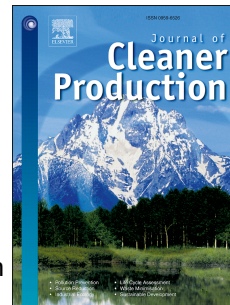


# Journal Pre-proof

Effects of lockdown due to COVID-19 outbreak on air quality and anthropogenic heat in an Industrial belt of India

Swades Pal, Priyanka Das, Indrajit Mandal, Rajesh Sarma, Susanta Mahato, Kim-Anh Nguyen, Yuei-An Liou, Swapan Talukdar, Sandipta Debanshi, Tamal Kanti Saha



PII: S0959-6526(21)00894-5

DOI: <https://doi.org/10.1016/j.jclepro.2021.126674>

Reference: JCLP 126674

To appear in: *Journal of Cleaner Production*

Received Date: 16 July 2020

Revised Date: 5 March 2021

Accepted Date: 6 March 2021

Please cite this article as: Pal S, Das P, Mandal I, Sarma R, Mahato S, Nguyen K-A, Liou Y-A, Talukdar S, Debanshi S, Saha TK, Effects of lockdown due to COVID-19 outbreak on air quality and anthropogenic heat in an Industrial belt of India, *Journal of Cleaner Production*, <https://doi.org/10.1016/j.jclepro.2021.126674>.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2021 The Author(s). Published by Elsevier Ltd.

## **Effects of lockdown due to COVID 19 outbreak on air quality and anthropogenic heat in an Industrial belt of India**

### **Credit author statement**

**Swades Pal:** Conceptualization, Methodology, Writing- Original draft preparation, Investigation, Writing- Original draft preparation, Writing- Reviewing and Editing., Supervision.

**Priyanka Das:** Writing- Reviewing and Editing

**Indrajit Mandal:** Methodology, Software, Formal analysis, Visualization, Data curation

**Rajesh Sarda:** Methodology, Software, Formal analysis, Visualization, Data curation

**Susanta Mahato:** Methodology, Software, Formal analysis, Visualization, Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing.,

Kim-Anh Nguyen: Writing- Original draft preparation, Writing- Reviewing and Editing

Yuei-An Liou: Investigation, Methodology, Writing- Original draft preparation, Writing- Reviewing and Editing, Supervision, Project administration, Funding acquisition.

**Swapan Talukdar:** Writing- Original draft preparation

**Sandipta Debanshi:** Writing- Original draft preparation, Writing- Reviewing and Editing

**Tamal Kanti Saha :** Writing- Original draft preparation

## Effects of lockdown due to COVID-19 outbreak on air quality and anthropogenic heat in an Industrial belt of India

### **Swades Pal**

Assistant Professor, Department of Geography, University of Gour Banga, Malda, India  
Email : [swadespal2017@gmail.com](mailto:swadespal2017@gmail.com)

### **Priyanka Das**

Assistant Professor, Department of Geography, Malda Women's College, Malda, India  
Email : [priyankadas694@gmail.com](mailto:priyankadas694@gmail.com)

### **Indrajit Mandal**

Research Scholar, Department of Geography, University of Gour Banga, Malda, India  
Email: [indrajitgeofarakka@gmail.com](mailto:indrajitgeofarakka@gmail.com)

### **Rajesh Sarda**

Research Scholar, Department of Geography, University of Gour Banga, Malda, India  
Email: [rajeshsarda127@gmail.com](mailto:rajeshsarda127@gmail.com)

### **Susanta Mahato**

Senior Research Fellow, Department of Geography, University of Gour Banga, Malda, India  
Email: [mahatosusanta2011@gmail.com](mailto:mahatosusanta2011@gmail.com)

### **Kim-Anh Nguyen**

Postdoc Fellow, Center for Space and Remote Sensing Research (CSRSR), National Central University, Taoyuan 32001, Taiwan.  
Email: [nguyenrose@csrsr.ncu.edu.tw](mailto:nguyenrose@csrsr.ncu.edu.tw)

