended use closing time and offices[a] // 0)
Parents-assisted Children PC [5–14, assisted: *can autonomously move but are generally assisted by their parents*]	{W}: (8–13 // 0) – at school (1–7 and 14–24 // 1) – at home {H}: (1–24 // 1) – at home	{W and H}: (intended use opening time // 1); (intended use closing time and offices[a] // 0)
Young Autonomous YA [15–19, autonomous: *can be considered as autonomous users, and relate to students*]	{W}: (8–13 // 0) – at school[b] (1–7 and 14–24 // 1) – at home {H}: (1–24 // 1) – at home	{W and H}: (intended use opening time // 1); (intended use closing time and offices[a] // 0)
Adults AU [20–69, autonomous *can be considered as autonomous users, and relate to workers or university students*]	{W}: (8–18 // 0.09) – at work/university (1–7 and 14–24 // 1) – at home {H}: (1–24 // 1) – at home	{W and H}: (intended use opening time // 1); (intended use closing time // 0)
Elderlies EU [70+, assisted: *may have poorer motion capabilities*]	{W and H}: (1–24 // 1) – at home	{W and H}: (intended use opening time // 1); (intended use closing time and offices[a] // 0)

[a] Offices include intended uses close to the public, and are considered occupied only by Adults users.
[b] According to the common Italian teaching timetable, but they could change if specific sources on daytime openings are available, such as in full-time primary or secondary schools (see also Appendix D).

according to national (or local) regulations on timetables of buildings open to the public[3], considering the specific application context (i.e. in this work, the Italian context).

Similarly, in Table 2 users are listed in *age ranges* (De Lotto et al., 2019; Quagliarini, Lucesoli, & Bernardini, 2021), so as to consider possible common conditions in motion (Bosina & Weidmann, 2017). Moreover, temporalities are considered by means of a "presence coefficient" *cp* [−] evaluated on the basis of the users' age range, familiarity with the POS, and daily and hourly timetables (which is equal to 1 if users are present, 0 if users are absent, and 0.09 to consider unemployed[4] users spending their time at home).

[3] Regulations on opening timetables: https://www.mise.gov.it/index.php/it/mercato-e-consumatori/concorrenza-e-commercio/risposte-ai-quesiti/orari-di-apertura-e-chiusura (last access: 09/02/2021 – in Italian).

Table 3
POSC-related KPIs.

KPI [unit of measure]	*C: Calculation methods M: Meaning*	*Specific conditions and related symbols [unit of measure if needed]*
Percentage of *outdoor areas* per typology [%]	C: the ratio between specific and overall *outdoor areas* M: tracing areas with particular use patterns depending on their accessibility and use rules	Percentage values per typology: carriageable areas **CAp**, walkable areas **WAp**, unwalkable areas **UAp**, dehors **Dp**, private courtyards **CYp**
Presence of special buildings or special uses [Boolean], [number of items per POS]	C: presence or not of special buildings or uses M: defining special buildings or uses to be considered in the square as possible attractors for temporalities, exposure, and specific individual vulnerabilities	Presence of special buildings/uses **SB** [Boolean] Number of special buildings/uses **SBn** [number of items per POS][a]
Ratio between indoor and outdoor features [−]	C: the ratio between the specific indoor and outdoor areas of the POS M: rapidly characterizing the built environment and defining the spaces in which vulnerability and exposure are higher	Ratios between the *indoor area* and the *outdoor area* **AIOr**

[a] The median area of the special buildings SBA [m^2] has been also calculated for the most recurrent category of special buildings and uses.

Data about the population distributions (age and gender) can be obtained from local registers or census databases. For what it concerns the Italian Municipalities, the online website of the ISTAT provides the percentage distribution of the population based on the annual reports[5], allowing the organization of the data per age range (AP_a [%] where *a* indicate the ranges of Table 2) and for gender (Mp for male and Fp for female [%]). According to the purpose of a quick-to-apply approach (Bernabei et al., 2021; De Lotto et al., 2019), these distributions are reasonably assumed valid considering the POS as a part of the whole urban scenario to which Municipalities-related data are referred.

In view of these considerations, the maximum number of users NU [pp] to consider within the POS has been first evaluated on hourly sampling according to Eq. (1):

$$NU = \sum_{i,a} SU_i \bullet OL_i \bullet AP_a \bullet cp \quad (1)$$

where:

- SU_i [m^2] is the effective surface of the *i*-th type of area (first column of Table 1);
- OL_i [pp/m^2] is the Occupant Load of the *i*-th type of area (third column of Table 1);
- AP_a [%] is the users' age percentage distribution of the *a*-th age range (first column of Table 2);
- cp [−] is the presence coefficient (second and third columns of Table 2).

[4] According to national data from www.istat.it/it/archivio/occupati+e+disoccupati (last access: 09/02/2021).
[5] For 2020: http://demo.istat.it/popres/index.php?anno=2020&lingua=ita (last access: 25/07/2021). As an alternative, data from tuttitalia.it website could be used at https://www.tuttitalia.it/lazio/33-roma/statistiche/popolazione-eta-sesso-stato-civile-2020/ (last access: 25/07/2021), as 5 years-wide classes of population are already available.

Table 4
UHC-related KPIs.

KPI [unit of measure]	*C: Calculation methods M: Meaning*	*Specific conditions and related symbols [unit of measure if needed]*
Users' density considering the *outdoor areas* [pp/m^2]	C: the ratio between the users' overall number and the *outdoor area* M: it essentially considers that all the users can contemporarily move out of the buildings, e.g. as for evacuation scenarios in SUODs	Users' overall outdoor density **UOod**, considering both outdoor and indoor users out of the buildings
Percentage of users considering familiarity with the POS [%]	C: percentage ratio between specific users' typologies and the users' overall number UOn M: scaling the number of users into the POS with respect to main behavioral issues such as those due to risk-perception and preparedness issues	Calculated for: only outdoor users **OOp**; prevalent outdoor users **POp**; residents **Rp**; non-residents **NRp**.

3.2. Typological characterization of users' vulnerability and exposure

In this section, the data collected in the previous Section 3.1, are converted into KPIs useful to perform local-scale analyses on the single case study. The KPIs are resumed in the following according to three classes, together with their specific calculation methods and meanings:

1. **Public Open Space Characterization (POSC):** they do not directly express the users' quantification and typologies, but they trace exposure- and vulnerability-influencing issues depending on the general square features and regardless of the daily/hourly POS use (Table 3).
2. **Users' Hourly Characterization (UHC):** they provide a detailed overview of the users' distribution based on an hourly sampling methodology (Table 4).
3. **Users' Daily Characterization (UDC):** they provide a general overview of the users' distribution considering the days as a whole (Table 5).

UHC- and UDC-related KPIs are organized both for working days and holidays, and Table 4 and Table 5 also remark on how they are able to trace the conditions for the overall users' sample, as well as distinguish users by their familiarity with the POS and by age ranges. It is also worth noting that some KPIs could have different meanings for different types of disaster assessment. For instance, users can decide to move indoor or outdoor depending on the type of hazard. In this sense, critical interactions conditions in *indoor areas* and *outdoor areas* of the POSs (as the sum of WA, D, and CA, and so considering the carriageable areas as available for users gathering in case of emergency) are assessed through the users' density [pp/m^2] (Jia et al., 2014; Li et al., 2019).

3.3. Statistical analyses

KPIs introduced in Section 3.2 are organized according to the following statistical to trace typological scenarios depending on the general recurring conditions of the considered POSs, and so, in this study, of the whole sample of squares.

For *POSC-related KPIs*: (a) Boolean parameters (i.e. SB) are investigated according to two possible classes (true or false), and the recurring condition of the sample is represented by the class with the higher frequency. (b) Parameters expressed in discrete classes, such as the number of items (i.e. SBn), are assessed through a quartile-based approach (de Sá, 2007; Rousseeuw & Hubert, 2011), which has been also adopted by previous works on built environment typologies definition (D'Amico et al., 2021; Fleischmann et al., 2021). Outliers are retrieved according to the InterQuartile Range IQR method (fence: 1.5 IQR) (Rousseeuw & Hubert, 2011), so as to define boundary conditions in the sample that cannot be considered typologically relevant. In this case, the mean value calculation is excluded because of the discrete value of this KPI, while the median value of the KPI is used to derive the typological description of the squares sample in a "robust to outliers" perspective (Rousseeuw & Hubert, 2011).

Table 5
UDC-related KPIs.

KPI [unit of measure]	*C: Calculation methods M: Meaning*	*Specific conditions and related symbols [unit of measure if needed]*
Users' density considering the *indoor areas* [pp/m^2]	C: the ratio between the (specific) maximum number of users and the *indoor area* M: it essentially considers an average density of users in *indoor areas* and the possibility that users from outdoor contemporarily move into *indoor areas*, e.g. as for "invacuation" scenarios in SUODs or heatwaves conditions	Users' overall indoor density **UOid**, considering both outdoor and indoor users in the buildings Users' indoor density **Uid**, considering the normal fruition of the buildings (R + NR)
Users' density considering the *outdoor areas* [pp/m^2]	C: the ratio between the users' overall number and the *outdoor area* M: it essentially considers that all the users can contemporarily move out of the buildings, e.g. as for evacuation scenarios in SUODs	Users' overall outdoor density **UOod**, considering both outdoor and indoor users out of the buildings
Ratio between indoor and outdoor features [−]	C: the ratio between the number of users of the indoor and outdoor spaces M: it allows evaluate how users are distributed in *indoor* and *outdoor areas* during the day	Ratios **UIOr** between users in *indoor areas* (R + NR) and users in *outdoor areas* (OO + PO)
Percentage of users considering familiarity with the POS [%]	C: percentage ratio between specific users' typologies and the users' overall number UOn M: scaling the number of users into the POS with respect to main behavioral issues such as those due to risk-perception and preparedness issues	Calculated for: only outdoor users **OOp**; prevalent outdoor users **POp**; residents **Rp**; non-residents **NRp**.
Percentage of users' considering individual vulnerability [%]	C: percentage ratio between specific users' typologies and UOn M: scaling the maximum users' number into the POS with respect to main individual vulnerabilities affecting response and motion	Calculated for: toddlers **TUp**, parent-assisted children **PCp**, young autonomous **YAp**, adult **AUp**, elderly **EUp**. Depending on their gender: male **Mp**, female **Fp**

UHC- and *UDC-related KPIs*, as well as continuous *POSC-related KPIs* (i.e. Percentage of outdoor areas per typology, AIOr) are assessed through the same quartile-based approach. In particular, *UHC-related* values are firstly organized considering the whole sample of squares, and the quartile-based approach allows to trace the overall distribution of each KPI by pointing out extreme (i.e. maximum and minimum, excluding outliers according to the IQR methods), and other recurring values, i.e. the median.

Then, *UHC-related* values are merged for each of the squares, in a separate manner, to trace the related *UDC-related* values. Minimum and maximum values for each square have been collected together to

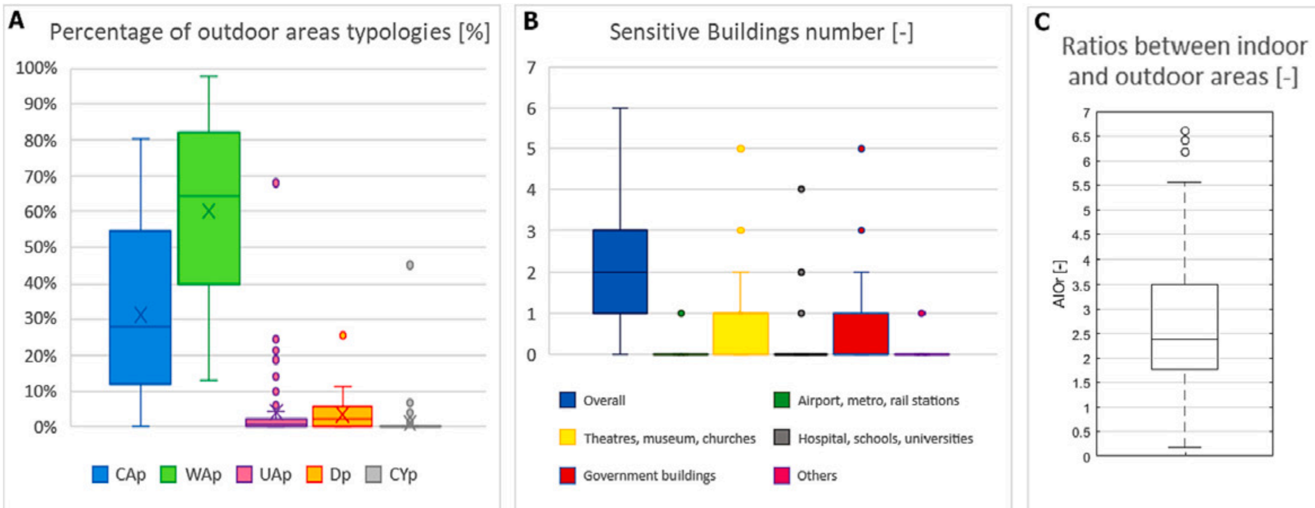

Fig. 3. POSC-related KPIs - Quartile-based analysis of: (A) Percentage of outdoor areas er typology; (B) Sensitive Buildings number per square SBn; (C) Ratios between the indoor and outdoor areas (AIOr). Outliers are shown by the dots.

