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Living environment matters: Unravelling the spatial clustering of COVID-19 hotspots in Kolkata megacity, India

Arijit Das, Sasanka Ghosh, Kalikinkar Das, Tirthankar Basu, Ipsita Dutta, Manob Das

Department of Geography, University of Gour Banga, Malda, India
Department of Geography, Kazi Nazrul University, Asansol, India

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ABSTRACT

The emergence of COVID-19 has brought a serious global public health threats especially for most of the cities across the world even in India more than 50 % of the total cases were reported from large ten cities. Kolkata Megacity became one of the major COVID-19 hotspot cities in India. Living environment deprivation is one of the significant risk factor of infectious diseases transmissions like COVID-19. The paper aims to examine the impact of living environment deprivation on COVID-19 hotspot in Kolkata megacity. COVID-19 hotspot maps were prepared using Getis-Ord-Gi* statistic and index of multiple deprivations (IMD) across the wards were assessed using Geographically Weighted Principal Component Analysis (GWPCA). Five count data regression models such as Poisson regression (PR), negative binomial regression (NBR), hurdle regression (HR), zero-inflated Poisson regression (ZIPR), and zero-inflated negative binomial regression (ZINBR) were used to understand the impact of living environment deprivation on COVID-19 hotspot in Kolkata megacity. The findings of the study revealed that living environment deprivation was an important determinant of spatial clustering of COVID-19 hotspots in Kolkata megacity and zero-inflated negative binomial regression (ZINBR) better explains this relationship with highest variations (adj. R2: 71.3 %) and lowest BIC and AIC as compared to the others.

1. Introduction

Coronavirus disease (COVID-19) is an epidemic illness that was discovered in Wuhan of China at the end of 2019 (World Health Organization (WHO), 2020a, 2020b). Shortly after, it spreads worldwide rapidly to emerge as a global public health concern (Das, Das, & Ghosh, 2020; Das, Das et al., 2020). As of May 3, 2020, COVID-19 has affected about 3.26 million people and claimed over 229971 deaths globally (World Health Organization (WHO), 2020c) and these figures are increasing every day. The WHO declared the COVID-19 as a global pandemic on 10th March 2020 (World Health Organization (WHO), 2020c) and these figures are increasing every day. The WHO declared the COVID-19 as a global pandemic on 10th March 2020 (World Health Organization (WHO), 2020c). The United Nations (UN) realizing the wider consequences of this pandemic declared it as a social, human, and economic crisis (United Nations, 2020). UN also recognized that this pandemic will create socio-economic burdens differently in developed and developing counties of the World due to loss of human resources (United Nations, 2020).

In India, the first COVID-19 case was reported on January 30, 2020, in Kerala (Tomar & Gupta, 2020). Thereafter, big cities such as Mumbai, Ahmedabad, Pune, Chennai, and Kolkata became the epicentres of COVID-19 spreads in India (Hindustan Times, 2020s). To anticipate the COVID-19, nationwide lockdown was imposed on March 24, 2020 in India (Hindustan Times, 2020b). The COVID-19 incidences were not uniformly distributed in India and based on the risk profile of COVID-19 infection, the districts (sub-states) have been categorized into red, orange, and green zone (https://www.mohfw.gov.in). The districts which are not included in the red zone category and have reported at least one COVID-19 case were classified as orange zone (https://www.mohfw.gov.in). As of May 04, 2020, out of total 732 districts, 130 districts belong to the Red zones, 319 districts are in the Green zones and 284 districts are in the Orange zone across India. Kolkata megacity region belongs to the red zone, is one of the worst affected megacities in India and most affected in the state West Bengal (Kolkata megacity region reported over half of the Covid-19 cases of

* Corresponding author.

E-mail addresses: arijit3333@gmail.com (A. Das), sasankaghoshsg@gmail.com (S. Ghosh), geokinkar@gmail.com (K. Das), basu.tirthankar89@gmail.com (T. Basu), ipsitadutta25@gmail.com (I. Dutta), dasmanob631@gmail.com (M. Das).

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West Bengal). The COVID-19 incidences reported from the neighbour-
hoods (residential colony and mohalla) either in the form of a large
cluster (Hapal, 2020) in Kolkata. Due to spatial clustering of COVID-19 affected
neighbourhoods, cluster containment strategy has been adopted for
breaking the chain of transmission to prevent its spread to other
neighbourhoods. As of May 4, 2020, there are 316 such containment
zones have been identified (https://wb.gov.in). These containment
zones are placed under geographic quarantine for more than 40 days (on
May 05, 2020, it was 41st Day lockdown) where to and from movement
of population (including movement for maintaining essential services
which are being provided by the local government) is not be permitted
except emergency services.

Recent studies have shown multiple environmental factors such as
air temperature (Liu et al., 2020; Núñez-Delgado, 2020; Wang et al.,
2020; Yongjiana, Jingube, Fengmingb, & Liqingb, 2020; Zhu & Xie,
2020), humidity (Auler et. al., 2020; Ma et. al., 2020; Gupta et. al.,
2020), air pollution (Wu, Nethery, Sabath, Braun, & Dominici, 2020),
smoking (Taghizadeh-Hesary & Akbari, 2020) determine the severity as
well as rapid spread of COVID-19. After a quick review of the previous
studies, few notable gaps have been identified. Firstly, most of the
previous studies focused to examine the impact of meteorological pa-
rameters (such as air temperature, humidity, rainfall) on COVID-19 outbreak
(Liu et al., 2020; Núñez-Delgado, 2020; Wang et al., 2020;
Yongjiana et al., 2020; Zhu & Xie, 2020; Auler et. al., 2020; Ma et. al.,
2020; Gupta et. al, 2020) rather than socio-economic conditions of the
people. Secondly, Living environment deprivation, especially in mega-
cities, may increase the risk of COVID-19 spread by affecting the survival
and transmission of the virus in a variety of ways, considerable evidence
exists for higher incidences of certain infectious diseases reported in an
urban setting from deprived small neighbourhoods (Hughes and Gorton,
2014), overcrowded slums (Baker M, et al., 2000), and segregated
low-class residential areas (Acevado-Garcia D., 2000). But still now no
studies have been performed to assess the impact of overall living condi-
tions of the households on COVID-19 cases. Thirdly, in few recent
studies very few indicators have been considered to understand the
urban vulnerability to COVID-19 (Misra et al., 2020; Das, Ghosh et al.,
2020). However it is very difficult to understand the relationship be-
tween living conditions and COVID-19 particularly in large megacities
by considering these few indicators. Fourth, very few studies have been
performed to examine the relationship between living conditions of the
people and outbreak of COVID-19 (Wang & Su, 2020; Wang & Wang,
2020). Particularly it remained unexplored in Indian context.