### **Yuei-An Liou**

Distinguished Professor, Center for Space and Remote Sensing Research (CSRSR), National Central University, Taoyuan 32001, Taiwan.  
Email: [yueian@csrsr.ncu.edu.tw](mailto:yueian@csrsr.ncu.edu.tw)

### **Swapn Talukdar**

Senior Research Fellow, Department of Geography, University of Gour Banga, Malda, India  
Email: [swapantalukdar65@gmail.com](mailto:swapantalukdar65@gmail.com)

### **Sandipta Debanshi**

Research Scholar, Department of Geography, University of Gour Banga, Malda, India  
Email : [debanshi.sandipta93@gmail.com](mailto:debanshi.sandipta93@gmail.com)

### **Tamal Kanti Saha**

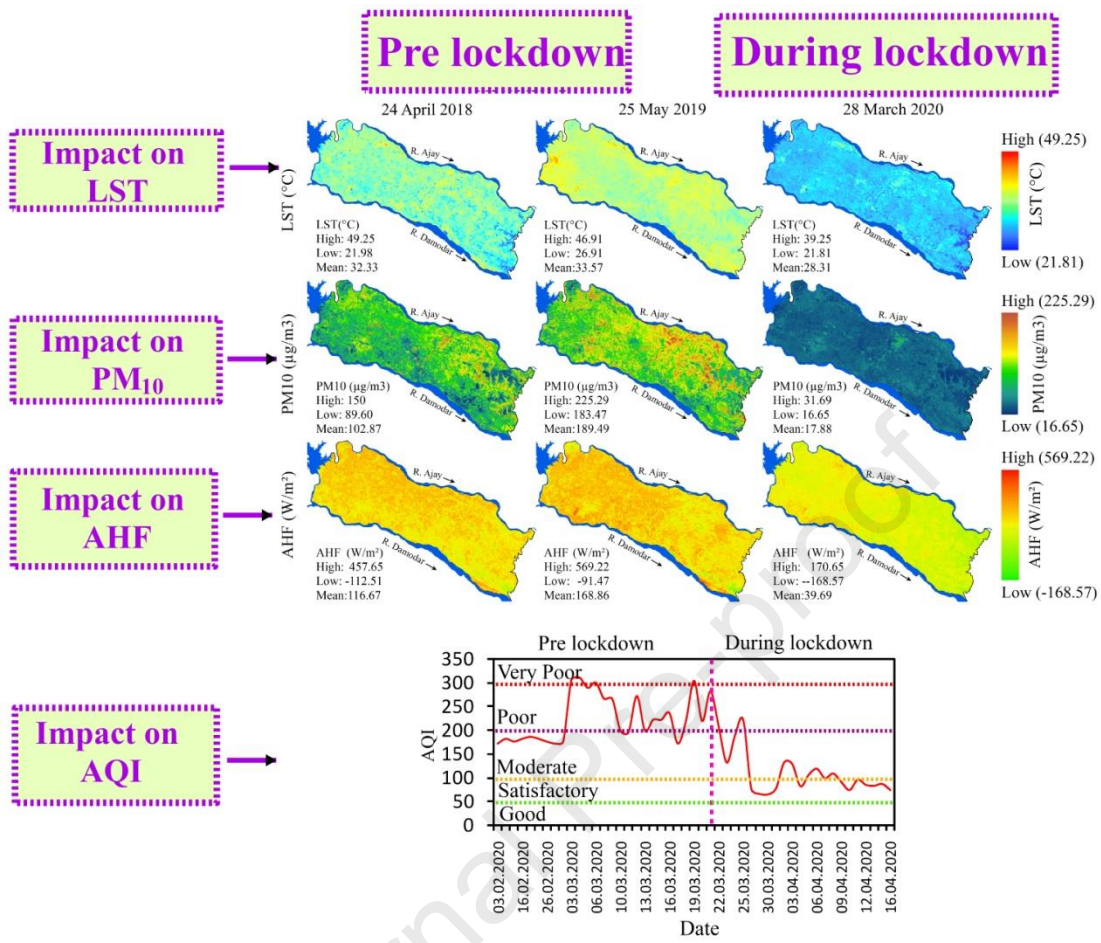
Senior Research Fellow, Department of Geography, University of Gour Banga, Malda, India  
Email : [tamalkantisaha999@gmail.com](mailto:tamalkantisaha999@gmail.com)