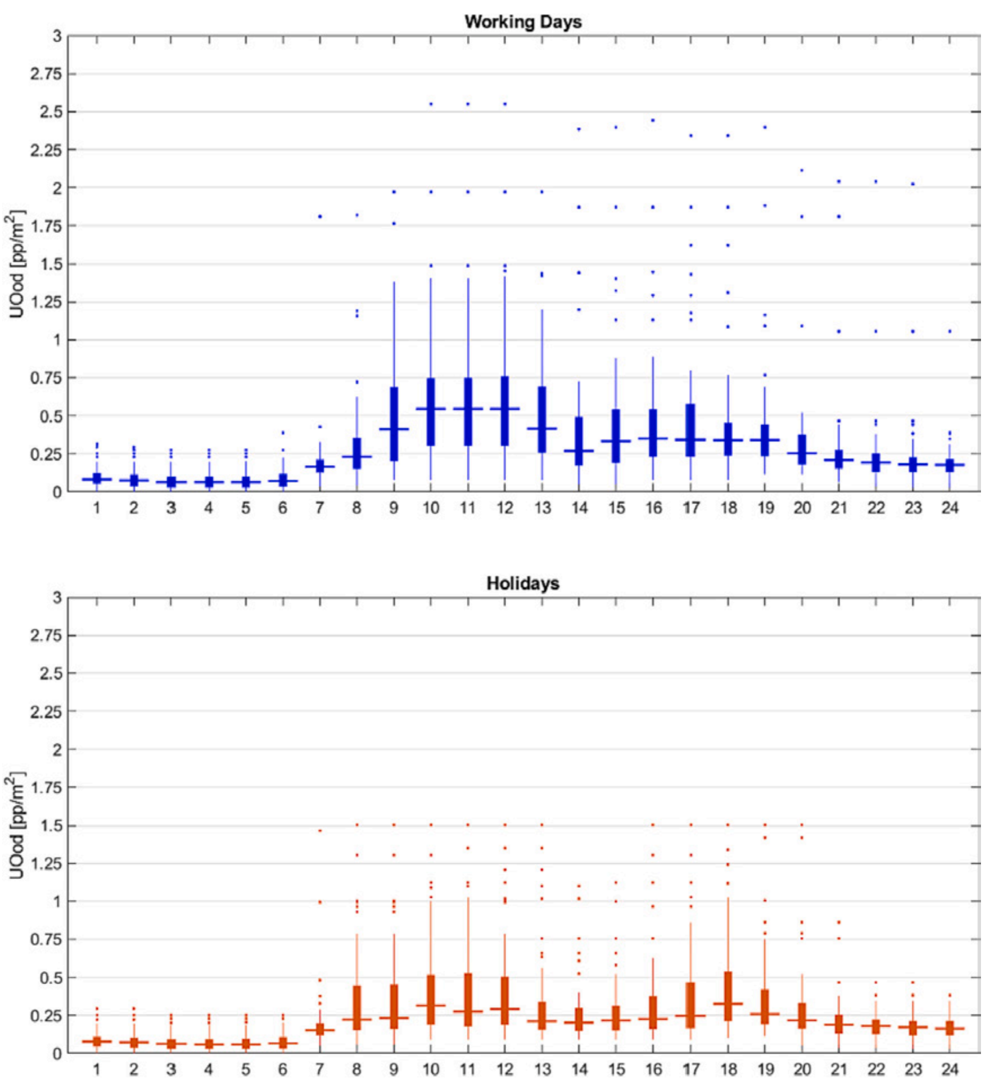

Fig. 4. UHC-related KPIs - Quartile-based analysis of the Users' Overall outdoor density (UOod) on working days (in blue) and holidays (in orange). Outliers are shown by the dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

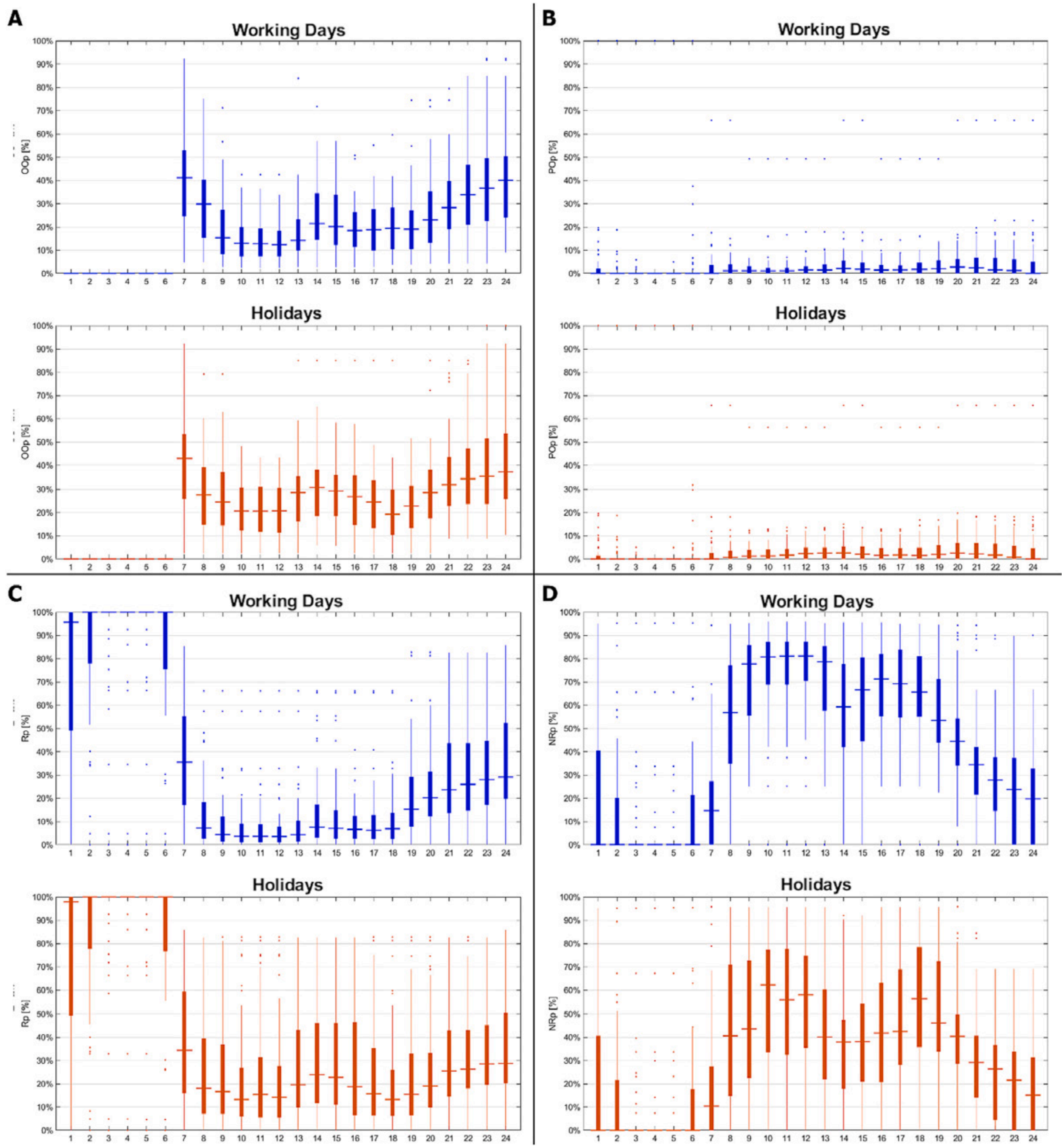

Fig. 5. UHC-related KPIs – Quartile-based analysis of: (A) Only Outdoor users percentage OOp; (B) Prevalent Outdoor users percentage POp; (C) Residents users percentage Rp; (D) Non-residents percentage NRp. Working days are in blue, holidays in orange. Outliers are shown by the dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

provide separated subsets of data, respectively representing under/overcrowding conditions of the sample. Similarly, median values are collected into a separated subset to represent recurring conditions of use. These three subsets have been separately analyzed using the same quartile-based approach, by also applying the IQR method. In this way, quartile-based representations of maximum, minimum, and median KPIs values for the whole sample of squares have been retrieved for each subset.

4. Results

Results are organized according to classes of KPIs introduced in Section 3.2 (Public Open Space Characterization, Users' Daily Characterization, and Users' Hourly Characterization) referring to the sample of squares assessed in this work as relevant POSs (see Appendix B).

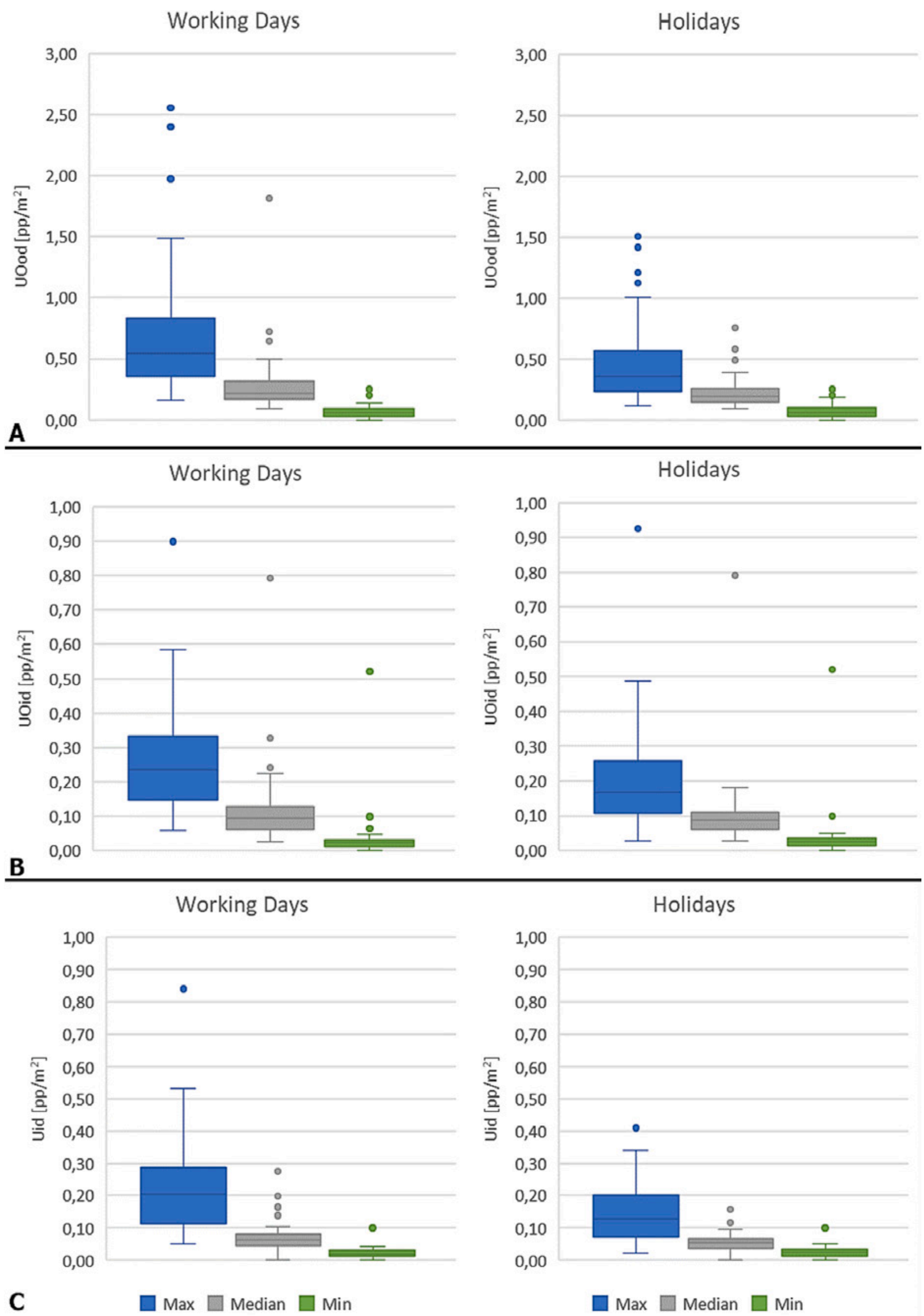

Fig. 6. UDC-related KPIs - Quartile-based analysis of: (A) Users' Overall outdoor density UOod; (B) Users' Overall indoor density; (C) Users' indoor density Uid in working days and holidays. Outliers are shown by the dots.

4.1. Public Open Space Characterization

The square sample is mainly characterized by the presence of walkable areas (median WAp = 65 %) as highlighted in Fig. 3A, while a non-negligible part is occupied by carriageable areas and transportation systems (median CAp = 30 % circa). However, considering walkable and carriageable areas as a whole (thus considering those areas that can be ideally used in case of an evacuation), they cover almost the entire area of the squares, while the remaining space is occupied by dehors, monuments, and/or private courtyards (up to about 10 %).

82 % of the analyzed squares are characterized by the presence of at least one special building or special use within the square (SB). Fig. 3B shows that the most recurring condition regardless of the special building and use types (blue boxplot) can be described by SBn = 2 as the

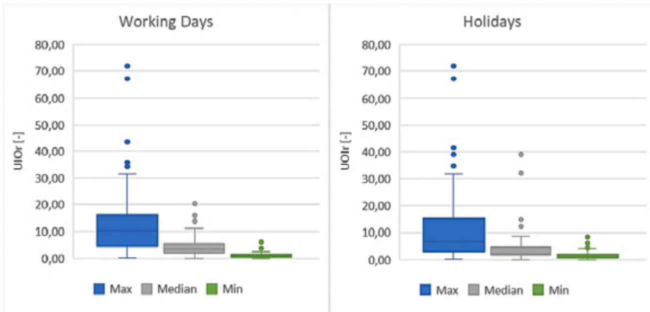

Fig. 7. UDC-related KPIs - Quartile-based analysis of UIOr in working days and holidays. Outliers are shown by the dots.

median value. “Theatres, Museums, Religious buildings” and “Government buildings” are the most frequent special buildings and uses in the squares, being consistent also in view of the specificities of the historic cities assessed in this research, as these kinds of functions are usually hosted in historic buildings (Memluk, 2013). Considering the identified sensitive buildings typologies, the median area SBA is equal to 1310 m^2 for Theatres, 940m^2 for Museums, 880m^2 for Religious Buildings, and 1770 m^2 for Government Buildings. As shown in Fig. 3C, *indoor areas* are about 2.5 times larger than *outdoor areas* considering the median value of AOIr.