Urban living environment deprivation is a multidimensional phe-
nomenon that results from the complex interaction of socio-
demographic, socio-economic, and eco-environmental factors.
The urban induced adverse eco-environmental impacts such as decreasing
vegetation cover (Du et al., 2019; Gui, Wang, Yao, & Yu, 2019; Sussman,
Raghavendra, & Zhou, 2019; Yao, Cao, Wang, Zhang, & Wu, 2019),
increasing impervious surfaces and the concomitant rise in land surface
temperature (Li, Zhang, Mirzaei, & Zhao, 2018; Portela, Massi,
Rodrigues, & Alcantara, 2020; Sejati, Buchori, & Rudiarto, 2019;
Sultana & Satyanarayana, 2020; Zhang, Esoto, & Murayama, 2017; Fu &
Weng, 2016; Yang, Sun, Ge, & Li, 2017; Jiang, Fu, & Weng, 2015;
Fonseka et al., 2019; Bian, Ren, & Yue, 2017; Guo et al., 2015; Zhang &
Sun, 2019; Arulbalaji, Padmalal, & Maya, 2020); socio-demographic
factors such as high density population and households (HHs)
(negative influences urban living environment deprivation (Ni, Chen,
& Yuan, 2020; Musse et al., 2018). The urban living environment
derprivation leads to deterioration of health and human comfort in cities
that increases the susceptibility of infectious diseases (EPA, U., 2008).
Therefore, it is logical to assess whether and how urban living envi-
ronment deprivation affects the spread of COVID-19. But till now to
the best of our knowledge, no study has addressed this issue on severely
COVID-19 affected megacities in India. To fill-up the existing research
gap, the relationship between spatial clustering of COVID-19 contain-
ment zones and living environment deprivation in Kolkata megacity has
been assessed in this study. The goal of this study is to provide scientific
evidence about the influence of living environment deprivation on
spatial clustering of COVID-19 hotspots in Kolkata megacity. Since, the
socio-economic depriations of HHs itself are determined by multiple
aspects that negatively influence the quality of living of the HH (Mishra,
2018; Baud, Pfeffer, Sridharan, & Nainan, 2009).

2. Materials and methods

2.1. Study area

Kolkata megacity (22°34’N, 88°22’E) is the third-largest metropolis in India (after Mumbai and New Delhi) with a population of 4.5 million (https://censusindia.gov.in). It is the most important urban centre in Eastern India, which has a typical subtropical, warm humid, monsoon climate classified as A_w (tropical wet and dry) in the Köppen climate classification (Kottek, Grieser, Beck, Rudolf, & Rubel, 2006). With mild and moderate winters and very hot summers, the average annual temper-
2.2. Data Sources

To execute this study, three sources of information were used: 1) The numbers of COVID-19 containment zones were collected from the official
websites of the Department of Health & Family Welfare, Govt. of West Bengal (www wbhealth gov.in); 2) variables required for devising
IMD obtained from Census of India, 2020 (https://censusindia.gov.in);
Landsat OLI/TIRS satellite images of April 6, 2020, identified by path 138 and row 44, collected from by the United States Geological Survey
(USGS) 2020 website (https://earthexplorer.usgs.gov)
radiance of spectral bands, and finally derivation of land surface temperature (Musse, Barona, & Rodriguez, 2018). The biophysical indicators from the processed image were obtained by using the equations shown in Table 2 using the ‘raster’ package of the ‘R’ programming language.

The dimensions and indicators of urban multidimensional deprivation indices built so far varied in time and space based on objectivity. The dimensions and indicators selected to devise an IMD for 141 electoral wards of Kolkata megacity are slightly different from IMDs developed earlier (see Table 1).

2.4. Comparison of indicators considered for this study and other studies in Kolkata megacity

Before executing GWPCA to device the IMD for Kolkata megacity, the overall significance of the indicators (the factorability test) was performed by using Kaiser–Meyer–Olkin (KMO) test and Bartlett’s Test of Sphericity (Antony & Visweswara Rao, 2007; Bartlett, 1950). In this study, KMO value was more than 0.800 and the chi-square value is 0.00 which indicates the indicators were very much suitable to devise IMD for Kolkata megacity. Initially, 25 indicators were selected, but 3 indicators were dropped due to multi-collinearity (1 indicator with |r| < 0.2 dropped which was practically uncorrelated and 2 indicators dropped because they were very tightly correlated (|r| > 0.8). The IMD is devised by employing GWPCA. GWPCA is now recognized as a very effective tool for the detection of the local non-stationary effects of variance in a data structure (Harris, Brunsdon, & Charlton, 2011; Kumar, Lal, & Lloyd, 2012; Lloyd, 2010). The local principal components and local variance derived from GWPCA are suitable in devising IMD (Mishra, 2018).

Mathematically, the local eigen decomposition of GWPCA transformation can be written in its algebraic expression as:

$$LVL^T (u, v) = \Sigma (u, v) = X^T W (u, v) X$$  (1)

W (u,v) is a diagonal matrix obtained from optimal bandwidths (here adaptive) based on the ‘Bi-square’ kernel weighting scheme. The details description on GWPCA is given in the Appendix A section. To reduce noise and locate important factors of IMD, the first 3 PCs with eigenvalues greater than 1 (i.e., \( \lambda_i \geq 1 \)) were retained (Hair, Black, Babin, Anderson, & Tatham, 2006).

The GWPCA derived dimension weights computed by multiplying the squared component loads and the proportion of variance explained by the corresponding PC and summing across PCs. Weights are therefore derived using Eq. 02

$$W_k = \sum_{k=1}^{3} PC_{i,k}^2 \times \frac{\sqrt{\lambda_k}}{\sum_{j=1}^{3} \sqrt{\lambda_j}}$$  (2)

W_k is the weight given to IMD Dimension i (either Housing Condition, Asset Possession, WaSH Services, Household Amenities and Services, and Gender disparity) \(PC_{i,k}\) is the component load in k^th PC (column of L), \(\lambda_k\) is the eigen-value of the k^th PC (in V) and j is the number of PCs retained (here 3).

