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Exploring the effect of COVID-19 pandemic lockdowns on urban cooling: A tale of three cities

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Abstract

COVID-19 pandemic has had a major impact on our society, environment and public health, in both positive and negative ways. The main aim of this study is to monitor the effect of COVID-19 pandemic lockdowns on urban cooling. To do so, satellite images of Landsat 8 for Milan and Rome in Italy, and Wuhan in China were used to look at pre-lockdown and during the lockdown. First, the surface biophysical characteristics for the pre-lockdown and within-lockdown dates of COVID-19 were calculated. Then, the land surface temperature (LST) retrieved from Landsat thermal data was normalized based on cold pixels LST and statistical parameters of normalized LST (NLST) were calculated. Thereafter, the correlation coefficient (r) between the NLST and index-based built-up index (IBI) was estimated. Finally, the surface urban heat island intensity (SUHII) of different cities on the lockdown and pre-lockdown periods was compared with each other. The mean NLST of built-up lands in Milan (from 7.71 °C to 2.32 °C), Rome (from 5.05 °C to 3.54 °C) and Wuhan (from 3.57 °C to 1.77 °C) decreased during the lockdown dates compared to pre-lockdown dates. The r (absolute value) between NLST and IBI for Milan, Rome and Wuhan decreased from 0.43, 0.41 and 0.16 in the pre-lockdown dates to 0.25, 0.24, and 0.12 during lock-down dates respectively, which shows a large decrease for all cities. Analysis of SUHII for these cities showed that SUHII during the lockdown dates compared to pre-lockdown dates decreased by 0.89 °C, 1.78 °C, and 1.07 °C respectively. The results indicated a high and substantial impact of anthropogenic activities and anthropogenic heat flux (AHF) on the SUHII due to the substantial reduction of huge anthropogenic pressure in cities. Our conclusions draw attention to the contribution of COVID-19 lockdowns (reducing the anthropogenic activities) to creating cooler cities.

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Keywords: COVID-19; Lockdown; Surface urban heat island intensity; Anthropogenic heat flux; Cool cities; Remote sensing

1. Introduction

The world’s urban population has been increasing rapidly and official forecasts suggest that the urban population will reach about 70 per cent of the world’s population by 2050 (United Nations, 2018; X. Wang et al.,

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Urbanization not only increases urban energy consumption, but also impacts the urban landscape changing significantly by converting land cover from green cover to grey cover, i.e., impervious surfaces cover (ISC) (Yu et al., 2014; Silva et al., 2018; Yu et al., 2019; Zou et al., 2021). Another side-effect of urbanization is the excessive heat release due to human activities, which has a major role in the formation and increase in surface urban heat island intensity (SUHI) (Firozjai et al., 2018; Zhou and Chen, 2018; Fahed et al., 2020; Liu et al., 2020; Nadizadeh Shorabeh et al., 2020; Yuan et al., 2020a; Tepanosyan et al., 2021).

Anthropogenic heat flux (AHF) is the heat released into the atmosphere by human activities, which is regarded as one of the products of urbanization. Sources of AHF include the cooling and heating of buildings, vehicle traffic, industrial processes, human metabolism and road and non-road transport (Sailor and Vastrieddy, 2006; Allen et al., 2011; Chen and Hu, 2017; Chrysoulakis et al., 2017; Chen et al., 2019; Chen et al., 2020; Li et al., 2020). Urbanization and AHF interact with each other (Firozjai et al., 2020c). For example, population growth, the expansion of built-up lands and increased energy consumption lead to increased AHFs (Wong et al., 2015).

In contrast, AHF has a significant negative effect on urban living quality, thermal comfort, energy consumption, microclimate change in the urban environment and, ultimately, the quality of human life (Zhu et al., 2007; Van Hove et al., 2015; Xie et al., 2016; Nie et al., 2017; Mijani et al., 2019; Mijani et al., 2020). For example, AHF is one of the main contributors to the formation and increase of SUHI (Fan and Sailor, 2005; Argüeso et al., 2014; Zheng and Weng, 2018; Firozjai et al., 2020b; Yuan et al., 2020a). Also, anthropogenic activities influence the urban thermal environment by changing both latent and sensible heat fluxes (Nie et al., 2014; Zhao et al., 2016). Understanding and mastering AHF and its spatial and temporal changes is very important to understand and represent the effects of urbanization on human society and the environment (S. Wang et al., 2020).

Coronavirus disease 2019 (COVID-19) is an infectious disease induced by the SARS-CoV-2 virus, which has impacted global health and the economy, among others (Gorbalenya et al., 2020; Lai et al., 2020). The outbreak of COVID-19 was first reported in Wuhan on December 29, 2019 (Huang et al., 2020; Zhu et al., 2020) and spread rapidly around the world (Acter et al., 2020; JHU, 2020). The world health organization (WHO) declared COVID-19 a public health emergency with a pandemic spread on March 11, 2020 (McKay et al., 2020; Nakada and Urban, 2020; WHO, 2020b).

As of July 01, 2022, there have been 545,226,550 confirmed cases of COVID-19 globally, including 6,334,728 deaths reported to the WHO (WHO, 2022a). As the number of cases increases, most countries developed and reinforced some local and regional precautions to prevent outbreaks of COVID-19, including lockdowns, limited mobility and restricting public events, encouraging secure social/physical distancing, closing non-essential businesses, schools and universities, closing external borders and significantly reducing vehicle traffic, such as trains, buses and air travel (Saadat et al., 2020; Siciliano et al., 2020). These regulations and precautions have led to less damaging pressure on the environment as studies have shown (Mandal and Pal, 2020).