4.2. Users' Hourly Characterization

Fig. 4 compares the UOod trends over the daytime for working days and holidays, as an effect of the square temporalities, for the whole sample of squares. On working days, the UOod peak appears in the morning (up to 0.75 pp/m^2 between 9 and 12 am), when all the users' typologies are active in the square areas, i.e. especially those relating to NR hosted in buildings open to the public. UOod values decrease in the afternoon (about 0.25–0.50 pp/m^2) and the evening (about 0.15–0.25 pp/m^2) until dropping under 0.10 pp/m^2 in the night hours when most of the users are only R. These general trends appear to be comparable during holidays, except for the morning hours of the holidays when UOod barely overcomes 0.50 pp/m^2, thus suggesting a less intense use of the squares.

The effects of hourly temporalities can be better displayed according to the analysis of percentages of users considering their familiarity with the square. Fig. 5A shows that, for most of the day and both considering working days and holidays, median OOp is generally lesser than 30 % except at 7 and from 21 to 24 both for working days and holidays. However, since OO have been considered a non-time-dependent component (except during the night when they are absent), their percentage strictly depends on how other users' typologies populate the square (thus, on the dimensions of the indoor and outdoor areas and their related hourly temporalities).

As expected, PO represent the most limited part of the population, regardless of the daytime and day type, as the median POp always ranges between 0 and 5 % (Fig. 5B). This is due to the limited Dp value, and so the small surface, as discussed in Section 3.1. Outliers in Fig. 5B refer to non-stop activities, especially those hosted in squares without residential areas (during the evening and night-time), and for open markets (e.g. from 7 am to 7 pm), whose dimensions are considerably higher than the ones generally related to bars and restaurants with outdoor activities.

During the working hours of working days, i.e. from 8 am to 6 pm, R represent a small part of the population within the squares (Fig. 5C), as shown by Rp, which is at most equal to 10 % considering median values. This percentage increases to 10–40 % (7–12 pm) in the evening, and up to 70–100 % during the night (1–5 am), when OO are not accounted for, and most of the activities are closed (NR and PO). On the other hand, during holidays, R represent a larger part of the population because they are considered at home the whole day (on average, 15–35 % excluding the night hours, where working days outcomes are confirmed). Both the working day and the holiday conditions point out how the squares in the considered sample are mainly characterized as residential areas, as also remarked by the outliers that assume values near 0 %.

In view of the above, Fig. 5D shows how, during the working days, NRp is maximized during the working hours (8 am to 6 pm,), where median NRp is always >60 %, and minimized in the night-time (<30 %), where non-stop activities placed indoor and hotels host most of NR. Such trends are confirmed for holidays, but data also show a significant decrease concerning attendance in the central hours of the days (about -20 % with respect to the working days' trends between 8 am and 8 pm). However, in both conditions, outliers refer to hotels, accommodation structures, and non-stop activities.

4.3. Users' Daily Characterization

Fig. 6 arranges the data applying the adopted quartile-based approach to extreme conditions of square use (maximum and minimum boxplot) and the recurring conditions (median boxplot), for working days and holidays. Fig. 6A shows the UOod trends, thus considering all the users contemporarily in *outdoor areas*, such as in evacuation conditions. Considering the median data (grey boxplots), working days and holidays appear to be characterized by the same levels of density in outdoor (about 0.25 pp/m^2). On the other hand, in peak conditions, the difference between working days and holidays appears to be significant, as values decrease by about 30/35 % (blue boxplots). However, even considering the maximum subsets of data (blue boxplots) and excluding outliers (i.e. those for working days), the outdoor density is lesser than the critical value of 3.00 pp/m^2, which can lead to physical contact between individuals standing up, for instance, while waiting for the rescuers' access in emergency conditions excluding outliers (Bloomberg & Burden, 2006).

According to Fig. 6B, working days still represent more critical conditions than holidays considering UOid values, although density values are lower than those of UOod, thanks to the AIOr>1 (compare with Fig. 3B). This implies a slight impact of users outdoor on the overall conditions when particular circumstances can force them to move inside the buildings searching for safety or shelter (e.g., in case of terroristic attack outdoors; unacceptable environmental outdoor conditions related to air pollution or heatwaves).

Fig. 6C shows Uid conditions according to the same quartile-based approach, thus only considering NR and R users. On working days, according to Section 3.2 discussion, peak conditions of each subset of data can be traced back basically to hours between 10 and 12 am, when most of the offices and government buildings are open to the public (i.e., the ones that can host the higher number of users because of their dimension and occupant load). In holiday scenarios, Uid values are lower, and essentially affected by the opening conditions of theatres, museums, and religious buildings, which OL_T and dimensions are similar to those of other public buildings open on working days.

Previous outcomes about densities find confirmation by analyzing the ratio between users populating *indoor* and *outdoor areas* of the square (Fig. 7). Indeed, the median UIOr data ranges between about 2 and 5 both considering the working days and holidays scenarios (grey boxplots, quartiles 1 and 3), with maximum peak conditions up to 15, excluding outliers and data on maximum values subsets (blue boxplots). However, the median values of the minimum subset of UIOr (that is minimizing the indoor users and maximizing the outdoor users), remain around 1 (green boxplots in Fig. 7), meaning that indoor and outdoor users are at least equal in both working days and holidays.

The characterization of quartile-based analysis of users' depending on their familiarity with the POS, considering the whole daily data derived from the same KPIs on hourly temporalities in Section 4.2, rapidly traces the general features of the sample of squares investigated

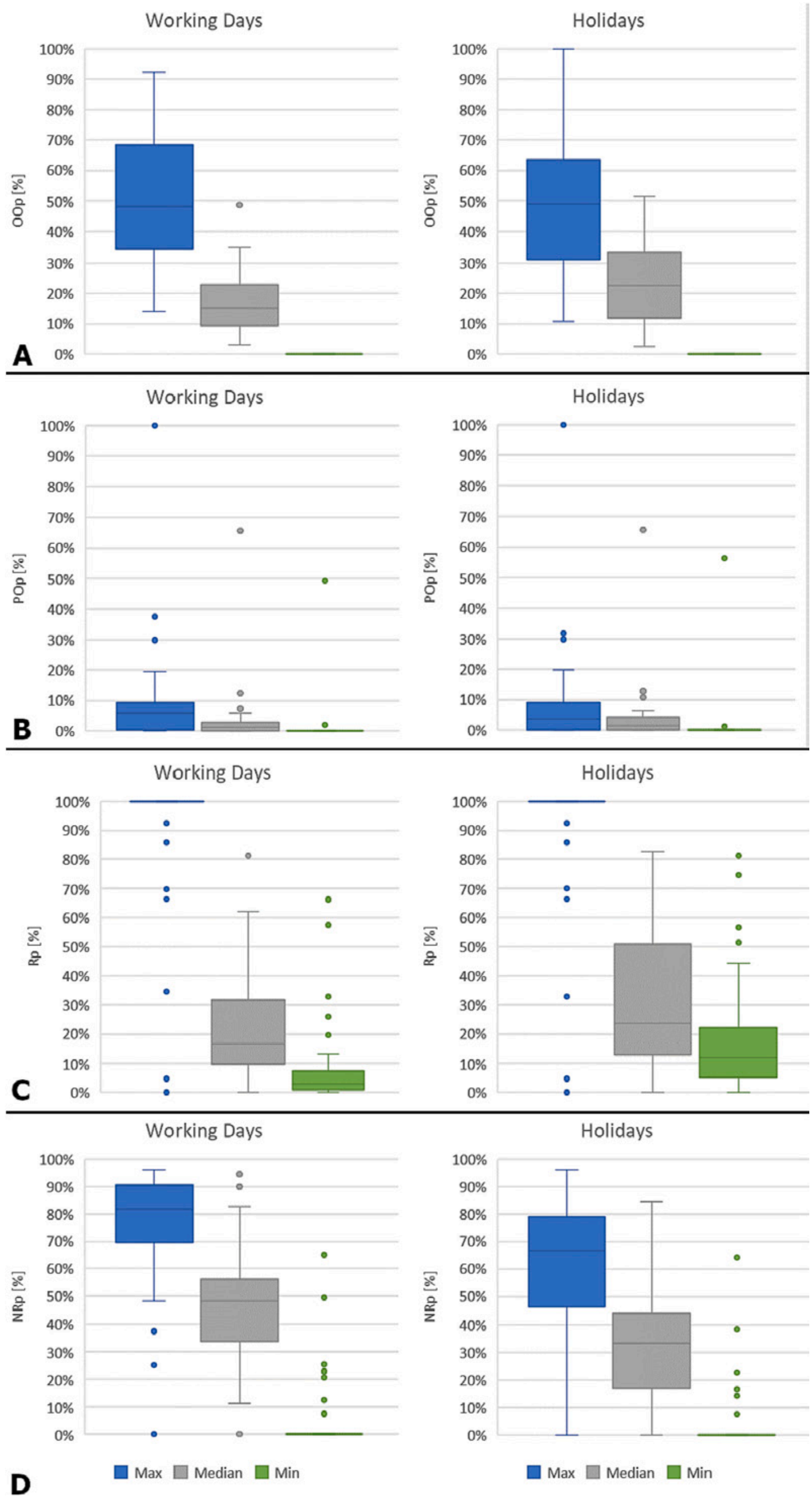

Fig. 8. UDC-related KPIs - Quartile-based analysis of: (A) Only Outdoor users percentage OOp; (B) Prevalent Outdoor users percentage POp; (C) Residents users percentage Rp; (D) Non-residents percentage NRp in working days and holidays. Outliers are shown by the dots.

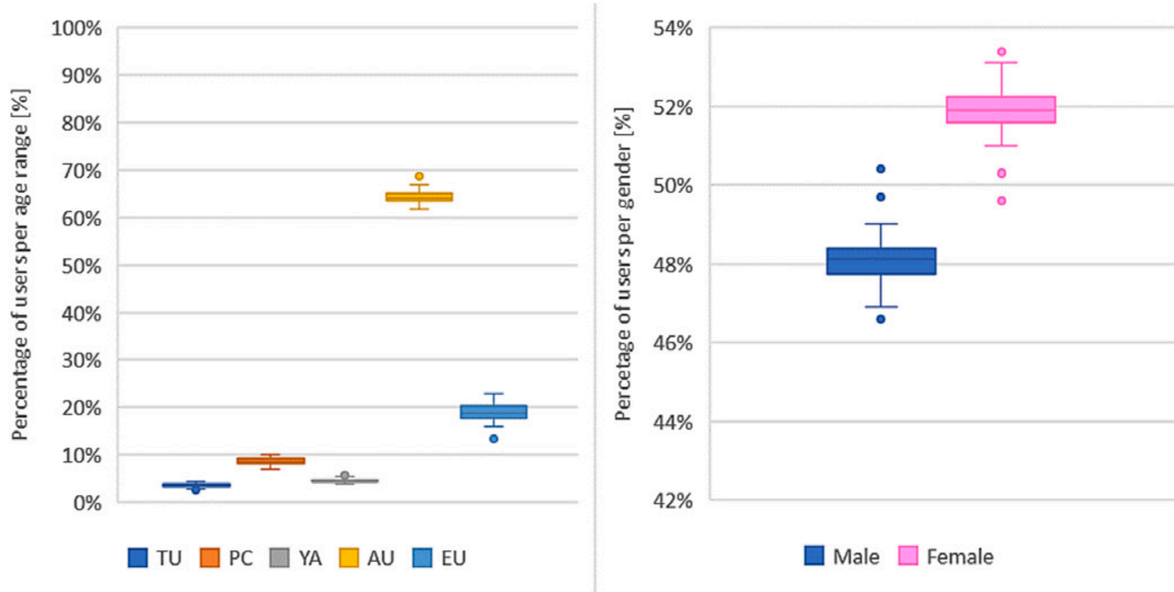

Fig. 9. UDC: Quartile-based analysis considering individual vulnerability (age and gender). Outliers are shown by the dots.

Table 6
Outline of the typological description of the square according to the median values of UDC-related KPIs.

KPI	Max (W : H)	Med (W : H)	Min (W : H)
UOod	0.55 : 0.36	0.22 : 0.20	0.06 : 0.06
UOid [pp/m^2]	0.24 : 0.17	0.10 : 0.09	0.02 : 0.02
Uid [pp/m^2]	0.20 : 0.13	0.06 : 0.05	0.02 : 0.02
UIOr [−]	10.26 : 6.64	3.47 : 2.15	0.94 : 1.04
OOp [%]	48 : 49	15 : 23	0 : 0
POp [%]	6 : 4	1 : 1	0 : 0
Rp [%]	100 : 100	17 : 24	3 : 12
NRp [%]	82 : 67	48 : 33	0 : 0

in this work. Fig. 8A shows that recurring conditions for OOp assume the range between about 10–30 % of the population (grey boxplots). As also pointed out in Fig. 5A, minimum values refer to the nighttime (0 %), while maximum refers to (a) particular hours of the day when most of the other users' typologies are absent (e.g., early in the morning) or (b) squares without residential buildings.

Fig. 8B underlines how, for both the working days and holidays, PO represent a limited part of the population also in peak condition (blue boxplots, expect outliers). Minimum data for each subset of values refer to closing time (or absent dehors areas). Outliers mainly describe covered/partially covered areas within the square, like permanent shelters for open markets (hosted during the day), whose dimensions are considerably higher than the ones generally related to bars and restaurants, as also displayed in Fig. 5B.