The initial deprivation index (Si) at the sub-city level for each megacity is a weighted aggregation of components scores (C).

$$S_i = \sum_{k=1}^{3} C_k W_k$$  (3)

Where, Si = Initial deprivation index, \(C_k\) = Value of a component score for k^th PC of ward i, and \(W_k\) = Combined weight of IMD components for k^th PCs for Ward i, m = 3.

Applying the min-max normalization method, the initial deprivation index score for 141 wards were standardized IMD (0–100). The IMD is obtained for sub-cities of Kolkata megacity using the following formula:
The Index of Multiple Deprivation (IMD) assigns a multiple deprivation score to each urban ward for Kolkata megacity. The IMD value '0' stands for the 'bottom ranking' sub-city, 100 for the 'top-ranking' electoral ward, and varies between '0' and '100' for other wards. Essentially, it tells us where a particular sub-city stands, between the 'top' and 'bottom' ranking sub-city on a linear scale. For instance, an IMD value of 50 means that the ward is situated in the “halfway” between the top and bottom ranking wards in terms of multiple urban deprivations. The higher value of IMD correspondence to the higher level of multiple deprivations and vice versa. The IMD devised in this study was validated by comparing with the results of Baud et al. (2009) and Mishra (2018), along with information obtained from Google earth images of randomly selected 100 neighbourhoods and local knowledge.

2.5. Hotspot spatial analyses of COVID-19 containment zones and IMD

Hotspot spatial analyses are widely used in the ecological study (Chen, Chen, & Liu, 2015; Jia, Zheng, & Miao, 2018) to determine spatial clusters of high values of a particular phenomenon. In this paper, the hotspot analysis tool of ArcGIS 10.2 software (Getis-Ord Gi*) was used to explore the spatial clustering of high containment Zones of COVID-19 and high IMD values.

2.6. Statistical modelling approach

A descriptive analysis was performed for all the data. The distribution of COVID-19 containment zones was discrete and positively skewed with many wards did not have any containment zones. The distribution of COVID-19 containment zones in Kolkata megacity was negative binomial because its variance was higher than the means. 5 count data regression models (Appendix B), namely, Poisson regression (PR), negative binomial regression (NBR), hurdle regression (HR), zero-inflated Poisson regression (ZIPR), and zero-inflated negative binomial regression (ZINBR) are considered to analyse the impact of living environment deprivation on the spatial distribution of COVID-19 containment zones in Kolkata megacity. The explanatory factors considered to perform the regression analysis are listed in Table 2. The best count data regression model is obtained by comparing the values of the likelihood ratio (LR) test, Akaike’s information criterion (AIC), the Bayesian information criterion (BIC), and the adjusted coefficient of determination (R2 adj). The values of AIC, BIC, and R2 adj are acquired using the following formula (Pinheiro & Bates, 2000; Zeng, 2015).

\[
\text{AIC} = -2\log\text{Lik} + 2(p+1)
\]

\[
\text{BIC} = -2\log\text{Lik} + (p + 1)\log(n)
\]

\[
R^2_{\text{adj}} = 1 - \frac{(n-1)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(n-p)\sum_{i=1}^{n}(\bar{y}_i - \overline{\bar{y}})^2}
\]

Where, yi, \(\hat{y}_i\), \(\bar{y}_i\) sequentially are observed value, the estimated value, and the mean value of the biomass; n is the number of samples; p is the number of parameters; t\(\alpha\) is the t value at confidence level with \(n-p\) degree of freedom; and logLik is the log-likelihood values of the non-linear regression model. The two-sided statistical analyses were carried out at a
Wang, 2020). For example, urban slums are more vulnerable to infectious diseases due to lack of availability, accessibility of households to basic services and amenities (Arifeen et al., 2001; Checkley et al., 2016; Corburn et al., 2020). Thus it is clear that living environment of the households largely influence transmissions of infectious diseases. In this study, an attempt has been made to examine the impact of living environment on COVID-19 transmissions using Index of Multiple Deprivation (IMD) for the first time in India. Most of the recent studies tried to interlink COVID-19 transmissions with WASH (water, sanitation and hygiene) provisions but ignored overall living conditions of the households. In addition to this, the COVID-19 hotspot maps were prepared (i) to understand the high-high and low-low concentrations of households. In addition to this, the COVID-19 hotspot maps were prepared (i) to understand the high-high and low-low concentrations of

| Table 1 |
|---|
| Domains | Variable Category | Variables | S V Mishra (2018) | ISA baud (2008) | Other(s) |
| Housing Condition | Type of structure of Census house | % of HH does not have a concrete roof | Das & Mistri, 2013 |  |
| Ownership | % of HH lives in a house not owned by them | Mishra, 2018 |  |
| Permanent House structure | % of HH having a semi-permanent or temporary structure | Das & Mistri, 2013 |  |
| HH with the single dwelling room | % of HH with the single dwelling room | Das & Mistri, 2013 |  |
| Banking | % of HH do not have access to banking facility | Isa Baud et al. (2008) |  |
| Radio | % of HH not owned radio | Das & Mistri, 2013 |  |
| Television | % of HH not owned television | Das & Mistri, 2013 |  |
| Computer and Laptop | % of HH do not have a computer or laptop | Das & Mistri, 2013, Bhan & Jana, 2015 |  |
| Telephone and Mobile Phone | % of HH without telephone or mobile phone | Das & Mistri, 2013, Bhan & Jana, 2015 |  |
| Bicycle | % of HH do not own bicycle | Das & Mistri, 2013 |  |
| Scooter/Motorcycle/moped | % of HH do not own scooter or Motorcycle or moped | Isa Baud et al. (2008) |  |
| Car/Jeep/Van | % of HH do not own car or jeep or van | Das & Mistri, 2013 |  |
| None of the Specified Assets | % of HH not having any of the assets- radio/ transistor, television, computer/ laptop (with or without internet), telephone/ mobile phone, scooter/ motorcycle/moped, car/jeep/van | Mishra, 2018 |  |
| Location of Drinking water | % of HH with the location of water source not within their premises | Das & Mistri, 2013 |  |
| Latrine Facility | % of HH with no latrine facility within the premise | Baud et al. (2008), McGranahan, 2015, Mishra, 2018 |  |
| Waste Water Disposal | % of HH with wastewater outlet is connected to公共卫生 system | Mishra, 2018 |  |
| Source of Drinking water | % of HH obtain drinking water from untreated sources | Mishra, 2018 |  |
| Cooking fuel | of HH using non-clean fuel for cooking | Das & Mistri, 2013 |  |
| Kitchen | % of HH have no separate kitchen | Das & Mistri, 2013 |  |
| Source of Lightning | % of HH with a source of lightning in the house is environmentally polluting | Baud et al. (2008) |  |
| Gender Disparity | Literacy | female illiteracy rate | Das & Mistri, 2013 |  |
| Worker | % of female Non-worker | Das & Mistri, 2013 |  |