**Acknowledgments:**

This research was financially supported by the Ministry of Science and Technology (MOST) of Taiwan under the codes MOST 109-2923-E-008-004-MY2 and MOST 108-2111-M-008-036-MY2.

Journal Pre-proof

Graphical Abstract



# Effects of lockdown due to COVID-19 outbreak on air quality and anthropogenic heat in an industrial belt of India

## Abstract

Highly urbanized and industrialized Asansol Durgapur industrial belt of Eastern India is characterized by severe heat island effect and high pollution level leading to human discomfort and even health problems. However, COVID-19 persuaded lockdown emergency in India led to shut-down of the industries, traffic system, and day-to-day normal work and expectedly caused changes in air quality and weather. The present work intended to examine the impact of lockdown on air quality, land surface temperature (LST), and anthropogenic heat flux (AHF) of Asansol Durgapur industrial belt. Satellite images and daily data of the Central Pollution Control Board (CPCB) were used for analyzing the spatial scale and numerical change of air quality from pre to amid lockdown conditions in the study region. Results exhibited that, in consequence of lockdown, LST reduced by  $4.02^{\circ}\text{C}$ ,  $\text{PM}_{10}$  level decreased from 102 to  $18\mu\text{g}/\text{m}^3$  and AHF declined from 116 to  $40\text{W}/\text{m}^2$  during lockdown period. Qualitative upgradation of air quality index (AQI) from *poor to very poor state to moderate to satisfactory state* was observed during lockdown period. To regulate air quality and climate change, many steps were taken at global and regional scales, but no fruitful outcome was received yet. Such lockdown (temporarily) is against economic growth, but it showed some healing effect of air quality standard.

**Keywords:** Lockdown; Industrial belt; Land surface temperature; Anthropogenic heat flux and Air quality index

## 1. Introduction

Climate change is among the highly argued topics in the contemporary world. The accelerated rise of global temperature and consequence has been among the vital concerns since 1850 (IPCC, 2013). Growing energy footprint was condemned as the dominant cause behind the rise of temperature (Aydin and Turan 2020). There is worldwide variation in energy footprint, usually high in the developed countries and low in the underdeveloped or developing countries. In the USA per capita, the carbon emission rate is 14.9 metric tons,

31 while, in India, it is only 1.57 metric tons. Massive combustion of fossil fuel in industrial,  
32 urban, and transport sectors, and consequent emission of carbon lead to temperature rise and  
33 air quality degradation (Zhang et al., 2020). The increased concentration of particulate matter,  
34 SO<sub>2</sub>, CO, etc causes deterioration of air quality (Xie and Deng., 2020; Dutta and Gupta 2021).  
35 Recently anthropogenic heat flux (AHF) in the highly urbanized and industrial sectors is  
36 another emerging concern (Nguyen et al., 2018; Liou et al., 2019; Yu et al., 2021).  
37 Anthropogenic heat means heat release to the atmosphere resulted from human activities like  
38 combustion of fossil fuel, human metabolism, industrial emission, thermally sensitive  
39 building materials, and traffic emission (Zheng et al., 2021). Ayanlade and Howard (2019)  
40 focused on the estimation of AHF from satellite images for the last two decades. Varquez et  
41 al. (2021) estimated future urban expansion and climate change effect in futuristic AHF. In  
42 this context, most of those works tried to compute AHF from image data. It was reported that  
43 estimated anthropogenic heat from the image was greater than source-specific field data-  
44 centric estimated heat (Wang et al., 2020), but field data based in situ measurements are  
45 highly dependent on data availability (Firozjaei et al., 2020) and in the third world country  
46 which puts a hindrance on such studies. On the other hand, remote sensing-based image data  
47 has become an alternative which helps to retrieve AHF of larger geographical area (Raj et al.,  
48 2020). From the previous studies, it became clear that with increasing human pressure and  
49 anthropogenic activities, AHF is getting enhanced and the global eco-environment has  
50 become more vulnerable (Nguyen and Liou, 2019a, b). Jin et al. (2020) reported the  
51 successful use of Landsat and MODIS data for estimating LST and anthropogenic heat  
52 distribution over Delhi and its surrounding region during both winter and summer seasons. It  
53 was observed that during 2000-2010 AHF (W/m<sup>2</sup>) had increased by nearly 150% over the  
54 settlement and solid structures.