Fig. 8C and Fig. 8D respectively trace the data for R and NR, during working days and holidays. As also demonstrated in Fig. 5C and Fig. 5D, most of the squares are mainly used for residential purposes, thus boosting the Rp values, especially during the holidays, that is considering most of the activities for NR close to the public. Minimum data of Rp values refers to working hours, while maximum data, up to 100 %, to night-time. However, in working days, considering the median subset of data for Rp and NRp (grey boxplots), it could be pointed out that NR higher affects the recurring daily conditions of the squares, since they range from 35 to 55 % (1st and 3d quartiles in Fig. 8D) in respect to 10–30 % referring to R (1st and 3d quartiles in Fig. 8C). During holidays, such values assume an opposite trend, with slight Rp differences of about +10 % in respect of working days, thanks to the limited impact of openings of public buildings (i.e. theatres, museums, religious buildings) during the daytime (i.e. compare Fig. 5C and Fig. 5D).

Fig. 9 shows results on the individual vulnerabilities according to the users' age and gender, which are consistent with Italian national statistics (ISTAT, 2018), also in view of the quick data source used in this work.

5. Discussion

Results demonstrate that this work provides an innovative and quick-to-apply methodology to collect and quantify data for the users' *vulnerability* and *exposure* characterization in POS, by both allowing deriving typological conditions and performing single case analyses (see Appendix E for an application example). In this sense, such results can be herein discussed to point out innovation (5.1), policy implications (5.2), and limitations and future aims (5.3).

5.1. Innovation of the results

Compared to the current state of the art, this work innovatively provides a new methodology for the typological description of a sample of POS (like squares) in cities prone to risks thanks to innovative KPIs concerning both general features of the built environment (POSC-related KPIs), and the users' temporalities affecting vulnerability and exposure issues (UHC- and UDC- related KPIs).

Considering such a typological perspective relying on the whole sample application (in this work, 56 Italian squares), the typological description firstly confirms previous works relating to POSC-related KPIs, as: (1) "Theatres, Museums, Religious buildings" and "Government buildings" are the most frequent special buildings and uses in the squares (Memluk, 2013); (2) the high built-up density of the considered squares (see AIOr) is one of the fundamental markers for the characterization of historic scenarios, especially in the Italian context (Fleischmann et al., 2021; He et al., 2021; Micelli & Pellegrini, 2018); (3) a non-negligible part of such scenarios is destinated to carriageable areas (see CAp) (Memluk, 2013).

Concerning UHC and UDC, the proposed approach to mesoscale analyses confirms how users' temporalities are fundamental to evaluate how exposure and vulnerability issues vary and evolve over space and time (Cherfaoui & Djelal, 2019; Sharifi, 2019b). In the considered case studies sample, UHC-related peak conditions of square use (compare Section 4.2) are gained between 10 and 12 am either on: (a) working days, when most of the functions and public office are open; and (b) holidays, because of the presence of religious building hosting a large number of users. Users in indoor areas represent the largest part of the population within the square, while outdoor users increase when activities hosting a large number of users are closed, that is early in the morning (e.g., restaurants, museums) and in the evening (e.g., offices). Finally, users' vulnerability issues depending on age and gender are in keeping with the national percentage distributions, mainly due to the low recurrences of functions that can vary the trend in the analyzed sample (e.g., schools, nursing homes).

In view of the above, Table 6 traces the users' daily characterization through the median values of the UDC-related KPIs (Rousseeuw & Hubert, 2011). It is worthy of notice that Table 6 provides no time-dependent quantification of the typological scenario, but it reliably offers a quick and general overview of the POS recurring features.

5.2. Policy implications

In view of Section 5.1 innovations, key findings of our works can be also exploited by local administrators and their low-trained technicians (mainly, municipalities or even public event managers) for risk assessment and mitigation purposes, for application to their single case studies that could be potentially affected by different SLODs and/or SUODs. Such policy implications are connected to two main issues.

First, technicians could use very simple and quick-to-apply outputs of Table 6 to depict the general scenario of their own POS according to UDC-related KPIs, just using the POS surface as a reference to evaluate the crowding level in it. Similarly, UHC-related KPIs can be then used to deepen the users' factors trends and roughly estimate peak conditions.

Second, stakeholders could directly apply the method to their specific POS, being guided towards the users' factors assessment in a structured manner. They can take advantage of easy-to-collect variables using open-data and freely accessible databases to easily evaluate the potential impact on users of peak conditions of use of the POS. These pre-emergency data can be then combined with particular circumstances leading all users to move towards outdoor (e.g., earthquakes), or indoor (e.g., to perform sheltering-in-place for terrorist acts, especially in holidays, or to mitigate effects of SLODs like heatwaves or air pollution).

In addition to such issues, the proposed methodology can be boosted and easily adapted to consider specific elements in the POS in presence of more detailed sources and analyses provided for instance by local authorities. In this sense, this task can be achieved by: (1) introducing specific data measuring the presence of certain users' typologies, like tourists or daily commuting; or (2) by considering the impact of seasonality that may influence the use of spaces, like weather conditions, hours of sun per day, shadow shapes, and so on). However, in view of the conservative approach proposed both for the data collection and the crowding conditions evaluation (according to the maximum occupant loads indicated by the current Italian regulations for the users' quantification), the present methodology is also suitable for providing basic conditions for more detailed analyses, such as those related to behavioral correlation with climatic factors, or the evaluation of pre-emergency conditions in the POSs (that is excluding the contemporary presence of SLOD or SUOD events). Therefore, enabling also comparisons between different study cases and/or different usage conditions.

5.3. Limitations and future aims

The authors are aware of limitations due to some simplifications in the POS analysis assumptions, which should be solved by future works, and mainly:

A. possible changing environmental conditions (e.g., due to seasonality, weather conditions, lightning conditions both during daytime and nighttime, and shape of the shadows during the daytime). They could highly influence the use of outdoor areas for public activities like bars, restaurants (in this work, *dehors*), as well as areas for leisure purposes and spontaneous gathering of users, so their presence, characterization, and spatiotemporal variations could be added by future efforts, by associating specific crowding indexes or use probabilities;
B. elements that can increase (e.g., green areas, blue areas, playgrounds, benches, monuments, and sights) or decrease (e.g., air and noise pollutants) the attractiveness of the spaces. As for previous point A, future efforts could better quantify the impact of them in how (mainly) walkable outdoor areas pedestrian densities can be modified, thus overcoming the assumption of the maximum occupant load of 0.10 pp/m^2 adopted in a homogeneous way for each case study in this work, and thus for both for monumental and leisure areas;
C. evaluate the influence that the cities' characteristics play on the POSs, including effects of touristification, daily commuting, and seasonal variations. Future efforts should be devoted to the same actions for previous point B, and could move towards the clustered organization of squares into more detailed sub-typologies depending on similar composition and geometrical features. To this end, the same approach of this work could be fully adopted, by increasing the sample dimension.

In view of the above, the current methodology could be easily updated for future application, such as by varying densities of some occupant loads depending on the application contexts (e.g., historical POS in several Countries) or by applying them for specific types of areas (e.g., indoor and outdoor sights that attract visitors "unfamiliar with the POS"). In this way, although the current computation only depends on the squares' geometrical features, we could still *rapidly* consider the presence of certain users' typologies regardless of aspects difficult to quantify without having particularly refined sources and analyses (e.g., touristification in a capital city is different than in smaller cities).

In addition to this, further research could improve the results of the adopted "robust-to-outliers" methodology by increasing the case-studies sample and then moving towards cluster analysis techniques (D'Amico et al., 2021; Dibble et al., 2019), which allow the organization of groups of squares by homogeneous classes and so the possibility to quickly identify the most probable typology of the square thanks to the KPIs combination. In this sense, some users-related KPIs proposed in this work could be selected as the most relevant ones, and the square description could combine them with morphological, functional, and physical features.

6. Conclusions

Understanding and organizing risk factors of urban built environments are basic steps to support risk assessment and risk reduction actions, so as to better face possible disaster conditions that can affect the users' safety. This work takes into account Public Open Spaces (POSs) placed in historic cities prone to sudden- and slow-onset disasters and proposes a novel methodology focused on users' factors, that are users' vulnerability and exposure, and able to:

A. quickly and easily collect data on their main features and users' vulnerability and exposure from real-world scenarios through common simple tools and data sources;
B. quantify such aspects by means of new synthetic criteria (Key Performance Indicators) easy to interpret and adapt to any urban context;
C. be applied to a single case to depict specific POSs conditions, as well as to derive typological conditions, that is statistically recurring, when applied to a sample of case studies in the same relevant contexts;

D. rapidly offer support to local authorities and their technicians (including non-expert ones) for improving the sustainability and the safety of the built environment in which we live since the method can provide an overview of the users' factors conditions (i.e. daily, hourly) and retrieve their peak (critical) conditions.

The POSs investigated by this work are squares in historic cities because of their risk factors (i.e. significant building vulnerability, location in complex urban layouts, the possibility of being urban attractors for tourists and citizens), and fundamental role for people's use before and during emergency conditions. The spatiotemporal distributions of the users (hourly and daily "temporalities") are merged with the generic features of these squares, deriving KPIs statistically assessed through minimum, maximum, and median values. These three significant values can point out significant scenarios for multi-risk assessment by including aspects and features of the open spaces and their use by people, and so identifying priority scenarios to be deeply investigated by safety designers. In this sense, additional local databases and in-situ surveys can integrate data from open-access and quick-to-apply repositories used in this work, thus increasing the reliability of collected data and their analysis.

In particular, the typological description obtained by the proposed KPIs represents the first step for quickly defining input scenarios concerning users' vulnerability and exposure in view of risk assessment and mitigation purposes. Recurring (as typological) or extreme (as peak) conditions obtained through the proposed KPIs could be used, for instance, to populate simulation-based scenarios and perform quantitative risk assessments also including users' behaviors during emergency conditions, depending on the specific disasters considered (Bernabei et al., 2021; Cheliotis, 2020; da Silva et al., 2022; Hassanzadeh, 2019; Wei et al., 2022). In this sense, the next steps in the research can combine the retrieved typological scenarios with typological hazards and vulnerabilities, depending on the specific risks in the city or the combination between them, from a multi-risk standpoint. For instance, Slow Onset Disasters conditions can be used to populate Sudden Onset Disasters scenarios as input for emergency evacuation simulations. Similarly, in this workflow, specific risk-increasing conditions (e.g., overcrowding due to mass gatherings) can be managed by the proposed methodology to populate high-impact, low-probability (extreme) events.

Finally, results firstly encourage future efforts to broaden the current analyses to a greater number of squares prone to multi-risk, so as to improve the statistical significance of typological scenarios definition. Moreover, thanks to the possibility to manage general features of the POSs, future research could easily apply the methods to any urban POSs, as well as to POSs composing wider elements of the urban form (i.e. at a single district/neighborhood scale), and also in different urban forms (e.g. non historic ones; characterized by other main land uses) and Countries.

CRediT authorship contribution statement

Enrico Quagliarini: Conceptualization, Methodology, Project administrator, Funding acquisition, Supervision, Writing – review & editing.
Gabriele Bernardini: Conceptualization, Methodology, Supervision, Validation, Formal analysis, Resources, Writing – original draft.
Guido Romano: Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Visualization, Writing – original draft.
Marco D'Orazio: Conceptualization, Funding acquisition, Supervision.

Declaration of competing interest

None.

Data availability

Data are available upon reasonable request, by direct contacting the corresponding authors of this work (g.bernardini@univpm.it).

Acknowledgements

This work was supported by the MIUR (the Italian Ministry of Education, University, and Research) Project BE S2ECURe - (make) Built Environment Safer in Slow and Emergency Conditions through behavioUral assessed/designed Resilient solutions (Grant number: 2017LR75XK).

Appendix A

Table 7
Symbols and acronyms explanation.

Symbols and acronyms	Unit of measure	Meaning	Note
AIOr	–	(Accessible) Indoor-outdoor area ratio	Ratio between the indoor area and the outdoor area
AP_a	[%]	Users' age percentage	Age percentage distribution of the a-th age range
AU	–	Adults	Users from 20 to 69 years
AUn	pp	Adults number	–
AUp	%	Adults percentage	Percentage value with respect to UOn
CA	m^2	Carriageable areas	Outdoor areas primarily occupied by vehicles, e.g. carriageway, parking lots
CAp	%	Carriageable areas percentage	Percentage value with respect to the overall outdoor areas
cp	[–]	Presence coefficient	Equal to 1 if users are present, to 0 if users are absent, and to the local percentage of unemployed users to consider their presence at home
CY	m^2	Private courtyards areas	Outdoor areas generally inaccessible to the public like fenced courtyards of dwellings
CYp	%	Private courtyards areas percentage	Percentage value with respect to the overall outdoor areas

(continued on next page)

Table 7 (*continued*)