| Table 2 |
|---|
| COVID-19 containment zones and its determining factors. |
| Indicators | Equation |
| Dependent Variable | Ward wise Number of Containment Zones |
| Explanatory Factors Urban Area | Number of urban Patch/ Hectare |
| Land Surface Temperature (LST) | $Tb = \frac{K_2}{NIR} \times ln \left( \frac{\lambda + 1}{\lambda - 1} \right)$ |
| Normalized Differential Vegetation Index (NDVI) | $NDVI = \frac{NIR - RED}{NIR + RED}$ |
| Normalized Differential Water Index (NDWI) | $NDWI = \frac{NIR - SWIR}{NIR + SWIR}$ |
| Normalized Differential Moisture Index (NDMI) | $NDMI = \frac{SWIR1 - NIRM}{SWIR1 + NIRM}$ |
| Index of Multiple Deprivation (IMD) Population Density (PDD) | No. of Population/ Area |
| Household Density (HHD) | No. of Household/ Area |

5% level of significance. All analyses were conducted using R software (version 3.5.3) with the “glm” and “pscl” package.

In some previous research studies, deprivation of the households were assessed across cities using GWPCA (Basu & Das, 2020; Charlton, Brunsdon, Densar, Harris, & Fotheringham, 2010). But recent studies reported that there were a close association of COVID-19 transmissions and living condition of the households (Wang & Su, 2020; Wang & Wang, 2020). For example, urban slums are more vulnerable to infectious diseases due to lack of availability, accessibility of households to the basic services and amenities (Arifeen et al., 2001; Checkley et al., 2016; Corburn et al., 2020). Thus it is clear that living environment of the households largely influence transmissions of infectious diseases. In this study, an attempt has been made to examine the impact of living environment on COVID-19 transmissions using Index of Multiple Deprivation (IMD) for the first time in India. Most of the recent studies tried to interlink COVID-19 transmissions with WASH (water, sanitation and hygiene) provisions but ignored overall living conditions of the households. In addition to this, the COVID-19 hotspot maps were prepared (i) to understand the high-high and low-low concentrations of households. In addition to this, the COVID-19 hotspot maps were prepared (i) to understand the high-high and low-low concentrations of

### 3. Results

#### 3.1. Spatial distribution of deprived areas in Kolkata megacity

To analyze the distribution of deprived areas, this study categorizes IMD into five different classes of multiple deprivations based on equal interval methods, with IMD < 20.00 as least deprived and IMD > 80.00 as a most deprived category. Table 3, is showing the distribution of wards across five IMD categories. The wards with IMD values > 60 were considered as deprived and 16.94 percent of the total wards belong to
### Table 3
Distribution of deprived wards.

| Deprivation Criteria       | IMD | No. of Wards | Percentage of Population |
|----------------------------|-----|--------------|-------------------------|
| 0 to 20.0 (Least Deprived) |     | 17           | 9.57                    |
| 20.1 to 40.0               | 47  | 32.18        |
| 40.1 to 60.0               | 59  | 41.30        |
| 60.1 to 80.0               | 15  | 14.20        |
| 80.1 to 100 (Most Deprived)| 63  | 2.74         |

this category.

As per the result of the study, it was observed that maximum number of wards (59) fall under the deprivation criteria between 40.1 and 60.0 (41.39 % population) followed by the criterion of 20.1–40.0 (47 wards comprising 32.18 % of population), 0–20.0 (17 wards comprising 9.58 % of population), 60.1–80.0 (15 wards comprising 14.20 % of population) respectively.

#### 3.2. Geography of multiple deprivations of Kolkata megacity

The spatial extent and distribution of IMD are unable to explore the geography of multiple deprivations in Kolkata megacity. The spatial heterogeneity of multiple deprivations in Kolkata megacity was examined using spatial hotspot analyses using the following formula:

\[
G' = \frac{\sum_{j=1}^{n} w_{ij} x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\left( \sum_{j=1}^{n} x_j \right)^2}}
\]

(7)

Where \( x_j \) is the feature attribute value for \( j \), \( w_{ij} \) represents spatial weight between feature \( i \) and \( j \), \( n \) indicating total number of features.

Whereas \( \bar{X} = \sum_{j=1}^{n} x_j/n \) and \( S = \sqrt{\sum_{j=1}^{n} (x_j)^2} - \left( \bar{X} \right)^2 \)

Hotspots of COVID-19 containment and multiple deprivations identified by IMD had obvious overlapping areas. Approximately 60.6 % of the COVID-19 hotspot area and 51.6 % of the multidimensional area deprivation was located in northern and central parts of the city (Fig. 3).

Most of the COVID-19 hotspots were reported from northern and central parts of the city that makes these areas COVID-19 hotspot within the city. Interestingly large proportions of areas (>50 %) with multidimensional deprivation were concentrated in particularly northern part of the city. In northern part of the city most of the urban slums are located. In addition to this, large proportion of multidimensional deprivation in northern part within the city clearly suggests that there are lacks of availability, accessibility as well as inequalities of basic services and amenities to the people in the city (see supplementary section) (Table 4).