While the outbreak of COVID-19 pandemic and the subsequent lockdowns arising from it have had a major negative effect on the conditions of economy, the environmental components have been slightly relieved of the great anthropogenic activities pressures, such as vehicle traffic, heat generation and large emissions of various pollutants (Chen et al., 2021; Firozjai et al., 2021; Mahato et al., 2020; Wu et al., 2021a; Wu et al., 2020). Some studies have examined the impact of COVID-19 pandemic lockdowns on urban environmental conditions. Nakada and Urban (2020) analyzed the effects of COVID-19 on quality of air during lockdown in the São Paulo state. Air quality data derived from the ground stations and S5p/TROPOMI data were used to investigate changes in air pollutant concentrations during the COVID-19 pandemic lockdown. Generally, strong reductions in nitrogen dioxide (NO2), nitrogen monoxide (NO) and carbon monoxide (CO) up to 70, 54.3 and 64.8 per cent, respectively were observed in urban regions. In contrast, an increase of about 30 per cent in ozone concentration was observed in urban regions that could be possibly due to a reduce in CO.

Tobías et al. (2020) studied changes in air pollution levels during the COVID-19 pandemic lockdown in Barcelona. In this study, traffic, urban background station data and S5p/TROPOMI remote sensing data were used. Data related to particulate matter of 10 µm or less diameter (PM10), NO2, ozone (O3), black carbon (BC) and sulfur dioxide (SO2) was collected. The daily average for the pre-lockdown and during lockdown periods was calculated and the change in the mean concentration and the relative change between the two periods were evaluated. The findings indicated that during the COVID-19 pandemic lockdowns, urban air pollution decreased substantially, and the most significant reductions were observed for NO2 and BC.

Mandal and Pal (2020) evaluated the effect of COVID-19 pandemic lockdowns on the environmental components including PM10, river water quality and noise in the middle catchment of Eastern India. In their study, remote sensing and field observation data were applied to calculate the environmental components in pre and during lockdown periods. The results indicated that the Maximum PM10 concentration from 189 to 278 µg.m⁻³ in the pre-lockdown period reduced to ranges from 50 to 60 µg.m⁻³ in the lockdown period. Also, the noise level was reduced from 85 to 65dBA and the quality of water improved. Firozjai et al. (2021) studied effect of the COVID-19 pandemic lockdown on Land Urban Surface Ecological Status (USES). The results of their study showed that the lock-
down had a major effect on the improving LUSES. Wu et al. (2021b) investigated the traffic density changes resulting from COVID-19 pandemic lockdowns using remote sensing data in cities across the world. Their findings demonstrated that traffic density decreased by an average of approximately 50% in the selected cities after lockdown.

The results of pervious researches prove that the lockdown during COVID-19 pandemic had a major effect on the environmental conditions of urban areas as well as improving air quality across global cities. The focus of these studies has been on the spatial and temporal variations of air pollution. However, one of the important factors affecting the creating cooler cities and the quality of human life in the urban environment is the SUHI (Steeneveld et al., 2011; Huang et al., 2016; Shen et al., 2016; Sejati et al., 2019). Therefore, the unprecedented reduction of human activities in the framework of the COVID-19 lockdown restriction measures has provided a good opportunity to realize the negative effects of AHF on the environment in cities and in particular the impact of COVID-19 on SUHI. Hence, this study aims to explore the effect of COVID-19 pandemic lockdowns on urban cooling.

2. Study area

In this study, three cities, Milan and Rome in Italy, and Wuhan in China were selected to assess the effect of COVID-19 pandemic lockdowns on the SUHI (Fig. 1). Since the emergence of COVID-19, Milan, Rome and Wuhan have been hotspots for COVID-19 infection/mortality. As of July 01, 2022, more than 1,004,434, 1,280,961, and 50,340 confirmed cases of COVID-19 in Milan, Rome and Wuhan, respectively were reported (WHO, 2022a), causing numerous infections, morbidity, and deaths. Most countries adopted lockdown measures to prevent outbreaks of COVID-19 due to the increased number of cases. Such restrictive measures were fully implemented from January 23 until April 8, 2020 (during the lockdown) in Wuhan, while in Rome and Milan, the lockdown measures were implemented from March 10 until April 18, 2020. The lockdown policies in Italy and China halted impactful human activities, such as industrial manufacturing, transport and consumption of energy for more than one month. The cities of Milan, Rome and Wuhan were among the first cities to be most affected by COVID-19, and lockdown restriction measures were implemented with more severely in these cities, so in this study, these cities were selected.

Wuhan is the capital of Hubei Province, with about 8.8 million population and overall area of 1,530 km². Wuhan is located between 29° 58’ and 31° 22’ N latitude and between 113° 41’ and 115° 05’ E longitude. Wuhan is the most populous city in central China and the ninth most populous city in China. Wuhan is the hub of finance, politics, economics, commerce and a key centre for industry and transport in central China. The annual mean air temperature and rainfall are 17.1 °C and 1,320 mm respectively. Wuhan is an industrial city and due to the vastness of the public transportation network in this city, it is the main centre of transportation with many railways, roads and highways that pass through the city and connect to the important cities in China.

Rome is the capital and the largest city in Italy, with 2.9 million inhabitants and it covers an total area of about 1,285 km², situated at latitude 41°53’ N and longitude 12°28’ E. It has an annual mean air temperature and rainfall 15.7 °C and 798 mm respectively.

Milan is located at 45° 28’ northern and 9° 13’ eastern and is a large industrial and agricultural area in northern Italy. Considering total area of the metropolis of Milan, it has a population of about 3.1 million.