Symbols and acronyms	Unit of measure	Meaning	Note
D	m^2	Dehors areas	Outdoor areas intended for open-air terraces of restaurants, bars, open markets, and other outdoor areas hosting a specific intended use or connected to a specific building, placed at the ground levels, and including both temporary (removable) and permanent structures
Dp	%	Dehors areas percentage	Percentage value with respect to the overall outdoor areas
EU	–	Elderlies	Users from 70 years onwards
EUn	pp	Elderlies number	–
EUp	%	Elderlies percentage	Percentage value in respect to UOn
Fp	%	Female users percentage	Percentage value in respect to UOn
H	–	Holidays	Sundays and other national holidays
IQR	–	InterQuartile Range	Difference between 3rd and 1st quartiles
KPI	–	Key Performance Indicator	–
Mp	%	Male users percentage	Percentage value with respect to UOn
NR	–	Non-residents	Users that occupy the private/public services and institutions
NRn	pp	Non-residents number	–
NRp	%	Non-residents percentage	Percentage value in respect to Uon
NU	[pp]	Maximum number of users	Sum of all the users considered within the POS
OL_i	pp/m^2	Occupant load	Occupant load of the i-th type of area
OO	–	Only outdoor users	Users that populate the walkable areas WA
OOn	pp	Only outdoor users number	–
OOp	%	Only outdoor users percentage	Percentage value in respect to Uon
PC	–	Parents-assisted children	Users from 5 to 14 years
PCn	pp	Parents-assisted children number	–
PCp	%	Parents-assisted children percentage	Percentage value in respect to UOn
PO	–	Prevalent outdoor users	Users that populate the dehors D
POn	pp	Prevalent outdoor users number	–
POp	%	Prevalent outdoor users percentage	Percentage value in respect to Uon
POS	–	Public Open Space	e.g., squares, streets, districts
POSC	–	Public Open Space Characterization	–
R	–	Residents	Users that occupy the residential buildings
Rn	pp	Residents number	–
Rp	%	Residents percentage	Percentage value in respect to Uon
SB	Boolean	Presence or not of special buildings or uses	–
SBA	m^2	Special buildings/uses area	–
SBn	number of items	Number of special buildings or uses per square	–
SLOD	–	Slow Onset Disaster	e.g., heatwaves, pollution, pandemic
SU_i	[m^2]	Effective surface	Effective surface of the i-th type of area
SUOD	–	Sudden Onset Disaster	e.g., earthquake, flood, fire
TU	–	Toddlers	Users from 0 to 4 years
TUn	pp	Toddlers number	–
TUp	%	Toddlers percentage	Percentage value with respect to UOn
UA	m^2	Unwalkable areas	Outdoor areas occupied by monuments, fountains, and fenced areas including greeneries
UAp	%	Unwalkable areas percentage	Percentage value with respect to the overall outdoor areas
UDC	–	Users' Daily Characterization	–
UHC	–	Users' Hourly Characterization	–
UId	pp/m^2	Users' indoor density	Ratio between the indoor users (as the sum of R + NR) and the indoor area
UIod	pp/m^2	Users' overall indoor density	Ratio between UOn and the indoor area
UIOr	–	Indoor-outdoor users ratio	Ratio between users in indoor areas (R + NR) and users in outdoor areas (OO + PO)
UOn	pp	Users' overall number	–
UOod	pp/m^2	Users' overall outdoor density	Ratio between UOn and the outdoor area (as the sum of WA, D, and CA)
W	–	Working days	Monday to Saturday
WA	m^2	Walkable areas	Outdoor areas accessible by pedestrians
WAp	%	Walkable areas percentage	Percentage value with respect to the overall outdoor areas
YA	–	Young autonomous	Users from 15 to 19 years
YAn	pp	Young autonomous number	–
YAp	%	Young autonomous percentage	Percentage value with respect to UOn

Appendix B

Table 8
List of case studies and their geo-localization.

City	Square	Link
Arezzo	Piazza Grande	https://goo.gl/maps/ae5dbepkakzRkosaA
Bari	Piazza Umberto I	https://goo.gl/maps/EURAUfoE9jb4mqHc9
Brindisi	Piazza Duomo	https://goo.gl/maps/wEDLsQAmdv5jiH7e8
Caldarola	Piazza Vittorio Emanuele	https://goo.gl/maps/M4Whe432J8h597H47
Carpi	Piazza Martiri	https://goo.gl/maps/pCFkm2UKKPos7qGA7
Carrara	Piazza Alberica	https://goo.gl/maps/RqzQigFeujdj4kUM7
Catania	Piazza Università	https://goo.gl/maps/n4TbZCTT3NYTF1Vb8
Cesena	Piazza del Popolo	https://goo.gl/maps/brGubNHGV69t1jET8
Cosenza	Piazza Duomo	https://goo.gl/maps/UQ7xegwSJ6umAvpRA
Crotone	Piazza Duomo	https://goo.gl/maps/NQb2yhpJDhUA6bgL9
Cuneo	Piazza Tancredi Galimberti	https://goo.gl/maps/CQnpMNTRsx7oW4ZD9
Fermo	Piazza del Popolo	https://goo.gl/maps/wyAy1L7JuG8GdFzZ6
Forlì	Piazza Aurelio Saffi	https://goo.gl/maps/rQPnXoSQgUBv97Yj6
Gorizia	Piazza della Vittoria	https://goo.gl/maps/z1wMAYTxCzLdsTxHA
Iglesias	Piazza Municipio	https://goo.gl/maps/JXU43keJv9itf1Ux8
Imperia	Piazza San Giovanni	https://goo.gl/maps/mdCsKgrkgxny8vZq9
Lodi	Piazza della Vittoria	https://goo.gl/maps/meTUapY56YazZmHSA
Lucca	Piazza dell'Anfiteatro	https://goo.gl/maps/BUUPfzVG5htibLbw6
Manfredonia	Piazza del Popolo	https://goo.gl/maps/4efwMtLeAfSoDwsT9
Mantova	Piazza Sordello	https://goo.gl/maps/gydun7svSSQJHdHs7
Messina	Piazza Duomo	https://goo.gl/maps/ysXJGQ5hDjDxbddMA
Milano	Piazza Emilia	https://goo.gl/maps/qhNzWJCRpXwBTpUS9
Milano	Piazza Fratelli Bandiera	https://goo.gl/maps/HAchC4nSWzoXV2Ev8
Modena	Piazza Grande	https://goo.gl/maps/LTA1u77TixoRP7KA6
Monza	Piazza Trento e Trieste	https://goo.gl/maps/wEb5pNQEz4SRyVzC7
Narni	Piazza dei Priori	https://goo.gl/maps/Gg9aD43aTfyWg4gE9
Padova	Piazza delle Erbe	https://goo.gl/maps/E96JV1Nu3ipM9yzL6
Pesaro	Piazza del Popolo	https://goo.gl/maps/hrn9oyME1s4i3ELq5
Pescara	Piazza della Rinascita	https://goo.gl/maps/Zm84L7yWYEcX7yiC6
Pisa	Piazza dei Cavalieri	https://goo.gl/maps/hfD2LV5NBG8EMjv8A
Pisa	Piazza XX Settembre	https://goo.gl/maps/fvtCLcLrSg1TMieq6
Prato	Piazza del Comune	https://goo.gl/maps/CkQ7LX7fKJipfbV87
Ravenna	Piazza del Popolo	https://goo.gl/maps/HzUGvRdQhUFwM1JM9
Reggio Calabria	Piazza Duomo	https://goo.gl/maps/vioURxSbSTFkXdnr8
Reggio Emilia	Piazza Camillo Prampolini	https://goo.gl/maps/9iXH88oc55rnoR3Z7
Rimini	Piazza Cavour	https://goo.gl/maps/Tpm9jxP1DdALDWNy6
Roma	Piazza della Pigna	https://goo.gl/maps/EjuqTzp4kQkHRmdYA
Roma	Piazza Lancellotti	https://goo.gl/maps/pKc8iAykigUS42Tm7
Rovigo	Piazza Vittorio Emanuele	https://goo.gl/maps/cgE1NzqFXEd6s2yUA
San Gemini	Piazza San Francesco	https://goo.gl/maps/6dwjeoK4xQBiHXdcA
San Giovanni in Persiceto	Piazza del Popolo	https://goo.gl/maps/dsDwkuEieYwafHue8
Savona	Piazza Sisto IV	https://goo.gl/maps/tEAFTUyTgKBd8yyF8
Siena	Piazza d'Ovile	https://goo.gl/maps/aBjSwkbXFmm3xkyu6
Siracusa	Piazza Minerva	https://goo.gl/maps/jyAExRHTDt4Jw5eU6
Sondrio	Piazza Garibaldi	https://goo.gl/maps/XEVHrK9EQ2bXbHF3A
Taranto	Piazza del Duomo	https://goo.gl/maps/yjussdG3KtH3z8x28
Torino	Piazza del San Carlo	https://goo.gl/maps/3Fqpvx28AKKKhESN9
Torino	Piazza Vittorio Veneto	https://goo.gl/maps/dJznvKhkpMVfYTuR7
Trapani	Piazza Lucatelli	https://goo.gl/maps/skbyZKYrxsgeoGLU7
Udine	Piazza Matteotti	https://goo.gl/maps/BcUzsnhsgJYm922U8
Varese	Piazza San Vittore	https://goo.gl/maps/xumkYe5MGDqR2Yvq9
Venezia	Campo Sant'Aponal	https://goo.gl/maps/4pf9YXQrY1oKk5GYA
Vercelli	Piazza Cavour	https://goo.gl/maps/8PzHEvYYsKBL2Hd58
Verona	Piazza dei Signori	https://goo.gl/maps/SisVkhQjvZsE9GzN8
Vibo Valentia	Piazza Armando Diaz	https://goo.gl/maps/Pj9tAHwNno5wXd7S6
Viterbo	Piazza del Plebiscito	https://goo.gl/maps/Hjn1k5qvcRtUDwbk7

Appendix C

Table 9
Quick OL_i values for different indoor areas' intended uses according to the Italian fire safety codes and methodologies, and previous works (Quagliarini, Lucesoli, & Bernardini, 2021).

Intended use *T*	*OL_T and notes*	References: Italian regulations
Residential buildings	Occupants loads approach: 0.05 pp/m^2 (assumed according to regulations)	DM 3/8/2015
Institutional buildings including architectural and historic ones used as offices, administrative/ government offices/buildings, police stations/ military bases	Occupants loads approach: closed to the public, 0.1 pp/m^2; open to the public, 0.4 pp/m^2; gathering areas open to the public, 0.7 pp/m^2. As an alternative, the certified number of occupants (e.g. workers) plus 25 % rounded to the upper bound.	DM 10/3/1998, DM 3/8/2015; for historical buildings: DM 20/5/1992, DPR 30/6/1995; for other public buildings used for cultural events: DM 19/8/1996, DM 6/3/2001, DM 3/8/ 2015
Religious buildings	Occupants loads approach: 0.7 pp/m^2 applied to the available area extension. As an alternative, the number of seats plus the number of standing places	Adopted referring to entertainment and public exhibition places: DM 19/08/1996, DM 6/3/2001, DM 18/12/2012
Hospital and healthcare buildings	Occupants loads approach: Ambulatory and similar, 0.1 pp/ m^2; Spaces for visitors, 0.4 pp/m^2. As an alternative, the number of in-service personnel plus the average number of visitors referring to at least three typical days	Adopted referring to working places: DM 10/3/1998
Educational buildings	Occupant loads approach: During lesson hours, 0.4 pp/m^2 applied to the available area extension. As an alternative, a maximum of 26 individuals in each classroom and annex (e. g., refectory, gym) plus 4 % of the people in the buildings for teachers and personnel. During non-lesson hours: 0.1 pp/ m^2, as for Offices closed to the public	DM 26/8/1992, DM 12/5/2016, DM 3/8/2015
Cultural and entertainment buildings (public exhibitions such as museums, art galleries, theatres and cinemas, and sports facilities)	Occupant load approach: 3 pp/m^2 applied to the available area extension. As an alternative, for theatres and cinemas, the number of seats for the public plus 20 % for the personnel; for museums and art galleries, data provided by tourism organizations and/or infields survey on the daily influx	DM 18/3/1996, DM 6/6/2005, DM 19/8/1996, DM 18/12/ 2012
Commercial buildings	Occupant load approach: 0.4 pp/m^2 applied to the available area extension	DM 27/7/2010, DM 3/8/2015
Accommodation facilities	Occupant load approach: 0.4 pp/m^2 applied to the available area extension. As an alternative, the number of beds plus 20 % for the personnel	DM 27/7/2010, DM 3/8/2015
Public shops such as restaurants bars and cafes	Occupant loads approach: Indoor, 0.7 pp/m^2 applied to the available area extension; Outdoor (i.e., see *Dehors*) 0.4 pp/ m^2	Adopted referring to: DM 19/8/1996, DM 6/3/2001, DM 18/12/2012; from a general point of view: DM 3/8/2015
Metro / train / bus stations	Occupants loads approach: common areas for travelers' passage, waiting, and other activities 0.2 pp/m^2, as a minimum value for precautionary evaluations, and extended to all the building area.	Assumed according to the draft document of the fire safety code for train stations[a]

[a] https://www.cni.it/images/bozza_RTV_stazioni_ferroviarie_CCTS.pdf (last access: 14/07/2021).

Appendix D

Table 11
Users' temporalities considering their age ranges (rows), and familiarity with areas occupied (super-columns), by including specific uses and opening times to the public both on working days (W) and Holidays (H) (sub-columns). [A]: 4 % relates to at least 1 teacher over 26 students (see Appendix C). The number of classes will have YA = 0.4 pp/m^2*1000m^2 = 400 pp.; AU = 400*4 % = 16 pp. [B]: 9 % relates to the percentage of unemployed users in Italy when the research was carried out (see footnote #4).