55 In India, several studies carried out by a good number of researchers like Mandal et al.  
56 (2020); Plocoste et al. (2021) investigated time series LST trend and PM level. Mahato and  
57 Pal (2018) focused on impact of land surface parameters on land surface temperature regime.  
58 Most of the studies reported the increasing trend of LST and PM in the urban and industrial  
59 area across the world. Moreover, spatial image data released from European Space Agency  
60 (ESA), NASA also reported a growing PM level in the atmosphere in most urban halves of  
61 the world. Growing economic activities like intensification in industry, transport, tourism,  
62 agriculture, and trade are the majorly responsible for this (Mandal et al., 2020). Nevertheless,  
63 fast-changing land use/land cover, squeezing green and blue space over the terrestrial land,

64 qualitative deterioration of terrestrial and aquatic ecosystems, and weakening of self-  
65 regulatory mechanism of the ecosystem are unable to refresh and restore the environment due  
66 to release of high-volume pollutants within a very short period (Du et al., 2020). A good  
67 number of world summits like annual United Nations Climate Change Conference (UNCOP)  
68 from 1995 till present were conducted; Intergovernmental Panel on Climate Change (IPCC)  
69 was periodically conducted with climate change contents reported, but no-good solution was  
70 found yet to combat the environmental deterioration. To keep the continuous economic  
71 growth, no strict measure was yet taken compromising with production volume.

72 However, COVID-19 pandemic started to outbreak since the second fortnight of December  
73 2019 around the world. Since beginning this disease rapidly spread over China, Italy, France,  
74 Spain, Germany, Russian federation, UK, USA, India, UAE, Australia Brazil, Argentina and  
75 many other countries. Till 25th of October it snatched more than 1,147,000 people and  
76 infected more than 42,500,000 people. Considering this emergency and to stop the threat of  
77 this virus, most of the world implemented lockdown (full or partial) since March 2020, which  
78 simultaneously froze the pollution effective economic sectors like industry, transport,  
79 tourism, etc. (Muhammad et al., 2020). This imposed measure caused a great economic loss  
80 around the world, but the nature got the opportunity to refresh its environment as  
81 demonstrated by Tobias et al. (2020). These studies clearly articulated the healing of air  
82 quality. A sharp and sudden fall of global carbon emission was observed due to the reduction  
83 in energy footprint (Wang and Su, 2020), stoppage of production in industry (Muhammad et  
84 al., 2020), break-in public traffic (Chen et al., 2020) etc. Temporary halt of economic  
85 activities not only reduced the carbon emission, but also restricted the discharge of several  
86 other Greenhouse Gases (GHGs) and pollutants like Sulfur Dioxide (SO<sub>2</sub>), Nitrogen Dioxide  
87 (NO<sub>2</sub>), and Particulate Matters 2.5 and 10 (PM<sub>2.5, 10</sub>) (NASA, 2020). In addition, about 25%  
88 reduction in CO<sub>2</sub>, equivalent to 1million tons of carbon, was detected in China (Wang and Su,  
89 2020). Mahato et al. (2020) carried out work on mega city Delhi, India and reported  
90 significant quality improvement in most parts of Delhi. Mahato and Ghosh (2020) reported  
91 most polluted Indian cities air quality conditions during the lockdown amid COVID-19.  
92 Sharma et al. (2020) reported AQI across 22 cities of India depicting improvement by 15-  
93 44%. Das et al. (2021) experienced that the air quality of the Indian megacities also improved  
94 by 50% amid lockdown and air quality hotspot has diluted amid lockdown but restored in  
95 partial lockdown. Travaglio et al. (2021) reported the crucial role of level of NO<sub>x</sub> and  
96 particulate matter to trigger COVID-19 infection in the UK. Zhang et al. (2021) have