Based on the Köppen-Geiger climate classification, Milan and Rome have Humid subtropical (Cfa) and Hot-summer Mediterranean (Csa) climates, respectively. While, Wuhan has a Humid subtropical (Cfa) climate (Rubel and Kottke, 2010).

3. Data and methods

3.1. Data and pre-processing

The analysis presented in this study is based on the reflective (OLI) and thermal (TIRS) Sensors Level 1 Terrain (Corrected) (L1T) data of the Landsat 8 satellite obtained from the United States Geological Survey (USGS). Landsat imagery were selected in such a way that seasonal conditions of the dates are close to each other. Also, climatic conditions (including relative humidity, air temperature, solar radiation and rainfall) and cloud cover at satellite overpass time have been considered in selected cities. According to these criteria, 12 images were selected. The data sets used for the cities of Milan, Rome and Wuhan were obtained for lockdown and pre-lockdown periods (see Table 1).

In the present study, the dates of T1, T2, T3 and T4 were used in order to identify the periods of pre-lockdown and lockdown, for a rapid comparison. For each of these cities, the seasonal and climatic conditions of the dates T4 and T2 as well as T3 and T1 are close to each other. Also, the difference in climatic and seasonal conditions of T4 and T3 dates are almost similar to the difference between T2 and T1, which are compared with each other. The dates of T1, T2 and T3 were taken into account as a representative of pre-lockdown time. It is also worth mentioning that the dates of T1, T2 and T3 indicative same time as pre-lockdown in previous year, same time as lockdown in previous year, and right before lockdown, respectively (see Table 1 and Fig. 2). The chosen date of T4 have been identified as indicative of ongoing lockdown periods, since the implementation of stringent measures that have forced the closure of almost all industrial and production activities and therefore a limitation of transport and movements.
L1T data of the Landsat 8 satellite contains nine reflective bands with 30 m spatial resolution (the resolution for panchromatic band is 15 m), and two thermal infrared (TIR) bands (thermal bands) with 100 m spatial resolution. The 100 m TIRS bands are resampled before distribution by cubic convolution to 30 m to match multispectral bands (for final users) (Roy et al., 2014; United States Geological Survey, 2015).

The images used in this study (L1T data of the Landsat 8 satellite) are geo-registration based on image-to-image method with RMSE less than 12 m (Irons et al., 2012; Storey et al., 2014; H Nguyen et al., 2020). Landsat 8 reflec-
Fig. 2. Conceptual framework of the study. Note: SVM: Support vector machine; SC: Single-channel; IBI: Index-based built-up index; LST: Land surface temperature; VHI: Vegetative health index; NLST: Normalized land surface temperature; r: Correlation coefficient; SUHI: Surface urban heat island.
tive bands were corrected atmospherically and converted to at-surface reflectance using the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) model (Adler-Golden et al., 1999; Cooley et al., 2002). Additionally, the Landsat 8 thermal band 10 was pre-processed and used for land surface temperature (LST) computation. In addition to the Landsat satellite imagery, the moderate resolution imaging spectroradiometer (MODIS)/Terra water vapor product (MOD07_L2) was utilized to generate LST from Landsat thermal data (Table 1). MODIS products were downloaded and used by LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov).

3.2. Methods

In this study, in order to investigate and evaluate the effect of COVID-19 pandemic lockdowns on the LST and the SUHII, the conceptual model showed in Fig. 2 has been used. In the first step, the surface biophysical characteristics, including index-based built-up index (IBI), LST and normalized difference vegetation index (NDVI) were estimated at different dates (Fig. 2), and land cover was classified using support vector machine (SVM). In the second step, in order to normalize the effect of climate conditions on LST, the LST of cold pixels was calculated and the LST obtained from satellite images were normalized at each date based on LST cold pixels. In the third step, the standard deviation and mean of the normalized LST (NLST) for different dates in the whole area and land cover scales were calculated and compared. In the fourth step, the correlation coefficient (r) between the NLST and the ISC for the pre-lockdown and lockdown dates was estimated and compared. Finally, the SUHII of different cities on the pre-lockdown and lockdown dates was calculated and compared with each other.

3.2.1. Modelling surface biophysical characteristics and land cover classification

In this study, the surface characteristics, including NDVI, IBI and LST were calculated. To calculate the LST using satellite images, it is necessary to consider the amounts of spectral radiance and brightness temperature recorded by the sensor at thermal infrared wavelengths, atmospheric effects and the land surface emissivity (LSE). In this study, the single-channel (SC) model (Jiménez-Munoz and Sobrino, 2003; Jiménez-Munoz et al., 2008) is used to calculate the LST (Eq. (1)).

\[
LST = \gamma \left( \frac{1}{LSE} \left( \psi_1 L_{\text{sen}} + \psi_2 \right) + \psi_3 \right) + \delta \quad (1)
\]

where \( L_{\text{sen}} \) is the radiance of top-of-atmosphere (TOA) (\( W(m^2 \text{sr} \mu m) \)), \( \delta \) and \( \gamma \) are parameters related to Planck’s function, and \( \psi_1, \psi_2 \) and \( \psi_3 \) are atmospheric functions. To calculate the atmospheric functions, the amount of water vapor in the atmosphere \( (\frac{e}{p}) \) obtained from MOD07 was used. In this study, the LSE has been calculated using the threshold for NDVI values (Sobrino et al., 2008; Li et al., 2016).