Users' age ranges	Only Outdoor users (OO)	Prevalent Outdoor users (PO) – opening time	Resident users (R)	Non-Resident users (NR)					
				Educational buildings: primary and secondary schools		All the uses (excluding primary and secondary educational buildings)			
				Lesson time (depending on the educational stage system, e.g., 8 am to 1 pm)	Normal closure to scholars, that is out of lessons time	Intended use *open to the public* (excluding universities) – opening time	Universities (depending on the lesson time, e.g., 8 am to 8 pm) – opening time	Intended use *close to the public* - opening time	Religious buildings
Toddlers (TU)	W, H: equal to OOn [pp] * TUp [%] from 7 to 24; elsewhere 0 [pp]	W, H: equal to POn [pp] for the considered *outdoor area* use * TUp [%]	W, H: equal to Rn [pp] * TUp [%]	W, H: 0 [pp]	W, H: 0 [pp]	W, H: equal to NRn [pp] for the considered building * TUp [%]	W, H: 0 [pp]	W, H: 0 [pp]	W: 0 H: equal to NRn [pp] for the considered building * TUp [%]
Parent-assisted Children (PC)	W, H: equal to OOn [pp] * PCp [%] from 7	W, H: equal to POn [pp] for the considered	W: equal to 0 [pp] from 8 am to 1 pm;	W: considering 0.4 pp/m^2, all the users are	W, H: 0 [pp]	W, H: equal to NRn [pp] for the considered	W, H: 0 [pp]	W, H: 0 [pp]	W: 0 H: equal to NRn [pp] for the

(continued on next page)

Table 11 (*continued*)

Users' age ranges	Only Outdoor users (OO)	Prevalent Outdoor users (PO) – opening time	Resident users (R)	Non-Resident users (NR)					
				Educational buildings: primary and secondary schools		All the uses (excluding primary and secondary educational buildings)			
				Lesson time (depending on the educational stage system, e.g., 8 am to 1 pm)	Normal closure to scholars, that is out of lessons time	Intended use *open to the public* (excluding universities) – opening time	Universities (depending on the lesson time, e.g., 8 am to 8 pm) – opening time	Intended use *close to the public* - opening time	Religious buildings
	to 24; elsewhere 0 [pp]	*outdoor area* use * PCp [%]	elsewhere Rn [pp] * PCp [%] H: equal to Rn [pp] * PCp [%]	PC in the case of primary schools H: 0 [pp]		building * PCp [%]			considered building * PCp [%]
Young Autonomous users (YA)	W, H: equal to OOn [pp] * YAp [%] from 7 to 24; elsewhere 0 [pp]	W, H: equal to POn [pp] for the considered *outdoor area* use * YAp [%]	W: equal to 0 [pp] from 8 am to 1 pm; elsewhere Rn [pp] *YAp [%] H: equal to Rn [pp] * YAp [%]	W: considering 0.4 pp/m^2, all the users are YA in the case of secondary schools H: 0 [pp]	W, H: 0 [pp]	W, H: equal to NRn [pp] for the considered building * YAp [%]	W, H: 0 [pp]	W, H: 0 [pp]	W: 0 H: equal to NRn [pp] for the considered building * YAp [%]
Adults (AU)	W, H: equal to OOn [pp] * AUp [%] from 7 to 24; elsewhere 0 [pp]	W, H: equal to POn [pp] for the considered *outdoor area* use * AUp [%]	W: equal to Rn [pp] * AUp [%] * 0.09[(B)] from 8 am to 6 pm; elsewhere Rn [pp] *AUp [%] H: equal to Rn [pp] * AUp [%]	W: 4 % of the users in the building, derived from PC (primary schools) or YA (secondary schools) [A] H: 0 [pp]	W: considering 0.1 pp/m^2, all the users are AU H: 0 [pp]	W, H: equal to NRn [pp] for the considered building * AUp [%]	W: considering 0.4 pp/m^2, all the users are AU H: 0 [pp]	W: considering 0.1 pp/m^2, all the users are AU H: 0 [pp]	W: 0 [pp] H: equal to NRn [pp] for the considered building * AUp [%]
Elderly (EU)	W, H: equal to OOn [pp] * EUp [%] from 7 to 24; elsewhere 0 [pp]	W, H: equal to POn [pp] for the considered *outdoor area* use * EUp [%]	W, H: equal to Rn [pp] *EUp [%]	W, H: 0 [pp]	W, H: 0 [pp]	W, H: equal to NRn [pp] for the considered building * EUp [%]	W, H: 0 [pp]	W, H: 0 [pp]	W: 0 [pp] H: equal to NRn [pp] for the considered building * EUp [%]

Appendix E

This section is dedicated to the application of the proposed methodology to a single case study, then to the comparison with the typological conditions retrieved in Sections 4 and 5. The selected POS here presented is Piazza del Popolo in Manfredonia, of which Fig. 10 shows the aerial. The outdoor areas are composed of 25 % of carriageable areas (CA), 71 % of walkable areas (W), 3 % of dehors (D), and 1 % of unwalkable areas (UA). No private courtyards (CY) are present. The indoor areas are composed of 47 % of residential uses (mainly at the upper floors of the buildings), and 53 % of non-residential uses, among which: the Church (S1), the Municipality (S2), and some commercial activities on the ground floors.

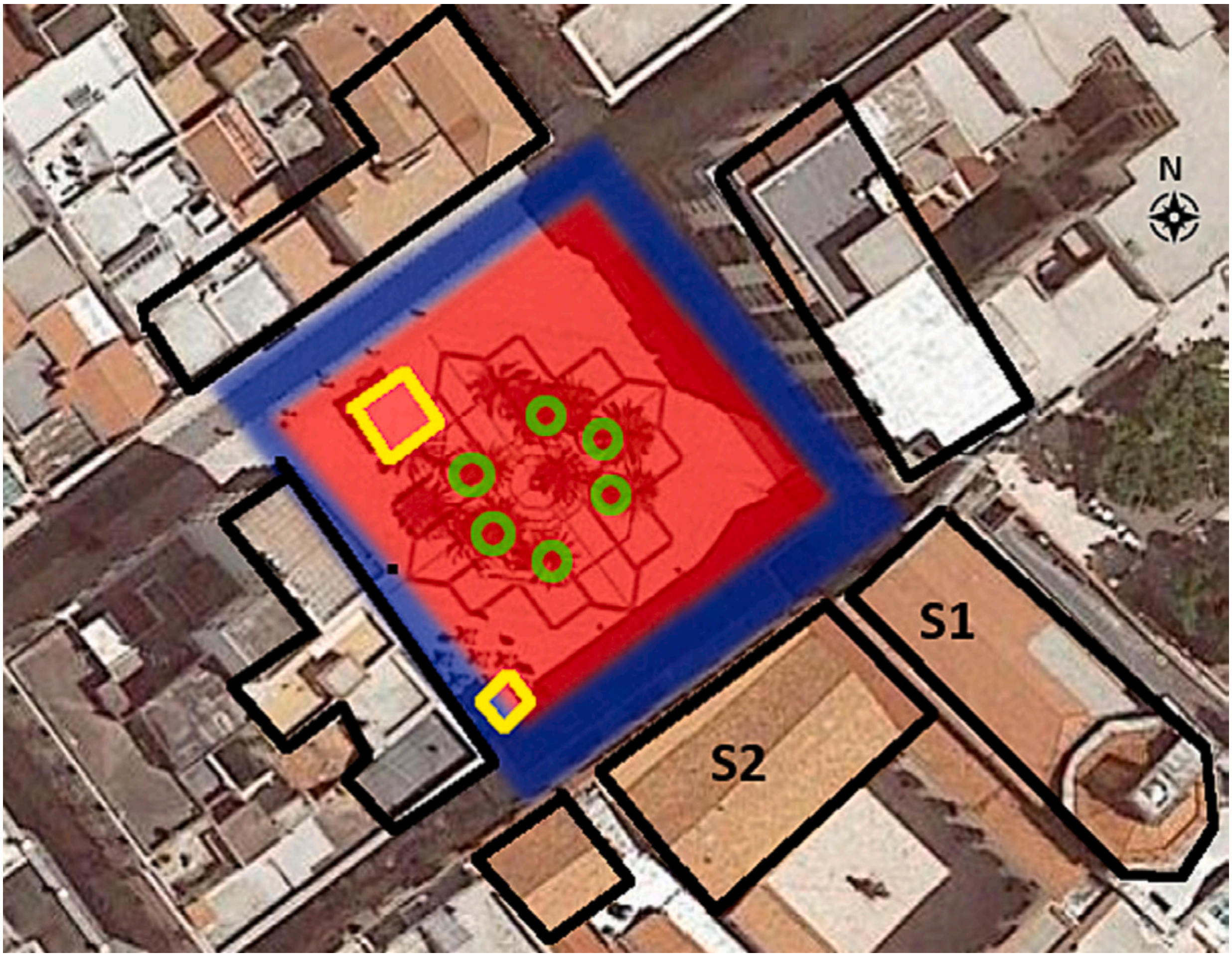

Fig. 10. Aerial view of Piazza del Popolo, Manfredania (IT). Blue areas are Carriageable Areas (CA), red areas are Walkable Areas (WA), the yellow square indicates Dehors (D), green circles indicate Unwalkable Areas (UA), and black bordered areas indicate the indoor areas considered. Special buildings are signed with the letter "S". (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The layout of the given POS, together with the users' age range percentages (Table 11) and their daily and hourly temporalities within the intended uses (see Appendices C and D of the manuscript), provide the data necessary for the KPIs calculus, therefore to quantify the users' vulnerability and exposure in the given case study. In particular, the main temporalities timetables are resumed in the following[6]: (1) the Church is occupied by users only during the Sunday services, that is between 8–10, and 18–20 of the Holiday scenario; (2) the Municipality is closed in the Holiday scenario; (3) most of the commercial uses' opening time range between 9 and 13 both on Working Days and Holidays.

Table 11
Users' age distribution of the a-th age range AP_a [%] in the city of Crotone.

Users' typology	Age range	AP_a [%]
T - TODDLERS	0–4	3,6 %
PC - PARENT-ASSISTED CHILDREN	5–14	9,7 %
YA - YOUNG ADULTS	15–19	5,5 %
AU - ADULTS USERS	20–69	64,7 %
EU - ELDERLY USERS	70+	16,5 %

[6] Data retrieved from https://www.google.it/maps/?hl=it (last access: 25/07/2021).

Table 12
POSC-related KPIs comparison between the typological scenario (Section 4.1 of the revised version of the manuscript) and the case study of Manfredonia.

KPI	Typological scenario:Manfredonia	KPI	Typological scenario:Manfredonia
CAp [%]	28 : 25	SBn [−]	2 : 2
WAp [%]	64 : 71	AIOr [−]	2.38 : 1.66
UAp [%]	1 : 1		
Dp [%]	2 : 3		
CYp [%]	0 : 0		

Table 13
Comparison between the typological scenario and the case study of Manfredonia according to the median values of UDC-related KPIs. W stands for Working Days, H for Holidays.

KPI	Max (W : H)	Med (W : H)	Min (W :H)	Manfredonia (W : H)
UOod	0.55 : 0.36	0.22 : 0.20	0.06 : 0.06	0.19 : 0.16
UOid [pp/m^2]	0.24 : 0.17	0.10 : 0.09	0.02 : 0.02	0.11 : 0.10
Uid [pp/m^2]	0.20 : 0.13	0.06 : 0.05	0.02 : 0.02	0.07 : 0.05
UIOr [−]	10.26 : 6.64	3.47 : 2.15	0.94 : 1.04	1.99 : 1.53
OOp [%]	48 : 49	15 : 23	0 : 0	25 : 27
POp [%]	6 : 4	1 : 1	0 : 0	4 : 0
Rp [%]	100 : 100	17 : 24	3 : 12	16 : 25
NRp [%]	82 : 67	48 : 33	0 : 0	44 : 31

POSC-related KPIs are summarized in Table 12, which shows how the configuration of the outdoor areas of the case study is in line with the typological description derived from the recurring conditions [7]. In particular, the largest percentage is occupied by walkable areas (WAp), then by carriageable ones (CAp), and there is a limited presence of unwalkable areas (UAp) and dehors (Dp). Furthermore, the ratio between indoor and outdoor areas (AOIr) is slightly lower than the same KPI’s median value, and closer to the 1st quartile value (1.80). Finally, the most recurring condition concerning the number (and type) of special buildings is confirmed (SBn = 2), and in the case of Manfredonia they are represented by a religious building and a government building.

As a result, also UDC-related KPIs are in line with the recurring conditions traced by the median values (Table 13), especially for what it concerns density parameters (i.e., UOod, UOid, Uid) that straightly depend on the square geometrical features (as well as n users’ temporalities). It can also be noticed how, similarly to what is shown by the previous KPIs, indoor areas have a lower impact than the typological scenario, as the ratio between users in indoor and outdoor areas is closer to the 1st quartile (“Min” column) both on working day and holidays. As a result, outdoor users’ percentages (OOp and POp) in the case of Manfredonia are higher than the median values.

However, it is worthy of notice that Table 13 provides no time-dependent quantification of the typological scenario, although it reliably offers a quick and general overview of the POS recurring conditions. Therefore, a more detailed picture can be obtained by analyzing hourly temporalities through UHC-relate KPIs. The comparisons between the case study of Manfredonia and the most recurring conditions are shown in Fig. 11 (in terms of users’ densities) and Fig. 12 (in terms of users’ percentages). The main results highlight how:

- On working days:
  - o UOod is in line with the median values during the night and the afternoon, while in the morning hours (i.e., between 9 and 14) the level of crowding is slightly lower and settles around the 1st quartile values;
  - o With the respect to the recurring conditions, in the morning hours, OOp increases (close 3rd quartile) and NRp decreases (close 1st quartile) as a result of the limited presence of commercial activities; on the other hand, Rp and POp are in line with the median values.
- On Holidays:
  - o UOod is in line with the median values basically during all the day, except for the Sunday service hours (that is between 8 and 10, and between18 and 20), as the Church is characterized by a larger surface and a higher occupant load than the other intended uses;
  - o As a result of the previous point, in the aforementioned hours, NRp settles around the 3rd quartile, as well as OOp in the rest of the day, while Rp and POp are in line with the median values.