#### 3.3. Relationship between COVID-19 hotspots and living environment deprivation

The result of the study showed that COVID-19 hotspots are mainly concentrated in areas with relatively less availability as well as accessibility of basic services and amenities. Therefore it is necessary to find out the relationship of COVID-19 hotspot with living environmental parameters. As per spearman’s correlation coefficients, COVID 19 containment has significantly negative relationship with LST \((r = -0.633, p = 0.008)\), NDVI \((r = -0.75, p = 0.004)\), NDWI \((r = -0.413, p = 0.048)\), and positive correlation with IMD \((r = 0.823, p = 0.001)\), PPD \((r = 0.734, p = 0.006)\), HHD \((r = 0.532, p = 0.007)\), UPD \((r = 0.431, p = 0.043)\) and no statistically significant relationship with NDMI \((r = 0.391)\). The interrelation of IMD with various eco-environmental indicators was also very striking. However, the socio-economic variables are negatively correlated with eco-environmental variables (Fig. 4).

For a better presentation of the relationship between COVID-19 containment clustering (hotspots) and its various covariates of living environment deprivation, we have selected four clusters (2 from COVID-19 hotspot and 2 from Cold Spot) namely Window-A, Window-B, Window-C, and Window-D. Table 5 shows the cluster-specific distribution of COVID-19 containment zones and their association with living environment characteristics. It is clear from Table 5 that there are striking differences in the living environment deprivation between COVID-19 hotspots and cold spots. This provides strong initial evidence that the living environment deprivation has a strong influence on spatial clustering of hotspots in Kolkata megacity.

#### 3.4. Zero-inflated negative binomial regression analysis

The descriptive analysis was performed for all the data. Table 6 summarizes the descriptive statistics for IMD, remotely sensed metrological, and other socio-demographic variables. The mean of IMD, PPD, HHD, UPD, LST, NDVI, NDWI, and NDMI were 41.69 (with Max. = 100, Min. = 0.00, S.D = 17.25), 40,738 persons/km² (with...
7

Max. $= 111067.00$, Min. $= 3427.33$, S.D $= 25378.56$, 8805.00 HH/km

Max. $= 23295.00$, Min. $= 785.00$, S.D $= 4709.00$, 42917.59/hect.

Max. $= 52768.16$, Min. $= 17467.14$, S.D $= 7018.02$, 38.77$^\circ$C

Max. $= 41.83$, Min. $= 33.65$, S.D $= 1.68$, 0.16 (with Max. $= 0.27$, Min. $= 0.07$, S.D $= 0.04$), -0.14 (with Max. $= -0.24$, Min. $= -0.07$, S.D $= 0.03$), and 0.03 (with Max. $= 0.14$, Min. $= -0.03$, S.D $= 0.03$), respectively.

The comparisons of test statistics presented in Table 7 and the values of LR, AIC, and BIC indicate that the ZINBR model was the best fit for this study. The value of LR, AIC, and BIC is lowest for the ZINBR, which suggests that the model is better. ZINBR with two-sided tests, and $p < 0.05$ was considered statistically significant.

Estimated coefficients from the ZIPR and ZINBR models are presented in Table 8 for comparison purposes. Although both the ZIPR and ZIBR model identify IMD, PPD, and LST as significant contributors to the COVID-19 containment zones, HD, PPD, and NDMI were added as Table 4

| Frequency of Containment Zones | IMD | PPD | HHID | UPD | LST | NDVI | NDWI | NDMI |
|--------------------------------|-----|-----|------|-----|-----|------|------|------|
| Frequency of Containment Zones | 1   | 0.823** | 0.734** | 0.532** | 0.431* | -0.633** | -0.675** | -0.413* |
| IMD                            | 0.823** | 1   | 0.434* | 0.228 | 0.390* | 0.376* | -0.370* | 0.093 | 0.115 |
| PPD                            | 0.734** | 0.434* | 1     | 0.972** | 0.618** | 0.745** | -0.780** | 0.752** | -0.766** |
| HHID                           | 0.532** | 0.228 | 0.972** | 1     | 0.662** | 0.729** | -0.791** | 0.763** | -0.800** |
| UPD                            | 0.431*  | 0.390* | 0.618** | 0.662** | 1     | 0.703** | -0.817** | 0.771** | -0.877** |
| LST                            | -0.633** | 0.376* | 0.745** | 0.729** | 0.703** | 1     | -0.827** | -0.811** | -0.791** |
| NDVI                           | -0.675** | 0.370* | -0.780** | -0.791** | -0.817** | -0.827** | 1     | 0.994** | 0.923** |
| NDWI                           | -0.413* | 0.093 | 0.752** | 0.763** | 0.771** | -0.811** | 0.994** | 1     | -0.885** |
| NDMI                           | 0.391   | 0.115 | -0.766** | -0.800** | -0.877** | -0.791** | 0.923** | -0.885** | 1     |

*Correlation is significant at the 0.01 level (2-tailed).
**Correlation is significant at the 0.05 level (2-tailed).

Fig. 4. Clustering patterns of COVID-19 containment zones and its relationship with socio-economic, socio-demographic and bio-physical covariates.
additional significant predictors by the better fitting ZINBR count data model.

When all other variables were constant, according to ZIPR the wards with high IMD probability of having COVID-19 containment zones was 37 % higher compared to the wards with lower IMD (RR = $e^{0.321} = 1.38$, 95 % CI 1.14–1.62). Whereas, as per the estimate of ZINBR, the wards with high IMD, chances of having COVID-19 containment zones was 121 % higher compared to the wards with lower IMD (RR = $e^{0.754} = 2.21$, 95 % CI 1.97–2.45). Similarly, wards with high HHD have 88 % higher chances of having COVID-19 containment zones compared to the wards with lower housing density (RR = $e^{0.632} = 1.88$, 95 % CI of 1.64–2.12). Also, the wards with higher LST have 35 % (RR = $e^{-0.425} = 0.65$, 95 % CI of 0.41 to 0.89) lower chances of having COVID-19 containment zones compared to the wards with lower LST (Table 9).