97 statistically shown the association between COVID-19 spread and air pollution in China. Ju  
98 et al. (2021) experienced that in Korea air pollution level has been identically reduced during  
99 the pandemic of COVID-19. From heavy industry dominated areas of North and Northeast  
100 China, the emission of NO<sub>2</sub> extensively reduced in the first week of lockdown (European  
101 Space Agency, 2020). Almost 50% crash in air pollution in New York City (USA) was  
102 identified in March 2020 in comparison to the same period of 2019 (Saadat et al., 2020). NO<sub>2</sub>  
103 emission cut rate was also significantly high in different European countries, like Spain, UK,  
104 Italy, France, Germany as captured by satellite images (Ficetola and Rubolini, 2020). PM<sub>2.5</sub>,  
105 PM<sub>10</sub>, CO<sub>2</sub>, and NO<sub>2</sub> concentration levels reduced by 43%, 31%, 10%, and 18%, respectively,  
106 in comparison to previous year over 22 Indian cities (Sharma et al., 2020). Apart from air  
107 quality improvement, Bashir et al. (2020) also found a strong positive association of air  
108 quality indicators with other climatic variables. It is the fact that increment of greenhouse  
109 gases can enhance the temperature retaining capacity of the atmosphere and this, in turn,  
110 regulates several other components of climate (Xu and Cui, 2021). The Smog Effect in  
111 megacities like Delhi is very well known to the world among this.