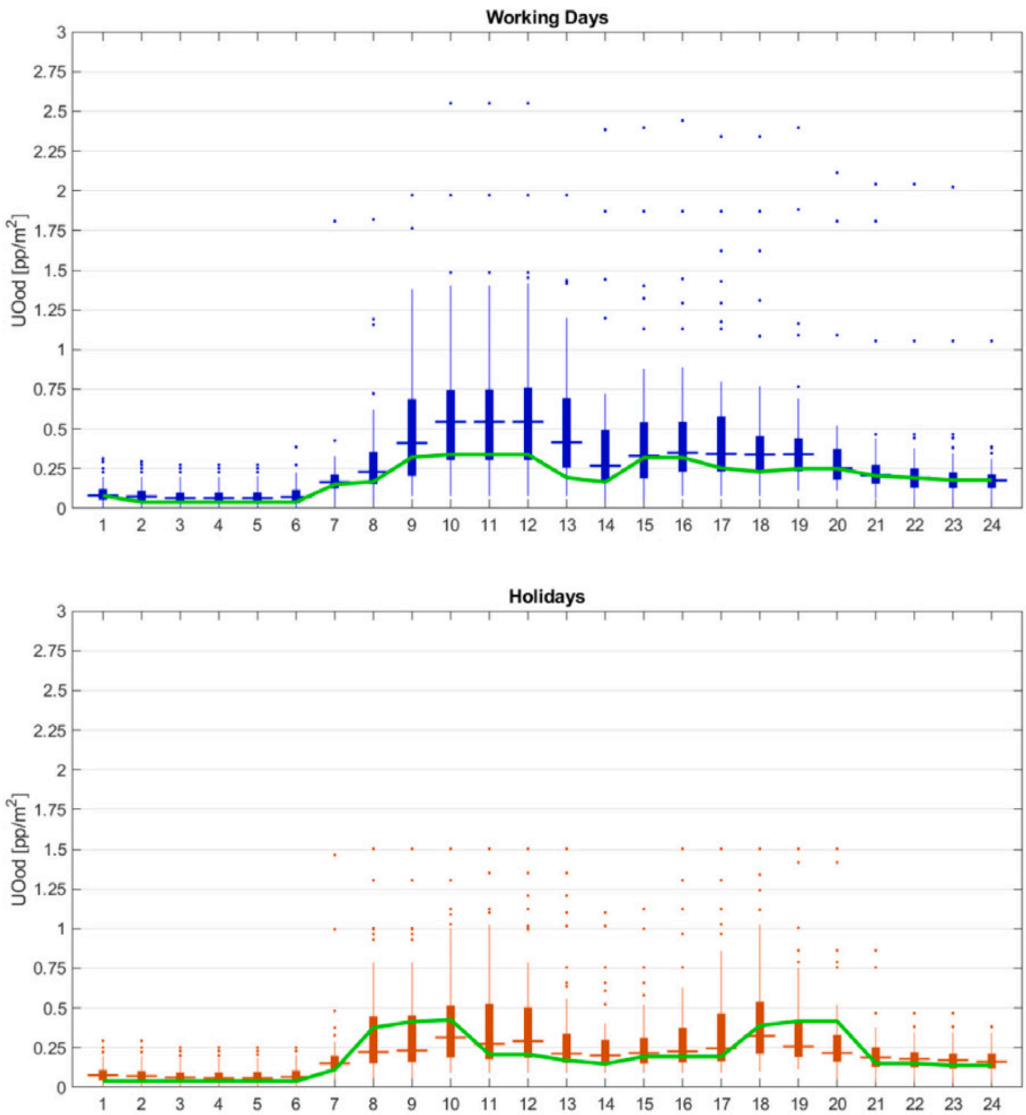

Fig. 11. UHC-related KPIs – Comparison between Piazza del Popolo in Manfredonia (in green) and the quartile-based analysis of the Users' Overall outdoor density (UOod) on working days (in blue) and holidays (in orange). Outliers are shown by the dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

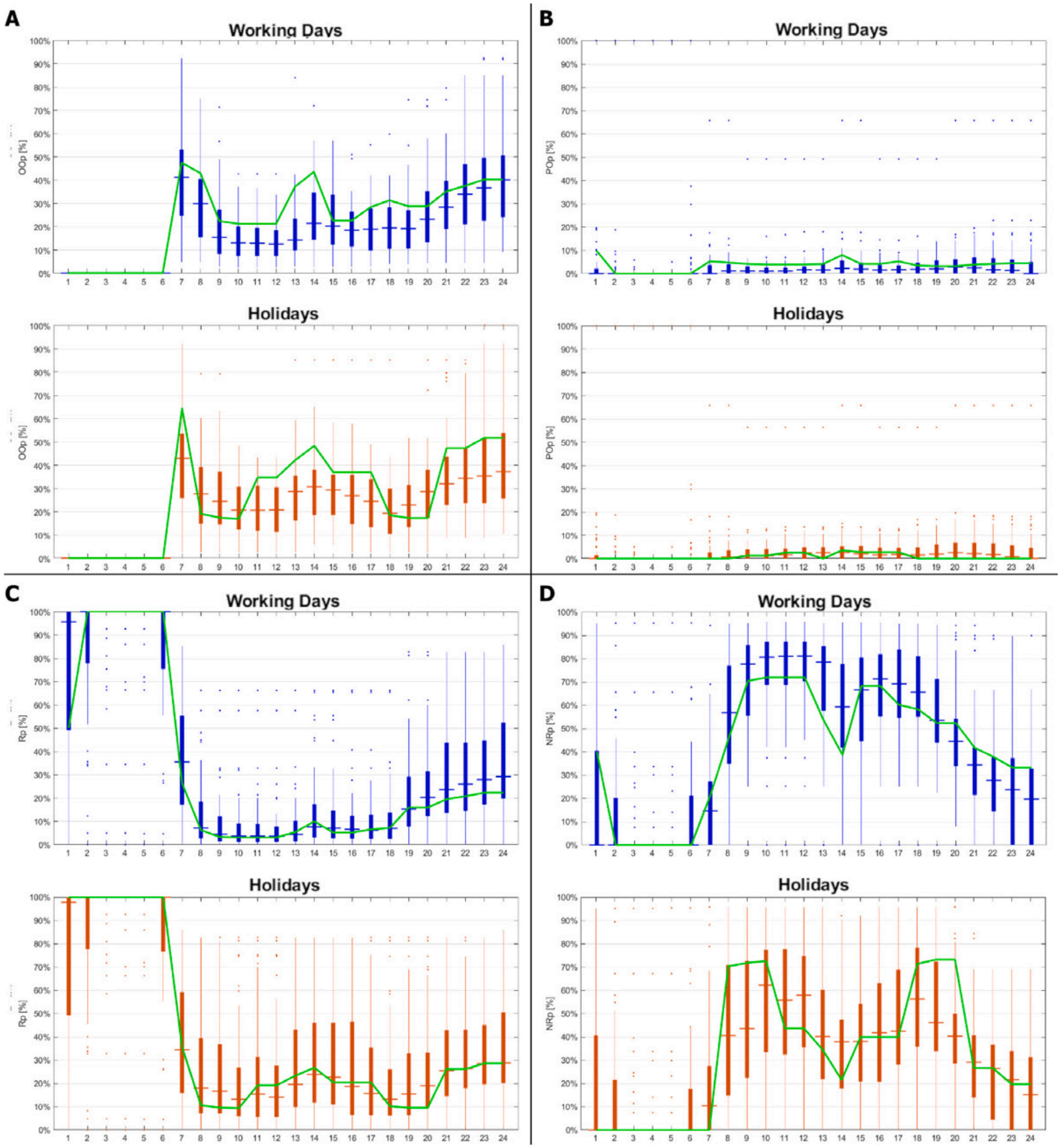

Fig. 12. UHC-related KPIs – Comparison between Piazza del Popolo in Manfredonia (in green) and the quartile-based analysis of: (A) Only Outdoor users' percentage OOp; (B) Prevalent Outdoor users percentage POp; (C) Residents users percentage Rp; (D) Non-residents percentage NRp. Working days are in blue, holidays in orange. Outliers are shown by the dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

References

Afriyanie, D., Julian, M. M., Riqqi, A., Akbar, R., Suroso, D. S. A., & Kustiwan, I. (2020). Re-framing urban green spaces planning for flood protection through socio-ecological resilience in Bandung City, Indonesia. *Cities, 101*, Article 102710. https://doi.org/10.1016/j.cities.2020.102710

Angelidou, M., Karachaliou, E., Angelidou, T., & Stylianidis, E. (2017). Cultural heritage in smart city environments. In *, 42. International archives of the photogrammetry, remote sensing and spatial information sciences - ISPRS archives*. https://doi.org/10.5194/isprs-archives-XLII-2-W5-27-2017

Angelidou, M. (2014). Smart city policies: A spatial approach. *Cities, 41*, S3–S11. https://doi.org/10.1016/j.cities.2014.06.007

Apró, D., Tóth, R., Orova, M., Kiss, I., & András Reith, D. (2016). Can smart city tools support historical cities become more resilient and regenerative?. In *32th international conference on passive and low energy architecture. - Cities, buildings, people: Towards regenerative environments*.

ARUP. (2010). Smart cities. In https://www.arup.com/perspectives/publications/research/section/smart-cities https://www.arup.com/perspectives/publications/research/section/smart-cities.

Askarizad, R., & Safari, H. (2020). The influence of social interactions on the behavioral patterns of the people in urban spaces (case study: The pedestrian zone of Rasht Municipality Square, Iran). *Cities, 101*. https://doi.org/10.1016/j.cities.2020.102687

Bernabei, L., Mochi, G., Bernardini, G., & Quagliarini, E. (2021). Seismic risk of open spaces in historic built environments: A matrix-based approach for emergency management and disaster response. *International Journal of Disaster Risk Reduction, 65*, Article 102552. https://doi.org/10.1016/j.ijdrr.2021.102552

Bernardini, G., D'orazio, M., & Quagliarini, E. (2016). Towards a "behavioural design" approach for seismic risk reduction strategies of buildings and their environment. *Safety Science, 86*. https://doi.org/10.1016/j.ssci.2016.03.010

Bloomberg, M., & Burden, A. (2006). *New York City pedestrian level of service study–phase 1*.

Booth, A., Chmutina, K., & Bosher, L. (2020). Protecting crowded places: Challenges and drivers to implementing protective security measures in the built environment. *Cities, 107*. https://doi.org/10.1016/j.cities.2020.102891

Bosina, E., & Weidmann, U. (2017). Estimating pedestrian speed using aggregated literature data. *Physica A: Statistical Mechanics and its Applications, 468*, 1–29. https://doi.org/10.1016/j.physa.2016.09.044

Buzási, A., Pálvölgyi, T., & Csete, M. S. (2021). Assessment of climate change performance of urban development projects – Case of Budapest, Hungary. *Cities*, 114. https://doi.org/10.1016/j.cities.2021.103215

Cardona, O. D., Van Aalst, M. K., Birkmann, J., Fordham, M., Mc Gregor, G., Rosa, P., Pulwarty, R. S., Schipper, E. L. F., Sinh, B. T., Décamps, H., Keim, M., Davis, I., Ebi, K. L., Lavell, A., Mechler, R., Murray, V., Pelling, M., Pohl, J., Smith, A. O., & Thomalla, F. (2012). In *, 9781107025. Determinants of risk: Exposure and vulnerability. Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change* (pp. 65–108). https://doi.org/10.1017/CBO9781139177245.005

Carmona, M. (2021). Public places urban spaces: The dimensions of urban design. In *Public places urban spaces: The dimensions of urban design*. https://doi.org/10.4324/9781315158457

Cheliotis, K. (2020). An agent-based model of public space use. *Computers, Environment and Urban Systems, 81*(December 2019), Article 101476. https://doi.org/10.1016/j.compenvurbsys.2020.101476

Cherfaoui, D., & Djelal, N. (2018). Change in use and development of public squares considering daily temporalities.: The case of emir abd El Kader Square in Algiers. *Articulo – Revue de Sciences Humaines.*. https://doi.org/10.4000/articulo.3809

Cherfaoui, D., & Djelal, N. (2019). Assessing the flexibility of public squares the case of grande poste square in Algiers. *Cities, 93*. https://doi.org/10.1016/j.cities.2019.04.017

Choi, D., Kang, M., & Yoon, J. (2021). Utility of mixed-use development by reducing aggregated travel time for multiple non-work activities: A case of Seoul, Korea. *Cities*, 109. https://doi.org/10.1016/j.cities.2020.103007

Choi, Y., Yoon, H., & Kim, D. (2019). Where do people spend their leisure time on dusty days? Application of spatiotemporal behavioral responses to particulate matter pollution. *The Annals of Regional Science, 63*(2), 317–339. https://doi.org/10.1007/s00168-019-00926-x

Coaffee, J. (2018). In *Beyond concrete barriers innovation in urban furniture and security in public space*.

Curt, C. (2021). Multirisk: What trends in recent works? – a bibliometric analysis. *Science of the Total Environment, 763*, Article 142951. https://doi.org/10.1016/j.scitotenv.2020.142951

da Silva, L. B. L., Alencar, M. H., & de Almeida, A. T. (2022). A novel spatiotemporal multi-attribute method for assessing flood risks in urban spaces under climate change and demographic scenarios. *Sustainable Cities and Society, 76*(July 2021), Article 103501. https://doi.org/10.1016/j.scs.2021.103501

Dai, Q., Zhu, X., Zhuo, L., Han, D., Liu, Z., & Zhang, S. (2020). A hazard-human coupled model (HazardCM) to assess city dynamic exposure to rainfall-triggered natural hazards. *Environmental Modelling & Software, 127*(May 2019), Article 104684. https://doi.org/10.1016/j.envsoft.2020.104684

D'Amico, A., Russo, M., Angelosanti, M., Bernardini, G., Vicari, D., Quagliarini, E., & Currà, E. (2021). Built environment typologies prone to risk: A cluster analysis of open spaces in italian cities. *Sustainability (Switzerland), 13*(16). https://doi.org/10.3390/su13169457

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction, 73*, Article 102829. https://doi.org/10.1016/j.ijdrr.2022.102829

De Lotto, R., Pietra, C., & Venco, E. M. (2019). Risk analysis: A focus on urban exposure estimation. In *Computational science and its applications – ICCSA 2019* (pp. 407–423). Cham: Springer. https://doi.org/10.1007/978-3-030-24296-1_33.

de Sá, J. P. M. (2007). *Applied statistics using SPSS*. Berlin Heidelberg: STATISTICA, MATLAB and R. Springer-Verlag.