IBI is used to model spatial variation of ISC. The IBI is a combination of thematic index-derived bands including Red, Green, near-infrared (NIR) and shortwave-infrared (SWIR) to impervious surfaces computation. The IBI was calculated using Eq. (2) (Xu, 2008).

\[
IBI = \left( \frac{2 \text{SWIR1} - \text{NIR}}{\text{SWIR1} + \text{NIR} + \text{Red}} \right) + \left( \frac{\text{Green}}{\text{Green} + \text{SWIR1}} \right) + \left( \frac{\text{NIR}}{\text{NIR} + \text{Red}} \right) - \left( \frac{\text{Green}}{\text{Green} + \text{SWIR1}} \right) \quad (2)
\]

Where SWIR1, NIR, Red and Green are the reflections in the short-wave infrared, near-infrared, red and green bands respectively. The IBI index ranges from \(-1\) to \(+1\), wherein positive values indicate the built-up lands, while negative values indicate vegetation cover and water body.

The land cover types in the study area include built-up, vegetation cover and agricultural, water body and bare lands. In this study, the accuracy of different methods including minimum distance classification (MDC), parallelepiped classification (PC), maximum likelihood classification (MLC) and SVM for land cover classification of Milan, Rome and Wuhan were compared. The results showed that for these cities, the efficiency of SVM in land cover classification is higher than other methods. Therefore, in this study, the SVM algorithm is used for image classification (Mountrakis et al., 2011; Maulik and Chakraborty, 2017). This algorithm is a supervised machine learning algorithm and the most common method for classification. This algorithm is one of the known non-parametric classifications that is used for supervised classification. Therefore, ground data is needed to classify land cover based on this method (Strahler, 1980; Otukei and Blaschke, 2010). As per the image classification, the training data was prepared for four land cover classes using visual interpretation of Landsat false colour composite images and Google Earth archive images. Finally, for classification accuracy assessment, the overall accuracy and kappa coefficient have been calculated based on the error matrix.

3.2.2. LST normalization

As 12 images acquired from different years were employed in the study, direct comparison and analysis of LST from one image to another would not be appropriate due to interannual and seasonal variability (Weng et al., 2011; Firozjaei et al., 2018; Firozjaei et al., 2019a; Weng et al., 2019b; Firozjaei et al., 2020c). Therefore, in order for the impact of human activities on LST on different dates to be comparable, LST values obtained from satellite images were normalized. For this purpose, (1) cold pixels including full and healthy vegetation cover and agricultural were extracted (Bastiaanssen et al., 1998; Allen et al., 2002),
(2) The mean LST was calculated for cold pixels. LST for these pixels indicate the effect of climate conditions on the study area LST. (3) The study area LST were normalized relative to the climate conditions, according to Eq. (3).

\[
\text{NLST} = \text{LST} - \text{LST}_{\text{Cold pixel}}
\]  

(3)

Where NLST is normalized LST relative to climatic conditions, LST represents LST obtained from satellite images, and LST\(_{\text{Cold pixel}}\) is the mean LST of cold pixels.

The concept of cold pixels is first introduced in the SEBAL. The surface temperature in the cold pixel is equal to the air temperature (Bastiaanssen et al., 1998; Allen et al., 2002). A cold pixel is not necessarily the coldest pixel. This is a relative concept. Pixel with the healthy and un-stressed vegetation cover is called cold pixels. Vegetation health index (VHI) has been used to determine cold pixels. It is useful to consider the amount of xanthophyll, nitrogen and chlorophyll to quantify the vegetation cover health status (Yang et al., 2020). Therefore, to consider these parameters related to vegetation cover health status, normalized difference senescent vegetation index (NDSVI) (Qi et al., 2002), nitrogen reflectance index (NRI) (Bausch and Duke, 1996), and NDVI indices were used. The information from these three indicators were combined based on the principal component analysis (PCA) method presented in (Abdi and Williams, 2010), and VHI was calculated. The first component of PCA (PC1) standardized between 0 and 1 indicates VHI. Pixels with VHI values greater than 0.9 were selected as cold pixels. The VHI is defined as follows (Eqs. (4)-(6)):

\[
\text{NRI} = \frac{\text{NIR}}{\text{Green}}
\]  

(4)

\[
\text{NDSVI} = \frac{\text{SWIR1} - \text{Green}}{\text{SWIR1} + \text{Green}}
\]  

(5)

\[
\text{VHI} = \frac{(\text{PC1} - \text{PC1}_{\text{min}})}{\text{PC1}_{\text{max}} - \text{PC1}_{\text{min}}}
\]  

(6)

3.2.3. The effect of COVID-19 pandemic lockdown on the LST and SUHI

The following steps were taken in order to explore the effect of COVID-19 pandemic lockdowns on SUHI:

1. The statistical parameters of LST and NLST of different cities at the pre and during lockdown periods were estimated and compared for the whole area, as well as per each land cover class.

2. The mean difference of the NLST of different cities on the pre-lockdown and lockdown dates were estimated and compared at the land cover classes scales and whole study area. Due to the characteristics of the groups studied in this study, including the difference in the number of samples in each group, this method has been selected for a significant comparison of the differences between the groups.

3. In this study, the r between the ISC and the NLST was calculated and evaluated for modeling the degree of impact of human activity on spatial changes in LST on the pre-lockdown and lockdown dates in different cities.