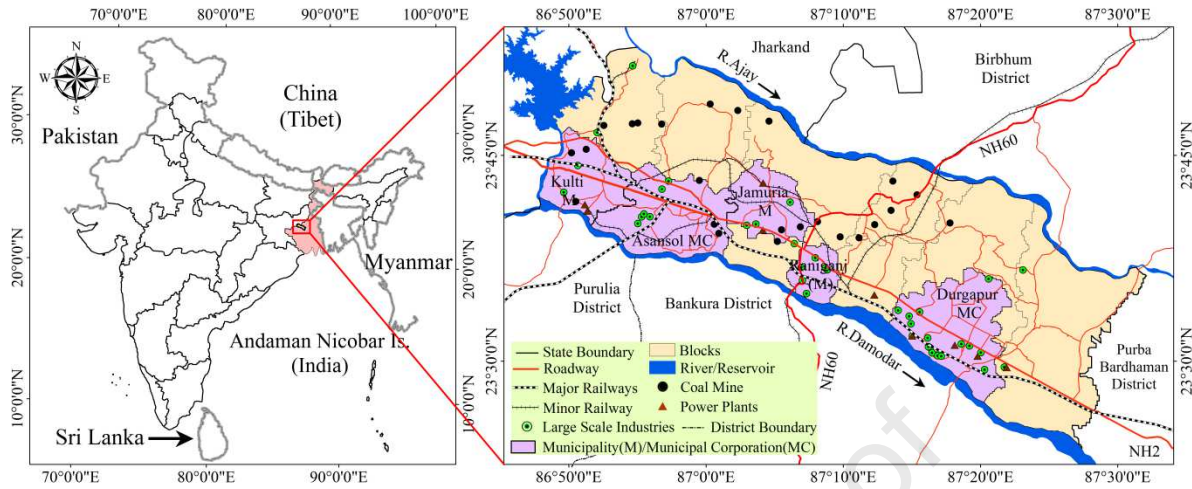
112 The existing works conducted regarding the environmental perspective of the COVID-19  
113 outbreak were focused either on entire world or on mega-cities, while what is the response of  
114 industrial area dominated cities beyond megacities was not addressed so far. In India, Sathe et  
115 al. (2021), Naqvi et al. (2021), Das et al. (2021), Mele and Magazzino (2021) and Mor et al.  
116 (2021) figured out the impact on air quality over city scale. In this regard, a lack of study was  
117 noticed addressing the improvement of air quality due to COVID-19 persuaded lockdown in  
118 heavy manufacturing based fast growing urban-industrial area influenced both by the primary  
119 and secondary economic activities of a third world nation. Beside air quality, rise of  
120 temperature caused by anthropogenic activities was another global concern that should be  
121 examined under the offsetting effects of lockdown, which did not receive enough attention.  
122 However, urban dominated industrial sector is a major source of greenhouse gases and  
123 anthropogenic heat. These research gaps can be addressed in reference to a world reputed  
124 large scale industrial area called Asansol Durgapur development region of Eastern India. This  
125 highly urbanized and densely populated region is characterized by simultaneous insertion of a  
126 primary economic sector like coal mining and a secondary economic sector in form of large  
127 industries along with two municipal corporations and three municipalities. The area is well  
128 known for heat island effect and high pollution level due to the coupled effects of urban  
129 expansion and industrial pollution. A fast-growing urban area with high population density

130 demands huge energy in mining, industrial, traffic and domestic sectors and emits diverse  
131 pollutants notably greenhouse gases. In India such proximate and dense association of urban  
132 sites, mining and industrial activities within an area is very rare in India. Study over this  
133 region in this aspect is not available. High temperature (40°C or more during summer season  
134 (April-May)), intensive urban growth, mining and industrial activities and high energy  
135 footprint are responsible for creating high intensity heat island effects, ejection of huge  
136 pollutants, which in turn caused for degrading air quality in this area. In addition, a huge  
137 amount of black particles that are ejected from the mining sites, which not only increase the  
138 concentration of particulate matters in the air, but also enhance the heat absorbing capacity  
139 intensifying heat island effect of the region. All these characteristics have inspired to select  
140 this urban-industry dominated area as a case. Lockdown situation has brought an opportunity  
141 to justify how far anthropogenic activities are responsible for creating heat island effect, AHF  
142 and air pollution, since the major economic sectors were stopped working. The gap of  
143 thermal state, AHF and pollution level between pre and amid lockdown may crudely  
144 highlight the role of anthropogenic activities in this regard. AHF is often neglected but its  
145 role is important for studying thermal effect. In this view, the present study intended to  
146 examine whether lockdown causes temporary dilution of heat island, reducing the AHF and  
147 improving the air quality and how far anthropogenic activities are responsible for heat island  
148 effect, growing AHF and pollution level.

## 149 **2. Materials and methods**

150 This industrial region (Fig. 1) is a planning area with coverage more than 1,600 km<sup>2</sup>  
151 administered by the Asansol-Durgapur Development Authority (ADDA) and represents one  
152 of the eight major industrial regions of India. Steel plants of the Steel Authority of India  
153 Limited (SAIL) and Indian Iron and Steel Company (IISCO) are the prime industries in this  
154 region. These industries are supported by coal, iron, and steel. Besides the Steel and Coal  
155 based industries, the region also consists of some other heavy industries, such as Durgapur  
156 Chemicals, Durgapur Thermal Power Station, Dishergarh Power Supply, Damodar Valley  
157 Power Corporation, etc. Eventually air pollution level is usually found high in this region in a  
158 normal situation. Apart from these, the region is characterized by the sub-humid monsoon  
159 climate with high seasonal difference in temperature between winter (December to January)  
160 and summer season (March to May). In addition, intensive economic activities make this  
161 region a densely populated urban where more than three fourth (77%) of its total population  
162 (2,400,000 people) is concentrated in the urban areas far above Indian average.