### 4. Discussion

In this research, we compiled 35 variables that could potentially explain the spatial pattern of COVID-19 hotspots in Kolkata megacity. These variables were grouped into two different aspects that determine the living environment deprivation, namely socio-economic and eco-environmental. A synthetic IMD was developed by employing GWPCA and using local variance as the weight for the dimensions. The widely used PCA cannot account for the local variance (Harris et al., 2011; Kumar et al., 2012; Lloyd, 2010). In this paper, hotspot analysis employed to explore the spatial clustering of COVID-19 containment Zones. Finally, an ensemble of IMD and other remotely sensed eco-environmental variables used to model (ZIBR) the geographic distribution of COVID-19 containment zones in Kolkata megacity. It was
found that the spatial context of COVID-19 containment zones was better explained by ZIBR compared to the other count regression models. ZIBR provided more reliability and flexibility in studying the spatial extent of COVID-19 containment in response to living environment deprivation. Based on our findings, a combination of four variables (IMD, PPD, HD, and LST) could explain the high variability (i.e. heterogeneous distribution) of the COVID-19 containment zones in Kolkata megacity. Continued monitoring of the areas in Kolkata megacity with relatively higher levels of living environment deprivation factors can improve the understanding of COVID-19 spreads in Kolkata megacity.

At the time of writing this manuscript, the Kolkata megacity was worst affected in the state of West Bengal with 316 number of containment zones spatially clustered in the northern and the central zone of the megacity have observed a large outbreak of COVID-19. The findings of ZIBR suggested a strong positive relationship of COVID-19 outbreaks and living environment deprivation in Kolkata megacity. This further strengthens the findings Ahmed, Ahmed, Pisarsik, and Stiglitz (2020) that the socioeconomic disadvantages and inequalities have a profound role in the spread of COVID-19. As the COVID-19 continues to spread, the areas with low social status of households and unfavourable demographic condition have more susceptibility to be affected like what happens in the United States (Mollalo, Mao, Rashidi, & Glass, 2019). Apart from these previous literatures, in recent studies it was well recognized that various types of infectious diseases like COVID-19 are largely determined by the living conditions of the people (Ahmed et al., 2020; Bhutta, Sommerfeld, Lassi, Salam, & Das, 2014; Patel et al., 2020). The living conditions of the people affect COVID-19 transmissions in a variety of way. Firstly, generally the economically weaker people reside in overcrowded areas (high population density).
Thus overcrowded or high population density is an important factor of infectious disease transmissions (Ai, Zhang, & Zhang, 2016; Alaniz, Bacigalupo, & Cattan, 2017; Jia et al., 2020) even in case of COVID-19 transmissions (Sun et al., 2020; Kodera, Rashed, & Hirata, 2020; Rocklov & Sjödin, 2020). Secondly, access to basic services and amenities (housing conditions, water availability, sanitations, limited outdoor spaces) can also affect respiratory disease as well as deadly COVID-19 transmissions (Das, Das et al., 2020; Mishra et al., 2020; Naddeo & Liu, 2020). Thirdly, the areas with socio-economically deprived are highly vulnerable because the people living in these areas are often employed in such an occupations that are not provide opportunities to work at their home. Thus from the overall analysis it was clear that the living conditions (or living environment) are closely linked with the transmissions of COVID-19. In this study also it was well documented that northern part of Kolkata megacity are relatively high vulnerable due to high population density as well as relatively limited availability as well as accessibility to the basic services and amenities of the people. The result also clearly suggests that there was an impact of living environment on COVID-19 transmissions. The findings suggested that socio-economic dynamics must be incorporated for formulating mitigation strategies to combat COVID-19 pandemic situation.

In most of the recent studies, the factors affecting COVID-19 transmissions were assessed either from different perspectives considering population density (Kodera et al., 2020; Rocklov & Sjödin, 2020; Sun et al., 2020), meteorological parameters such as temperature, humidity, wind speed, pressure, rainfall (Xie and Zhu, 2020; Yongjian et al., 2020; Liu et al., 2020; Wang et al., 2020; Auler, Cássaro, & da Silva, 2020; Ma et al., 2020; Gupta, Ghosh, Singh, & Misra, 2020; Wu et al., 2020; Jiang and Xu, 2020). However, to the best of our knowledge, no studies were performed previously to examine the impact of living environment (living conditions) in relation to COVID-19 transmissions.

A deprived household can be defined as the lack of accessibility as well as availability to the basic services and amenities. Thus limited access to the basic services and amenities influence overall living conditions of the households (Das, Das et al., 2020; Saroj, Goli, Rana, & Choudhary, 2020). Particularly the people living in slum like conditions are relatively more vulnerable to infectious disease due to limited access to basic services and amenities (Corburn et al., 2020; Mishra et al., 2020). More than 30 % of the total urban population in Kolkata lives in slum areas. Most of the slums are located in eastern and western (dock area) and northern (Gossipore) part of the city. Ray (2016), performed a study over some selected slums in Kolkata and findings of the study showed that there were only one community tap for entire slum areas (about 600 people collect water from this community tape). As per as findings of Bag and Seth (2016), more than 70 % slum dwellers are dependent on public sanitation facilities in Delhi, Kolkata and Mumbai. Being COVID-19 an infectious disease, is it not vulnerable for entire slum population? If there is single COVID-19 positive slum dweller, will it not increase the risk of COVID-19 transmissions? In previous studies it was also well documented that deprived people had very limited access to the basic services and amenities (Goswami, 2014; Phukan, 2014; Sajjad, 2014). Recent studies also reported that provision of basic services had significant impact on COVID-19 transmissions (Das, Das et al., 2020; Corburn et al., 2020; Mishra et al., 2020). Thus from the overall analysis, it was clear that deprivations of households may have significant impact on the formations of COVID-19 hotspots in Kolkata megacity also.

In northern part of Kolkata, the population density is relatively high as compared to south Kolkata. In recent studies, it was well recognized that the transmissions of COVID-19 is largely, determined by population density (Carozzi, 2020; Kodera et al., 2020; Rashed, Kodera, Gomez-Tames, & Hirata, 2020; Rocklov & Sjödin, 2020). Thus from overall analysis, it was clear that there were a strong positive correlation between population density and COVID-19 transmissions. Thus in North Kolkata, high population density may have a significant factor for COVID-19 transmission as compared to other parts of the megacity.