Dibble, J., Prelorendjos, A., Romice, O., Zanella, M., Strano, E., Pagel, M., & Porta, S. (2019). On the origin of spaces: Morphometric foundations of urban form evolution. *Environment and Planning B: Urban Analytics and City Science, 46*(4), 707–730. https://doi.org/10.1177/2399808317725075

Ebrahimian Ghajari, Y., Alesheikh, A. A., Modiri, M., Hosnavi, R., Abbasi, M., & Sharifi, A. (2018). Urban vulnerability under various blast loading scenarios: Analysis using GIS-based multi-criteria decision analysis techniques. *Cities, 72*, 102–114. https://doi.org/10.1016/j.cities.2017.08.006

Engel, M. S., Paas, B., Schneider, C., Pfaffenbach, C., & Fels, J. (2018). Perceptual studies on air quality and sound through urban walks. *Cities, 83*. https://doi.org/10.1016/j.cities.2018.06.020

Federal Emergency Management Agency. (2009). *Risk management series. Handbook for rapid visual screening of buildings to evaluate terrorism risks (FEMA 455)*.

Fleischmann, M., Feliciotti, A., & Kerr, W. (2021). Evolution of urban patterns: Urban morphology as an open reproducible data science. *Geographical Analysis.* , Article gean.12302. https://doi.org/10.1111/gean.12302

Garau, C., & Annunziata, A. (2022). Public open spaces: Connecting people, squares and streets by measuring the usability through the Villanova district in Cagliari, Italy. *Transportation Research Procedia, 60*, 314–321. https://doi.org/10.1016/j.trpro.2021.12.041

García-Palomares, J. C., Salas-Olmedo, M. H., Moya-Gómez, B., Condeço-Melhorado, A., & Gutiérrez, J. (2018). City dynamics through twitter: Relationships between land use and spatiotemporal demographics. *Cities, 72*. https://doi.org/10.1016/j.cities.2017.09.007

Giuliani, F., De Falco, A., & Cutini, V. (2020). The role of urban configuration during disasters. A scenario-based methodology for the post-earthquake emergency management of Italian historic centres. *Safety Science, 127*(February), Article 104700. https://doi.org/10.1016/j.ssci.2020.104700

Hahm, Y., Yoon, H., & Choi, Y. (2019). The effect of built environments on the walking and shopping behaviors of pedestrians; A study with GPS experiment in Sinchon retail district in Seoul, South Korea. *Cities*, 89. https://doi.org/10.1016/j.cities.2019.01.020

Hassanzadeh, R. (2019). Earthquake population loss estimation using spatial modelling and survey data: The Bam earthquake, 2003, Iran. *Soil Dynamics and Earthquake Engineering, 116*, 421–435. https://doi.org/10.1016/j.soildyn.2018.09.023

Haynes, K., Coates, L., van den Honert, R., Gissing, A., Bird, D., de Oliveira, F. D., D'Arcy, R., Smith, C., & Radford, D. (2017). Exploring the circumstances surrounding flood fatalities in Australia—1900–2015 and the implications for policy and practice. *Environmental Science & Policy, 76*, 165–176. https://doi.org/10.1016/J.ENVSCI.2017.07.003

He, Q., Larkham, P., & Wu, J. (2021). Evaluating historic preservation zoning using a landscape approach. *Land Use Policy, 109*, Article 105737. https://doi.org/10.1016/j.landusepol.2021.105737

ISTAT. (2018). Popolazione residente al 1° gennaio 2018. http://dati.istat.it/Index.aspx?DataSetCode=DCIS_POPRES1.

Jia, P., Qiu, Y., & Gaughan, A. E. (2014). A fine-scale spatial population distribution on the High-resolution Gridded Population Surface and application in Alachua County, Florida. *Applied Geography*, 50. https://doi.org/10.1016/j.apgeog.2014.02.009

Jian, I. Y., Chan, E. H. W., Xu, Y., & Owusu, E. K. (2021). Inclusive public open space for all: Spatial justice with health considerations. *Habitat International, 118*, Article 102457. https://doi.org/10.1016/j.habitatint.2021.102457

Kapucu, N. (2012). Disaster and emergency management systems in urban areas. *Cities, 29*, S41–S49. https://doi.org/10.1016/j.cities.2011.11.009

Koks, E. E., Jongman, B., Husby, T. G., & Botzen, W. J. W. (2015). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *Environmental Science & Policy, 47*, 42–52. https://doi.org/10.1016/j.envsci.2014.10.013

Langenheim, N., White, M., Tapper, N., Livesley, S. J., & Ramirez-Lovering, D. (2020). Right tree, right place, right time: A visual-functional design approach to select and place trees for optimal shade benefit to commuting pedestrians. *Sustainable Cities and Society, 52*, Article 101816. https://doi.org/10.1016/j.scs.2019.101816

Li, J., Li, J., Yuan, Y., & Li, G. (2019). Spatiotemporal distribution characteristics and mechanism analysis of urban population density: A case of Xi'an, Shaanxi, China. *Cities, 86*(May 2018), 62–70. https://doi.org/10.1016/j.cities.2018.12.008

Lindberg, F., & Grimmond, C. S. B. (2011). Nature of vegetation and building morphology characteristics across a city: Influence on shadow patterns and mean radiant temperatures in London. *Urban Ecosystems, 14*(4), 617–634. https://doi.org/10.1007/s11252-011-0184-5

Loda, M., Bonati, S., & Puttilli, M. (2020). History to eat. The foodification of the historic Centre of Florence. *Cities, 103*, Article 102746. https://doi.org/10.1016/j.cities.2020.102746

Luo, J., Boriboonsomsin, K., & Barth, M. (2018). Reducing pedestrians' inhalation of traffic-related air pollution through route choices: Case study in California suburb. *Journal of Transport & Health, 10*, 111–123. https://doi.org/10.1016/j.jth.2018.06.008

Mehan, A. (2016). Investigating the role of historical public squares on promotion of citizens' quality of life. *Procedia Engineering, 161*. https://doi.org/10.1016/j.proeng.2016.08.774

Memluk, Z. M. (2013). Designing urban squares. In *Advances in landscape architecture*. InTech. https://doi.org/10.5772/55826.

Micelli, E., & Pellegrini, P. (2018). Wasting heritage. The slow abandonment of the italian historic centers. *Journal of Cultural Heritage, 31*, 180–188. https://doi.org/10.1016/j.culher.2017.11.011

Ministry of Interior (Italy). (2015). *DM 03/08/2015: Fire safety criteria (Approvazione di norme tecniche di prevenzione incendi, ai sensi dell'articolo 15 del decreto legislativo 8 marzo 2006, n. 139.)*.

Miranda, F. N., & Ferreira, T. M. (2019). A simplified approach for flood vulnerability assessment of historic sites. *Natural Hazards*, (January)https://doi.org/10.1007/s11069-018-03565-1

Mouratidis, K., & Yiannakou, A. (2021). COVID-19 and urban planning: Built environment, health, and well-being in Greek cities before and during the pandemic. *Cities*. https://doi.org/10.1016/j.cities.2021.103491

Mouroux, P., & Brun, B. L. (2006). Presentation of RISK-UE project. *Bulletin of Earthquake Engineering, 4*(4), 323–339. https://doi.org/10.1007/s10518-006-9020-3

Natanian, J., Aleksandrowicz, O., & Auer, T. (2019). A parametric approach to optimizing urban form, energy balance and environmental quality: The case of Mediterranean districts. *Applied Energy, 254*, Article 113637. https://doi.org/10.1016/j.apenergy.2019.113637

Nemeškal, J., Ouředníček, M., & Pospíšilová, L. (2020). Temporality of urban space: Daily rhythms of a typical week day in the Prague metropolitan area. *Journal of Maps, 16*(1). https://doi.org/10.1080/17445647.2019.1709577

Osman, T. (2021). A framework for cities and environmental resilience assessment of local governments. *Cities, 118*. https://doi.org/10.1016/j.cities.2021.103372

Pasquinelli, C., Trunfio, M., Bellini, N., & Rossi, S. (2022). Reimagining urban destinations: Adaptive and transformative city brand attributes and values in the pandemic crisis. *Cities, 124*, Article 103621. https://doi.org/10.1016/j.cities.2022.103621

Paukaeva, A. A., Setoguchi, T., Luchkova, V. I., Watanabe, N., & Sato, H. (2021). Impacts of the temporary urban design on the people's behavior - The case study on the winter city Khabarovsk, Russia. *Cities*, 117. https://doi.org/10.1016/j.cities.2021.103303

Pietilä, M., Neuvonen, M., Borodulin, K., Korpela, K., Sievänen, T., & Tyrväinen, L. (2015). Relationships between exposure to urban green spaces, physical activity and self-rated health. *Journal of Outdoor Recreation and Tourism, 10*. https://doi.org/10.1016/j.jort.2015.06.006

Polese, M., Di Ludovico, M., Gaetani d'Aragona, M., Prota, A., & Manfredi, G. (2020). Regional vulnerability and risk assessment accounting for local building typologies. *International Journal of Disaster Risk Reduction, 43*. https://doi.org/10.1016/j.ijdrr.2019.101400

Ponce-Lopez, R., & Ferreira, J. (2021). Identifying and characterizing popular non-work destinations by clustering cellphone and point-of-interest data. *Cities, 113*. https://doi.org/10.1016/j.cities.2021.103158

PreventionWeb - UNDRR. (2021). PreventionWeb - UNDRR. https://www.preventionweb.net/understanding-disaster-risk/component-risk/disaster-risk.

Quagliarini, E., Fatiguso, F., Lucesoli, M., Bernardini, G., & Cantatore, E. (2021). Risk reduction strategies against terrorist acts in urban built environments: Towards sustainable and human-centred challenges. *Sustainability (Switzerland), 13*(2). https://doi.org/10.3390/su13020901

Quagliarini, E., Lucesoli, M., & Bernardini, G. (2021). How to create seismic risk scenarios in historic built environment using rapid data collection and managing. *Journal of Cultural Heritage, 48*, 93–105. https://doi.org/10.1016/j.culher.2020.12.007

Rousseeuw, P. J., & Hubert, M. (2011). Robust statistics for outlier detection. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 1*(1), 73–79. https://doi.org/10.1002/widm.2

Russo, M., Angelosanti, M., Bernardini, G., Cantatore, E., D'Amico, A., Currà, E., Fatiguso, F., Mochi, G., & Quagliarini, E. (2021). Morphological systems of open spaces in built environment prone to sudden-onset disasters. In J. Littlewood, R. J. Howlett, & L. C. Jain (Eds.), *Sustainability in energy and buildings 2020 (part of the smart innovation, systems and technologies book series - SIST, volume 203 - ISSN: 2190-3018)* (pp. 321–331). Singapore: Springer. https://doi.org/10.1007/978-981-15-8783-2_27.

Santos, C., Ferreira, T. M., Vicente, R., & Mendes da Silva, J. A. R. (2013). Building typologies identification to support risk mitigation at the urban scale - Case study of the old city centre of Seixal, Portugal. *Journal of Cultural Heritage, 14*(6), 449–463. https://doi.org/10.1016/j.culher.2012.11.001

Santos, M. M., Lanzinha, J. C. G., & Ferreira, A. V. (2021). Review on urbanism and climate change. *Cities, 114*. https://doi.org/10.1016/j.cities.2021.103176

Sharifi, A. (2019a). Resilient urban forms: A review of literature on streets and street networks. *Building and Environment, 147*(July 2018), 171–187. https://doi.org/10.1016/j.buildenv.2018.09.040

Sharifi, A. (2019b). Urban form resilience: A meso-scale analysis. *Cities, 93*, 238–252. https://doi.org/10.1016/j.cities.2019.05.010

Song, J., Chang, Z., Li, W., Feng, Z., Wu, J., Cao, Q., & Liu, J. (2019). Resilience-vulnerability balance to urban flooding: A case study in a densely populated coastal city in China. *Cities, 95*, Article 102381. https://doi.org/10.1016/j.cities.2019.06.012

UNDRR. (2016). *A/RES/71/276 Report of the open-ended intergovernmental expert working group on indicators and terminology relating to disaster risk reduction*.

UNDRR. (2021). In *Global Natural Disaster Assessment report 2020. UN annual report, October* (pp. 1–80).

Villagràn De León, J. C. (2006). Vulnerability: A conceptual and methodological review. In *Source - Studies of the university: Research, counsel, education (Issue 4)*.

Wei, B., Nie, G., Su, G., & Guo, X. (2022). Risk assessment of people trapped in earthquake disasters based on a single building: A case study in Xichang city, Sichuan Province, China. *Geomatics, Natural Hazards and Risk, 13*(1), 167–192. https://doi.org/10.1080/19475705.2021.2017358

WHO. (2016). *Ambient air pollution: A global assesment of exposure and burden of desease*.

Woo, G. (2015). Understanding the principles of terrorism risk modeling from Charlie hebdo attack in Paris. *Defence Against Terrorism Review-DATR, 7*(1), 1–11.

Yang, L., Hoffmann, P., Scheffran, J., Rühe, S., Fischereit, J., & Gasser, I. (2018). An agent-based modeling framework for simulating human exposure to environmental stresses in urban areas. *Urban Science, 2*(2), 36. https://doi.org/10.3390/urbansci2020036

Yao, Y., Zhang, Y., Yao, T., Wong, K., Tsou, J. Y., & Zhang, Y. (2021). A GIS-based system for spatial-temporal availability evaluation of the open spaces used as emergency shelters: The case of Victoria, British Columbia, Canada. *ISPRS International Journal of Geo-Information, 10*(2), 63. https://doi.org/10.3390/ijgi10020063

Yıldız, B., & Çağdaş, G. (2020). Fuzzy logic in agent-based modeling of user movement in urban space: Definition and application to a case study of a square. *Building and Environment, 169*, Article 106597. https://doi.org/10.1016/j.buildenv.2019.106597

Zakariya, K., Harun, N. Z., & Mansor, M. (2014). Spatial characteristics of Urban Square and sociability: A review of the City Square, Melbourne. *Procedia - Social and Behavioral Sciences, 153*. https://doi.org/10.1016/j.sbspro.2014.10.099

Zucker, P. (2003). The square in space and time. In *Time-saver standards for urban design*. McGraw-Hill Education. https://www.accessengineeringlibrary.com/content/book/9780070685079/chapter/chapter14.