163



164

165 **Fig. 1:** Geo-location of the study area along with different administrative units and other  
 166 supplementary information like the location of coal mines, large scale industries, and minor  
 167 roads.

168 For estimating surface temperature,  $PM_{10}$  and anthropogenic heat flux, and Landsat images  
 169 were involved. USGS website was subscribed to download images (path/row: 139/44, spatial  
 170 resolution: 30m) dated on 24th April 2018 and 25th May 2019 for the pre-lockdown periods  
 171 and on 28th March 2020 for the amid lockdown period. Daily average data of seven air  
 172 pollutants, namely particulate matter of two separate diameters ( $PM_{2.5}$  and  $PM_{10}$ ), Nitrogen  
 173 Dioxide ( $NO_2$ ), Sulphur Dioxide ( $SO_2$ ), Ozone ( $O_3$ ), Carbon Monoxide (CO), and Ammonia  
 174 ( $NH_3$ ), were extracted from the online portal containing air quality data of Central Pollution  
 175 Control Board (CPCB).

176 Land surface temperature (LST), particulate matter 10 ( $PM_{10}$ ) and anthropogenic heat flux  
 177 (AHF) were computed at pixel scale from Landsat images for both pre and during lockdown  
 178 periods. For showing the pre-lockdown state, images of 24th April 2018 and 25th May 2019  
 179 and during the lockdown state of 28th March 2020 were taken. Apart from this, daily data on  
 180  $PM_{10}$ ,  $PM_{2.5}$ ,  $SO_2$ , CO,  $NO_2$ ,  $NH_3$  and  $O_3$  both for pre and during lockdown were taken into  
 181 consideration for showing the effect.

## 182 **2.1 Computation of Land surface temperature (LST) and validation**

183 All the objects having a temperature above zero (K) radiate thermal electromagnetic energy.  
 184 Analyzing the radiation balance at the land-air interface, it is possible to extract LST with the

185 help of satellite images. The three most commonly used methods for LST computation are (1)  
 186 Radiative Transfer Equation (2) Single-Channel Algorithm (3) Split-Window Algorithm.  
 187 Among these methods, Garcia-Santos et al. (2018) reported a computable radiative transfer  
 188 equation better than the others. Considering this, the present work applied this method for  
 189 computing LST from image data (Eq. 1).

190 LST computation follows multi-step like (1) Conversion of the Digital Number (DN) to  
 191 Spectral Radiance, (2) conversion of spectral radiance to at satellite brightness temperature,  
 192 (3) LST extraction, (4) conversion of LST from Kelvin to degree Celsius. This method is  
 193 quite different in different sensors (Landsat 5, 7, 8). The detail method is available in the  
 194 guidelines put forward by the Landsat Project Science Office (2002). Detail steps for  
 195 computing LST are also given in supplementary material 1.

$$196 \text{ LST} = \frac{T_B}{[1 + \{(\lambda \times TB / \rho) \times \ln \varepsilon\}]} \quad (\text{Eq. 1})$$

197 where  $\lambda$  is the wavelength of radiated radiance in meter (Markham and Barker, 1985),  $\varepsilon$  is land  
 198 surface emissivity,  $\rho = h * c / \sigma$  ( $1.438 * 10^{-2} m \cdot K$ ),  $h$  is Planck constant ( $6.626 * 10^{-34} J \cdot s$ ),  $\sigma$  is  
 199 Boltzmann constant ( $1.38 * 10^{-23} J/K$ ), and  $c$  is the velocity of light ( $2.998 * 10^8$  m/s). Note that  
 200 LST estimated by Eq. (1) is in Kelvin.