4. The SUHII of different cities in the COVID-19 pre-lockdown and during lockdown periods were estimated and compared on the pre-lockdown and lockdown dates. SUHII indicates the difference in LST between the urban areas and the surrounding rural areas (Oke, 1982; Voogt and Oke, 2003; Li et al., 2019). In this study, the impervious surface distribution density (ISDD) algorithm was adopted to determine urban and surrounding rural areas. The details of this algorithm are given in Meng et al. (2018). SUHII on each date is calculated with the Eq. (7):

\[
\text{SUHII} = \text{Mean LST}_{\text{urban}} - \text{Mean LST}_{\text{rural}}
\]  

(7)

4. Results

It became evident from our results that the spatial and temporal distribution of LST in Wuhan, Rome and Milan is heterogeneous for different dates (Fig. 3). Visual inspection indicate that the LST of built-up lands exceed that of the remaining land cover classes. LST changed during COVID-19 lockdown in 2020 (T4) compared to the similar dates in 2018 (T2). Many regions with high values of LST on MT2 (Apr 18, 2018 (Milan)), RT2 (Apr 20, 2018 (Rome), and WT2 (Mar 23, 2018 (Wuhan)) became regions with low and medium LST on MT4 (Apr 14, 2020 (Milan)), RT4 (Apr 09, 2020 (Rome)) and WT4 (Feb 09, 2020 (Wuhan)).

The mean LST values of Milan, Rome and Wuhan vary across different dates. At a comparable date to lockdown in 2018 (T2), the lowest and highest mean LST values were observed in Wuhan (20.01 °C) and Rome (29.50 °C). The highest mean LST during lockdown dates was observed in Milan with 31.28 °C, while the lowest mean was 13.41 °C in Wuhan. In 2020, the mean LST until the start of the lockdown (T3) in Milan, Rome and Wuhan were 12.69 °C, 16.25 °C and 13.15 °C respectively, while these values during the lockdown (T4) were 31.28 and 26.79 °C in Milan and Rome respectively (i.e., increasing) and 13.41 °C in Wuhan (i.e., decreasing).

The changes of mean LST observed during the lockdown and similar periods in the past in the Wuhan were declining (up to −6.6 °C) and greater than in Milan and Rome. However, its value was high in Rome (up to −2.71 °C), but in Milan, significant changes was not observed (2.51 °C). The standard deviation of LST values at a similar time to lockdown in 2018 (T2) is 2.21 °C and 13.41 °C in Milan and Rome respectively (Table 2).

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The land cover and IBI maps of the cities under study are shown in Fig. 4. The Kappa coefficient of land cover maps (overall accuracy) prepared for the Milan, Rome, and Wuhan are shown in Table 2.
and Wuhan were 93 (0.91), 91 (0.90) and 89 (0.88), respectively. The area of built-up land for the cities of Milan, Rome, and Wuhan is 121.6, 222.7 and 760.2 km², respectively. Moreover, the mean IBI of these three cities is 0.61, 0.48 and 0.54 respectively.

The mean LST values of Milan, Rome and Wuhan vary across different land covers. The mean LST of built-up lands (bare lands) at the same time as lockdown in 2018 (T2), 30.30 °C (27.55 °C) in Milan, 32.07 °C (30.34 °C) in Rome and 22.21 °C (22.35 °C) in Wuhan, in which the mean LST of built-up lands is more than bare lands (Milan and Rome) and there was a slight difference in the Wuhan (Table 3). During the lockdown (T4), the mean LST of built-up lands (bare lands) for the Milan, Rome and Wuhan is 32.23 °C (36.47 °C), 28.22 °C (27.56 °C) and 14.31 °C (15.21 °C) respectively. The mean LST value of bare lands is higher than built-up lands, and a sharp decrease was observed during the lockdown (T4) compared to a similar date in 2018 (T3).

Compared with a regular day (the same time as lockdown in 2018 (T2)), the mean LST of built-up lands in the Rome and Wuhan during the lockdown decreased by 3.85 °C and 7.9 °C respectively. The results given in Table 3 indicate that the for Milan, the average LST of bare lands during the lockdown (T4) increased by about 9 °C compared to a comparable date in 2018 (T2), while the average LST of built-up lands under these conditions increased by approximately 2 °C. The lowest average LST values at different dates are for water bodies and vegetation cover and agricultural respectively.

The mean LST pixels with full and healthy vegetation cover and agricultural (cold pixels) for Milan, Rome and Wuhan during the lockdown dates (T4) are 29.9 °C, 24.01 °C and 13.41 °C respectively. Also, at a comparable date in 2018 (T2), these values are 22.59 °C for Milan, 25.28 °C for Rome and 18.78 °C for Wuhan (Fig. 5). LST changes of cold pixels at different dates indicate changes of climate conditions. Hence, the LST of the cold pixel in these cities during the lockdown (T4) and comparable date in 2018 (T2) is higher than the other dates (T3 and T1).

The mean NLST of Wuhan, Rome and Milan during the lockdown (T4) is −0.02 °C, 0.77 °C and 1.37 °C respec-
tively, while on a comparable date to lockdown in 2018 (T2), it was 1.45 °C, 1.50 °C and 6.17 °C (in Wuhan, Rome and Milan respectively). On all dates, the mean NLST of built-up is higher than the mean NLST in the whole area scale. On April 18, 2018, the difference between the mean NLST of built-up and bare lands for the Milan was 2.76 °C, which on April 14, 2020 reached –3.68 °C. Compared to the same date in 2018 (T2), mean NLST of the built-up lands during the lockdown period (T4) has decreased significantly. These results clearly indicate that