In developing countries, environmental issues received very less attentions in policy making framework and most of the time environmental degradation moves parallel with economic development (Das & Das, 2019b). Environmental factors (such as vegetation cover, land surface temperature, water bodies etc.) are largely influenced by socio-demographic and economic factors (such as population density, living environment of the households, household density). In recent studies it was documented that socio-demographic factors have crucial impact on COVID-19 (Sannigrahi, Pilla, Basu, Basu, & Molter, 2020; Kumar et al., 2020). In this study also, it was recorded that socio-economic status (living environment of the households) has an impact on COVID-19 transmissions. In developing countries like India, unplanned and haphazard expansion of cities not only affect quality of urban people but also degradation of environment (such as loss of forest cover, water etc.) (Capps, Bentsen, & Ramírez, 2016; Shahbaz, Sbia, Hamdi, & Ozturk, 2014; Azam & Khan, 2016; Das & Das, 2019a; 2019b; Chun, Wei, & Xin, 2020). In Kolkata megacity also, rapid urban expansion causes deteriorations of ecosystem health (Ghosh, Chatterjee, & Dinda, 2019; Das, Das et al., 2020). Thus from the previous studies, it was well recognized that there were a strong nexus between socio-economic and environmental factors.

Based on our study, three remotely sensed eco-environmental factors (LST, NDVI, and PUDI) have influential role spatial clustering of COVID-19 incidence in Kolkata megacity. The findings are similar to previous studies (Ma et al., 2020), but unlike these studies which have used meteorological data, we have obtained the eco-environmental data using remote sensing for the first time to explore the impact of bio-physical indices on COVID-19 incidences. While we did not find NDVI and MNDWI to be significantly influential in COVID-19 incidences.

4.1. Implementation of policies

A number of responses were created by the government across the world to reduce the rapid transmissions of COVID-19 such as lockdown, closing of shopping malls, travel restrictions, restrictions of public gatherings, investment in health care facilities etc. In spite of these policies, the cities across the globe were severely affected by this deadly disease (Misra et al., 2020). More than 90% of the total cases were reported from urban areas and 1400 cities of world are severely affected (UN-Habitat, 2020). In India also it was well recognized that the large cities are severely affected such as Mumbai, Delhi, Chennai, Hyderabad, Jaipur, Jodhpur, Ahmedabad etc. More than 50% of the total COVID-19 confirmed cases were reported from ten large cities in India. As per recent report of Indian Council of Medical Research (ICMR), risk of COVID-19 transmissions was 1.09 time higher in urban areas and 1.89 times higher in urban slum areas respectively (Swarajya, 2020). Thus from the above findings, it was obvious that the urban areas are more vulnerable to COVID-19 transmissions. The findings also clearly showed that only above mentioned policies are not enough to reduce the COVID-19 transmissions rather government must focus on the living environment of the urban dwellers and priority must be given on the availability as well as accessibility to the basic services and amenities (such as water, sanitations, housing conditions etc).

Government must provide adequate basic services and amenities to the poor urban dwellers to improve the quality of life through existing programmes such as Jawaharla Nehru Urban Renewal Mission (JNNURM), Integrated Housing and Slum Development Programs (IHSDP). The local government must focus on the proper effectiveness of policies and programmes without politicize. In addition to this, urban planners and policy makers must need deep research before implementation of any urban planning framework in future.

5. Conclusion

The study analyses the impact of living environment on COVID-19 hotspots in Kolkata megacity. The study also used a number of
statistical tools to understand the impact of living environment on COVID-19 hotspot in the city. As per as findings of the study, it was well recognized that the clusters of COVID-19 hotspots are largely determined by the availability as well as accessibility to the basic services and amenities (that determine the level of living conditions of the households). The result of the study documented that the concentrations of COVID-19 hotspots were relatively high in northern part of the city. Interestingly in northern part of the city population density was high with higher concentrations urban slums population. Such outcome of the study clearly suggests that there was strong association of COVID-19 hotspot areas with living conditions of the study. Thus this study has great scientific contributions towards the urban policy making frame work to combat with infectious disease in future. A number of multiple indicatorsthat influences living environment deprivation have been grouped into socio-economic and eco-environmental for better understanding the impact on spatial distribution of COVID-19 containment zones in Kolkata megacity. A synthetic IMD using advanced local statistics has been developed to examine the spatial pattern of deprivation within the city. Five regression models have been used and the performance of best fitted model (ZIBR) has been compared with other four count regression models. As per statistical modelling approaches, it was well recognized that the areas with high risk of COVID-19 incidences spill-over to occur in upcoming days. The findings of the study revealed the similar result performed by Mollalo et al. (2019) as it was recorded that living environment deprivation has a profound impact on the spatial distribution of COVID-19 containment zones in Kolkata megacity. To the best of our knowledge, still now there are limited studies over large as well as severely COVID-19 affected megacities across the world. Thus, this study can be regarded as a basis for future modelling of COVID-19 incidences at the megacity level as well as to understand the relationship between living environment of the households and COVID-19 hotspots.

One of the limitations of this study was the availability of the finest spatial granularity COVID-19 positive cases at the electoral ward level. However, the identification, containment areas and adaptation of strict geographic quarantine measures in these containment zones indicate the large outbreaks of COVID-19 in these areas. Therefore, making inferences on COVID-19 based on the spatial distribution of COVID-19 is not problematic until or unless an appropriate and best fit statistical analysis (count regression models in general and ZIBR in particular) is used to model the association between COVID-19 hotspots and living environment deprivation.

**Declaration of Competing Interest**

The authors report no declarations of interest.

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**Appendix A**

**Geographically Weighted Principal Component Analysis (GWPCA)**

GWPCA analysis helps to access the local level statistics, which utilizes the geographically weighted variance-covariance matrix to acquire the geographically weighted mean (Eq. A01) (Lloyd, 2010):

\[
\bar{y}_i = \frac{\sum_{j=1}^{n} y_j w_{ij}}{\sum_{j=1}^{n} w_{ij}}
\]  
(A1)

Following this, the geographical weights can be obtained by employing the Gaussian weighting scheme (Eq. A02) (Forberingham et al., 2002):

\[
w_{ij} = \exp[-0.5(d_{ij}/\tau)^2]
\]  
(A2)

Here, \(d_{ij}\) = inter-distance between the locations \(i\) and \(j\). \(\tau\) = bandwidth that signifies the kernel size.

Later on, by standardizing the geographic weights to one, then, geographic mean will be as:

\[
\bar{y} = \frac{\sum_{j=1}^{n} y_j w_{ij}}{\sum_{j=1}^{n} w_{ij}}
\]  
(A3)

Geographically weighted standard deviation is acquired using Eq. A04 (Lloyd, 2010).

\[
\sqrt{\sigma_i} = \left[ \sum_{j=1}^{n} (y_j - \bar{y}_i)^2 w_{ij} \right]^{1/2}
\]  
(A4)

Geographically weighted covariance of variables \(y_1\) and \(y_2\) for location \(i\) is obtained by (Eq.A05) (Lloyd, 2010):

\[
\text{cov}(y_{1i}, y_{2i}) = \frac{\sum_{j=1}^{n} w_{ij}(y_{1j} - \bar{y}_{1i})(y_{2j} - \bar{y}_{2i})}{\sum_{j=1}^{n} w_{ij}}
\]  
(A5)

Finally, geographically weighted correlation coefficient is computed by Eq. A06(Lloyd, 2010):

\[
r_i = \frac{\text{cov}(y_{1i}, y_{2i})}{\sqrt{\sigma(y_{1i})\sigma(y_{2i})}}
\]  
(A6)

Where \(\sigma(y_{1i})\) and \(\sigma(y_{2i})\) = Geographically weighted variances at location ‘\(i\’\) for the variables ‘\(y_1\’) and ‘\(y_2\’) . The obtained correlation matrix is used to derive the PC for each location.

**Appendix B. % count regression model**

In the following regression models, the number of COVID-19 affected contaminated zones is selected as dependent variables and the independents variables are deprivation score of Kolkata, population density, housing density, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Moisture Index (NDMI), Land Surface Temperature (LST), and Patch Built-up (PBU).
The Poisson Regression Model

In this regression, it is assumed that the Poisson incidence rate ($\mu$) can be determined by the set of ‘k’ regressor variables (the X’s). This relation can be expressed as Eq. A07. (https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Poisson_Regression.pdf)

$$\mu = \exp(\beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k)$$  \hspace{1cm} \text{(A7)}

Where $X_1 \equiv 1$; $\beta_1 = \text{intercept}$; The regression coefficient $\beta_1, \beta_2, ..., \beta_k$ represents the unknown parameters which are estimated from a data set. Following this notation, the Poisson regression model can be expressed for the observation ‘i’ as equation 12

$$\text{Pr}(Y_i = y_i | \mu_i, t_i) = \frac{e^{-\mu_i} (\mu_i)^y}{y!}$$  \hspace{1cm} \text{(A8)}

Where

$$\mu_i = t_i \mu (x', \beta) = t_i \exp(\beta_1 x_2 + ... + \beta_k x_k)$$

Here $Y_i = \text{Dependent variables}; X = \text{Independent or regressor variables}; t = \text{Exposure values}$

The Negative Binomial Regression Model

In this regression model, a set of ‘k’ regressor variable and the exposure time ‘t’ are used to determine the mean of ‘y’. The following relation can be expressed as Eq. A09 (https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Negative_Binomial_Regression.pdf)

$$\mu = \exp(\ln(t_i) + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_k x_{ik})$$  \hspace{1cm} \text{(A9)}

Where $X_1 \equiv 1$; $\beta_1 = \text{intercept}$; The regression coefficient $\beta_1, \beta_2, ..., \beta_k$ represents the unknown parameters which are estimated from a data set and the estimates are epitomized as $b_1, b_2, ..., b_k$. Following this notation, the negative binomial regression model can be expressed for the observation ‘i’ as Eq. A10

$$\text{Pr}(Y_i = y_i | \mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1}) \Gamma(y_i + 1)} \left( \frac{1}{1 + \alpha \mu_i} \right)^{\alpha^{-1}} \left( \frac{\mu_i}{1 + \alpha \mu_i} \right)^{y_i}$$  \hspace{1cm} \text{(A10)}

Here $Y_i = \text{Dependent variables}; X = \text{Independent or regressor variables}; t = \text{Exposure values}; \alpha = \text{Dispersion parameter which is estimated from the data by employing maximum likelihood}$

The Hurdle Regression Models

The hurdle model can be written as Eq. A11 (Hofstetter, Dusseldorp, Zeileis, & Schaller, 2016)

$$P(Y_i = y_i | x_i, z_i, \beta, \gamma) =$$

$$\frac{f_{\text{zero}}(0; z_i; \gamma) \cdot f_{\text{sum}}(y_i; x_i; \beta)}{(1 - f_{\text{zero}}(0; z_i; \gamma)) \cdot f_{\text{sum}}(0; x_i; \beta)}$$  \hspace{1cm} \text{(A11)}

Where $y_i = \text{dependent variable value for the i th observation} i = 1, ..., N, z_i = \text{vector of length ‘J’ denoting the predictor variables number in the zero part, } X_i = \text{vector of length ‘K’ denoting predictor variables numbers in the hurdle part, } \gamma = \text{vector of coefficients which belongs to ‘z’}, \text{ and } \beta = \text{vector of coefficients which is related to ‘x’}$ (Zeileis, Kleiber, & Jackman, 2008). $f_{\text{zero}} = \text{probability density function at least on } \{0, 1\} \text{ (binary) or } \{0, 1, 2, \ldots\} \text{ (count), and } f_{\text{sum}} = \text{probability density function on } \{0, 1, 2, \ldots\}.$

The Zero-inflated Poisson Regression Model

The zero-inflated poisson model deals with the two zero generating processes. The first one deals with the generation of the zero and the second one is associated with the Poisson distribution which generates counts. Within these counts, some of may be zero. The following fixates can be described as Eq. A12

$$\text{Pr}(y_i = 0) = \pi + (1 - \pi) e^{-\lambda}$$

$$\text{Pr}(y_i = k_i) = (1 - \pi) \frac{\lambda^{k_i} e^{-\lambda}}{k_i!}, k_i \geq 1$$  \hspace{1cm} \text{(A12)}

Where $y_i = \text{the outcome variable with the value of any non-negative integer}; \lambda = \text{expected poisson count at the ‘i’ th observation}; \pi \text{ represents the probability of the extra zeros}$.
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Abstract: The paper discusses the impacts of COVID-19 on urban environments and presents a comprehensive review of the latest research on the topic. It highlights the importance of understanding the environmental implications of the pandemic and the need for sustainable urban solutions to mitigate its effects.

Keywords: Sustainable cities, COVID-19, Urban environments, Pandemic, Sustainability.