|        | MT1     | MT2     | MT3     | MT4     |
|--------|---------|---------|---------|---------|
| **Milan** |         |         |         |         |
| Vegetation cover and agricultural | 9.25 (0.72) | 26.56 (1.77) | 12.56 (0.93) | 29.37 (1.95) |
| Built-up | 9.56 (1.03) | 30.30 (1.29) | 12.77 (1.09) | 32.23 (1.58) |
| Bare land | 9.84 (0.60) | 27.55 (1.07) | 13.29 (0.41) | 36.47 (1.67) |
| Water body | 7.44 (0.60) | 22.91 (1.47) | 9.56 (0.90) | 23.69 (2.23) |
| **Rome** |         |         |         |         |
| Vegetation cover and agricultural | 9.21 (1.15) | 26.79 (1.50) | 15.56 (1.28) | 24.79 (1.58) |
| Built-up | 9.91 (1.21) | 32.07 (1.70) | 16.35 (1.40) | 28.22 (1.71) |
| Bare land | 9.86 (1.53) | 30.34 (2.37) | 17.21 (1.77) | 27.56 (1.77) |
| Water body | 9.42 (0.70) | 24.63 (1.69) | 14.41 (0.98) | 22.17 (1.47) |
| **Wuhan** |         |         |         |         |
| Vegetation cover and agricultural | 8.51 (0.89) | 20.23 (1.71) | 13.03 (0.78) | 13.40 (1.02) |
| Built-up | 9.34 (1.67) | 22.21 (2.61) | 13.86 (1.54) | 14.31 (1.93) |
| Bare land | 9.82 (1.22) | 22.35 (1.83) | 14.60 (1.72) | 15.21 (1.72) |
| Water body | 7.33 (0.39) | 18.61 (3.37) | 11.93 (0.98) | 10.52 (0.08) |
Fig. 5. Cold pixel LST value for the Milan, Rome and Wuhan on different dates (°C).

Table 4
Mean NLST for the whole area and land covers in the Milan, Rome and Wuhan at different dates (°C).

|       | Milan | Rome | Wuhan |
|-------|-------|------|-------|
|       | Study area | MT1 | MT2 | MT3 | MT4 | Study area | RT1 | RT2 | RT3 | RT4 | Study area | WT1 | WT2 | WT3 | WT4 |
|       | Vegetation cover and agricultural | 1.52 | 6.17 | 0.13 | 1.37 | 0.02 | 1.50 | 0.18 | 0.77 | 0.72 | 1.50 | 0.18 | 0.77 |
|       | Built-up | 1.63 | 7.71 | 0.21 | 2.32 | 0.67 | 5.05 | 1.82 | 3.54 | 0.23 | 0.65 | 0.96 | 1.84 |
|       | Bare land | 1.91 | 4.95 | 0.73 | 6.56 | 0.23 | 1.50 | 0.18 | 0.77 | 0.02 | 1.05 | 0.16 | 0.77 |
|       | Water body | −0.48 | 0.32 | −3.00 | −6.21 | −0.34 | 1.45 | 0.01 | −0.02 | 0.48 | 3.43 | 0.84 | 0.88 |
|       |       |       |       |       |       |       |       |       |       |       |       |       |       |

Table 4
Mean NLST for the whole area and land covers in the Milan, Rome and Wuhan at different dates (°C).
lockdown has significant effects on reducing the mean NLST of built-up lands. Specifically, the mean NLST of built-up lands in Rome and Wuhan during the lockdown decreased from 5.05°C and 3.57°C to 3.54°C and 1.77°C respectively (see Table 4). Normalized LST difference maps of Milan, Rome and Wuhan for different dates are shown in Fig. 6.

Fig. 6 presents the mean difference of the NLST on different dates. For Milan, the mean difference of the NLST between the lockdown date and the same date in 2018 (MT4-MT2) at the scale of the whole area and built-up

|       | MT2-MT1 | MT4-MT3 | MT4-MT2 | MT3-MT1 |
|-------|---------|---------|---------|---------|
| Milan | Study area | 4.65 | 1.24 | −4.79 | −1.39 |
|       | Built-up | 6.07 | 2.12 | −5.38 | −1.42 |
| Rome  | Study area | RT2-RT1 | 3.77 | 1.91 | −1.44 | 0.41 |
|       | Built-up | 6.054 | 3.23 | −2.57 | 0.24 |
| Wuhan | Study area | WT2-WT1 | 2.10 | 0.01 | −1.73 | 0.353 |
|       | Built-up | 2.94 | 0.03 | −2.55 | 0.35 |

Table 6
The r between NLST and IBI.

|       | MT1 | MT2 | MT3 | MT4 |
|-------|-----|-----|-----|-----|
| Milan | Study area | 0.06 | 0.80 | −0.02 | 0.62 |
|       | Built-up | −0.16 | 0.43 | −0.20 | 0.25 |
| Rome  | Study area | RT1 | RT2 | RT3 | RT4 |
|       | Built-up | 0.29 | 0.81 | 0.21 | 0.61 |
| Wuhan | Study area | WT1 | WT2 | WT3 | WT4 |
|       | Built-up | 0.02 | 0.00 | 0.10 | −0.06 |
|       | Built-up | −0.18 | −0.16 | −0.03 | −0.12 |
lands is $-4.79$ °C and $-5.38$ °C respectively. Also, the mean difference of the NLST (whole area and built-up lands) of the other two cities is $-1.44$ °C and $-2.57$ °C (Rome (RT4-RT2)) and $-1.73$ °C and $-2.55$ °C (Wuhan (WT4-WT2)) (Table 5). The results showed that in all cities, the NLST changes on different dates in the built-up lands are more than the whole area. On April 18 and February 13, 2018, the average difference of the NLST of built-up lands is $-1.4$ °C in Milan, $0.24$ °C in Rome and $0.35$ °C in Wuhan. The average difference of NLST of built-up lands on April 14, 2020 and April 18, 2018 compared to April 18, 2018 and February 13, 2018 in all cities shows higher reduction values due to COVID-19 lockdowns (Table 5).

The absolute value of $r$ between NLST and IBI during the lockdown (T4) in all cities shows a significant declining trend, which indicates a decrease in human activities due to adopting lockdown restrictions. At all cities, compared to comparable date to lockdowns in 2018 (T2), the absolute value of $r$ between NLST and IBI decreased during the lockdown (Table 6) to 0.25 in Milan (0.43 before lockdown), 0.24 in Rome (0.41 before) and 0.12 in Wuhan (0.16 before), which shows that the lockdown measures had a greater effect at all cities.

The results showed that the SUHII of Milan during the lockdown (MT4) and the same date in 2018 (MT2) are 2.85 °C and 3.74 °C respectively. Also, on similar dates, the SUHII in other cities is $3.42$ °C and $5.2$ °C for Rome (RT4 and RT2) and $0.91$ °C and $1.98$ °C for Wuhan (WT4 and WT2) (Fig. 7). The SUHII of these cities due to lockdowns decreased by $0.89$, $1.78$ and $1.07$ °C, respectively ($\Delta T_{SUHII} = T_2 - T_4$). By contrast, at the other two times (T1 and T3), the changes in SUHII have been very low ($\Delta T_{SUHII} = T_1 - T_3$). The highest and lowest reductions of SUHII due to lockdown are for Rome and Milan respectively.

5. Discussion

A set of human activities, such as industrial activities, vehicles mobility, energy consumption, population density, etc. create and increase AHF in urban environments (Sailor and Lu, 2004; Zhou et al., 2012; Molnár et al., 2020). AHF is one of the major factors affecting the SUHI.
(Chow and Roth, 2006; Benz et al., 2015; Doan et al., 2019), hence further investigation and understanding of their relationship is worthwhile. Investigating the effect of COVID-19 pandemic lockdowns on LST and SUHI can be useful for drawing conclusions that provide solutions for climate change mitigation. COVID-19’s lockdowns resulted in a significant reduction in SUHI in the studied cities, which means that humans’ post- COVID-19 living habits should be revised for the sake of climate change mitigation before we reach the tipping point of climate change. Examples could be increasing the use of renewable energies, smart mobility solutions, urban gardening/forestry and remote work.

Given the impact of climate conditions on LST and SUHI, discussing the effects of lockdown is challenging. Therefore, in this study, the LST subtraction technique obtained from satellite images from cold pixel LST was used to eliminate climate effects on LST. LST in this pixel is close to the air temperature (Bastiaanssen et al., 1998; Allen et al., 2002). NLST relative to climatic conditions can show LST due to AHF with higher accuracy than LST obtained from satellite images. NLST is obtained from satellite imagery, but it is normalized to climatic conditions. LST in a pixel is a function of a set of different factors such as climatic conditions, anthropogenic activities, surface biophysical characteristics, and so on. Naturally, when the LST obtained from satellite imagery normalizes to climatic conditions, a higher percentage of the normalized LST than the initial LST is due to AHF. NLST obtained from satellite images for various parameters is one of the interesting and new topics in the field of thermal remote sensing. Firozjaei et al. (2020c) and Firozjaei et al. (2020a) used the normalizing surface temperature obtained from satellite images to more accurately model the Surface anthropogenic heat island and near surface temperature lapse rate. Specifically, the mean NLST of built-up lands in northern and central Italy (Milan and Rome) during the lockdown compared with a regular day (same time in 2018) was reduced from 7.71 °C and 5.05 °C to 2.32 °C and 3.54 °C respectively, and in Wuhan, China from 3.57 °C to 1.77 °C (Table 4). In pre-lockdown periods, the average LST of built-up is higher than the LST of bare lands. But during the lockdown, the average LST of built-up lands is lower than the LST of bare lands. These results showed that COVID-19 lockdowns reduced anthropogenic activity and, as a result, significantly reduced the NLST in the built-up lands (Table 3).

Increasing imperviousness decreases wetness and evapotranspiration values and increases LST and SUHI values (Kato and Yamaguchi, 2005; Singh et al., 2017). Regions with dense built-up land covers have the highest NLST and SUHI due to low vegetation and the amount of humidity, and high imperviousness, dryness and heat (Shorabeh et al., 2022). The amount of human activities in urban areas have a direct relationship to the ISC (Chen and Hu, 2017; Fu and Weng, 2018; Li et al., 2018; Gabey et al., 2019; Wang et al., 2019; Zhang and Cheng, 2019). Consequently, during lockdown dates compared to the pre-lockdown dates, the rate of decrease in the human activity in regions with a high imperviousness percentage is more than in areas with a low imperviousness percentage. Therefore, compared to pre-lockdown dates, the highest decrease during the lockdown in LST and SUHI is related to regions with a high imperviousness percentage.

Zhang and Cheng (2019) and Li et al. (2018) used the LST-ISC to model SUHII. If the correlation between LST and ISC is high, it indicates a higher impact of human activity on the SUHII of the city and vice versa. Utilizing appropriate ISC information is the most significant challenge of this method. The existing ISC databases have serious constraints, such as limitations of spatiotemporal coverage. Nonetheless, these challenges can be addressed using satellite imagery.

In previous studies, different spectral methods have been presented for ISC modeling (Zha et al., 2003; He et al., 2010; Firozjaei et al., 2019b). Firozjaei et al. (2020b) demonstrated that IBI had the best efficiency for SUHII modeling. Thus, in this study, the correlation between NLST and IBI was used as a metric to evaluate the effect of COVID-19 lockdown on the SUHII.

The results showed that the r between NLST and IBI on the lockdown dates (T4) has decreased significantly compared to similar dates in 2018 (T2). T2 and T4 dates are in warmer months than T1 and T3 dates. The spatial distribution of LST in a city in the cold months is more influenced by the topographical and three-dimensional (3D) characteristics of the city. In warm months, the effect of surface biophysical characteristics on the spatial distribution of LST is greater than the topographic and three-dimensional characteristics of the city (Weng and Lu, 2008; Weng et al., 2011; Sattari et al., 2018; Z. Wu et al., 2020). Hu et al. (2020) indicated that the LST in the warm season is affected by surface biophysical factors; However, its spatial distribution in the cold season is more affected by 3D factors. Hence, in T1 and T3 dates, the correlation coefficient between NLST and IBI is very low.

The results indicated that lockdowns due to COVID-19 pandemic significantly reduced LST and SUHI (Fig. 3 and Fig. 7). The results showed that the SUHII of Milan, Rome and Wuhan due to lockdowns decreased by 23, 34 and 54 %, respectively. The highest and lowest reductions of SUHII due to lockdown are for Wuhan and Milan respectively. Various studies have shown that lockdowns due to COVID-19 pandemic decreased air pollution (Dantas et al., 2020; He et al., 2020; Ranjan et al., 2020; Venter et al., 2020), energy consumption (Rugani and Caro, 2020), noise pollution and water pollution (Saadat et al., 2020). Therefore, the results of present study indicated that the reduction of anthropogenic activities as a controllable factor can be one of the most important and effective strategies for creating cooler cities, climate change mitigation and improve the thermal environment.
Heatwaves and greenhouse gases are the most important link between human activities and climate change. Over the past decades, heatwaves and greenhouse gas emissions have increased significantly with the increase of human activities. Human activities include industrial activities, transportation, physical growth of cities and land use changes, destruction of natural resources such as forests. By aggregating these effects for different cities, we will be faced with environmental phenomena such as climate change on a global scale that have many negative effects on human quality of life. Furthermore, the increase in climate change owing to human activities causes an increase in the heatwaves and subsequently, the deteriorate thermal environment and a reduction of thermal comfort in urban environments. The intensity of climate change has increased in recent years due to the increase in industrial activities and huge anthropogenic pressure, so that the concentration of toxic substances and carbon dioxide (CO2) in the atmosphere has reached critical levels and thermal pollutants have caused many changes in the albedo of different surfaces (Firozjaei et al., 2020c; Li and Wang, 2020).

The LST values in different conditions depending on the set of different factors such as temporal and geographical location, topographical, morphological and geometrical conditions, inherent characteristics, biophysical characteristics, thematic and landscape characteristics, synoptic and climatic parameters, subsurface conditions and anthropogenic activities are different (Huang and Wang, 2019; Weng et al., 2019a; Firozjaei et al., 2020c; Hu et al., 2020). The focus of this study is to explore the impact of anthropogenic activities on the spatial and temporal distribution of LST and SUHI. In general, the outbreak of the COVID-19 pandemic and the subsequent lockdowns by affecting the amount of anthropogenic activities in the urban environment, lead to a decrease in LST and SUHI. It is worth noting that the topography, morphology, and geometry factors are constant on the pre-lockdown and lockdown dates. Thus, the impact of these factors on LST and SUHI in a city is constant on the pre-lockdown and lockdown dates. Considering this, the lockdown has no effect on these urban factors. Hence, according to the objective of this study, the impact of these factors was ignored.

In view of all that has been mentioned so far, the reduction of human activities leads to creating cooler cities and communities. One of the limitations of this study was the lack of access to ancillary data indicating human activities. Considering the parameters related to human activity such as traffic and greenhouse gas emissions can be very useful and effective in investigating the effects of lockdowns caused by COVID-19 pandemic on environmental conditions. Also, the use of a limited number of satellite images is one of the limitations of the present study. In future studies, a set of other satellite imagery with daily spatial resolution and time series modeling can be used to model the effect of lockdown on the urban heat island.

6. Conclusions

There is a widespread concern today about increasing anthropogenic activity and SUHI throughout the world. The COVID-19 outbreak has had major negative impacts on human life. However, because of the decrease in human activities, the environment has improved significantly in different regions (Mahato et al., 2020; Tobias et al., 2020; X. Wu et al., 2020; Firozjaei et al., 2021). Hence, the aim of this study was to explore the impact of COVID-19 pandemic lockdowns on urban cooling. Landsat 8 satellite imagery were used to model and compare SUHI on pre-lockdown and lockdown dates. This study shows that there is a direct relationship between NLST and IBI. The decrease in anthropogenic activity as a result of lockdown measures has led to a decrease in NLST. The greatest NLST changes in different land covers are related to the built-up lands. Following unprecedented reduction in human activities in the framework of the COVID-19 lockdown restriction measures, the reduction of industrial activities, unnecessary businesses and transportation led to a significant reduction in SUHI (greater than 1 °C), especially in Milan and Rome in Italy and Wuhan, China. The highest and lowest reductions of SUHI resulted from lockdowns in Rome and Milan. The results of this study serve as a warning to human society about the thermal environment of cities. In general, the amount of human activity cannot be reduced to 0 in the urban environment. However, human activities can be managed using some strategies and prevent the increase of AHF in urban environment. This paper suggests some strategies to reduce the AHF and create cooler cities including the use of more high-albedo materials in the urban areas, fostering green city, green roofs and cool roofs, traffic management and introduction of low emission vehicles, use of exhaust heat from urban facilities, smart mobility solutions and increasing the use of clean technologies (e.g. renewable energies and accessible energy of solar irradiation).

Declaration of Competing Interest

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

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