201 Satellite data derived LST maps were validated with field measurements collected at 37 sites  
 202 across the study area in pre-lockdown period using thermal infrared thermometer. During  
 203 lockdown, LST map was validated using only three sites due to access restriction. Pearson's  
 204 correlation coefficient ( $r$ ) was then computed to assess the spatial association.

## 205 **2.2 Estimating particulate matter 10 ( $PM_{10}$ ) concentration**

206 Landsat 8 Operational Land Imager (OLI) data of USGS was taken for estimating  $PM_{10}$ .  
 207 Retrieval of  $PM_{10}$  from Landsat image was done by many scholars like Saraswat et al. (2017)  
 208 following the basic guideline of USGS: Landsat 8 Handbook, 2016. It follows following  
 209 steps like (1) Translation of DN value to Top of Atmospheric (TOA) radiance, (2)  
 210 Translation of DN value to TOA reflectance, (3) Sun angle corrected TOA reflectance, (4)  
 211 Atmospheric correction, (5) Path Radiance correction, (6) Aerosol optical thickness (AOT)  
 212 estimation, (7) AOT and  $PM_{10}$  correlation, and (8) Derivation of particulate matter ( $PM_{10}$ ).

213 After computing and mapping  $PM_{10}$ , validation of the map was done using Tem-top airing-  
 214 1000 air quality monitor (measuring range 0-999  $\mu g/m^3$ , resolution 0.1  $\mu g/m^3$ ) derived field  
 215 data at 80 sites for pre-lockdown period. However, it was not possible to validate maps of

216 lockdown phase using all those sites due to assess limitations. Field measurements from only  
 217 three sites including the monitoring station of CPCB were taken for validating the map.  
 218 Pearson's correlation coefficient was computed between the data derived from PM<sub>10</sub> image  
 219 and field data.

220

### 221 **2.3 Estimating anthropogenic heat flux (AHF)**

222 The anthropogenic heat consists of the total heat discharged from industries, vehicles, and  
 223 human activities. In urban and industrially rich areas, AHF is a significant heat contributor.  
 224 For computing spatial AHF, spatial data layers like net radiation, ground heat flux, latent  
 225 heat, sensible heat, are necessary. Net radiation ( $R_n$ ) denotes actual availability of solar  
 226 radiant energy at surface. It is the major component of surface energy balance and gets  
 227 influenced by surface albedo. In case of industry dominated urban area anthropogenic heat  
 228 ( $A$ ) was incorporated in the equation of surface energy balance which is a sum of total heat  
 229 released from industry, transportation and human activities. The rate of energy which is  
 230 transmitted by soil per unit time and area is referred as ground heat flux ( $G$ ). The loss of heat  
 231 due to gradients of temperature is referred as sensible heat flux whereas latent heat flux ( $L$ ) an  
 232 additional parameter of surface energy balance. First, all these data layers were computed and  
 233 based on equations 2 and 1. Figure 2 represents the spatial state of these parameters. Finally,  
 234 we estimated AHF following Zhang et al. (2013). The modified energy balance equation  
 235 ( $R_n+A=G+H+L$ ) Following Oke 1987 is the basis of computing AHF. This energy balance  
 236 equation was modified and differently developed for the heavy industrial and densely  
 237 populated urban areas where surface energy balance is different from natural landscape  
 238 because of the addition of huge amount of anthropogenic heat to the flux component. Present  
 239 study area belongs to this category for having both heavy industry and dense population.  
 240 Apart from that several other recent studies like Kotthaus and Grimmond, (2014); Ward et  
 241 al., (2016); Ziaul and Pal, (2018) successfully used this method to quantify AHF of urban  
 242 settlements. The particular method is provided in supplementary 1.

243 Anthropogenic heat discharge, expressed as  $H_n$  is estimated through the expression given  
 244 below in Eq. (2):

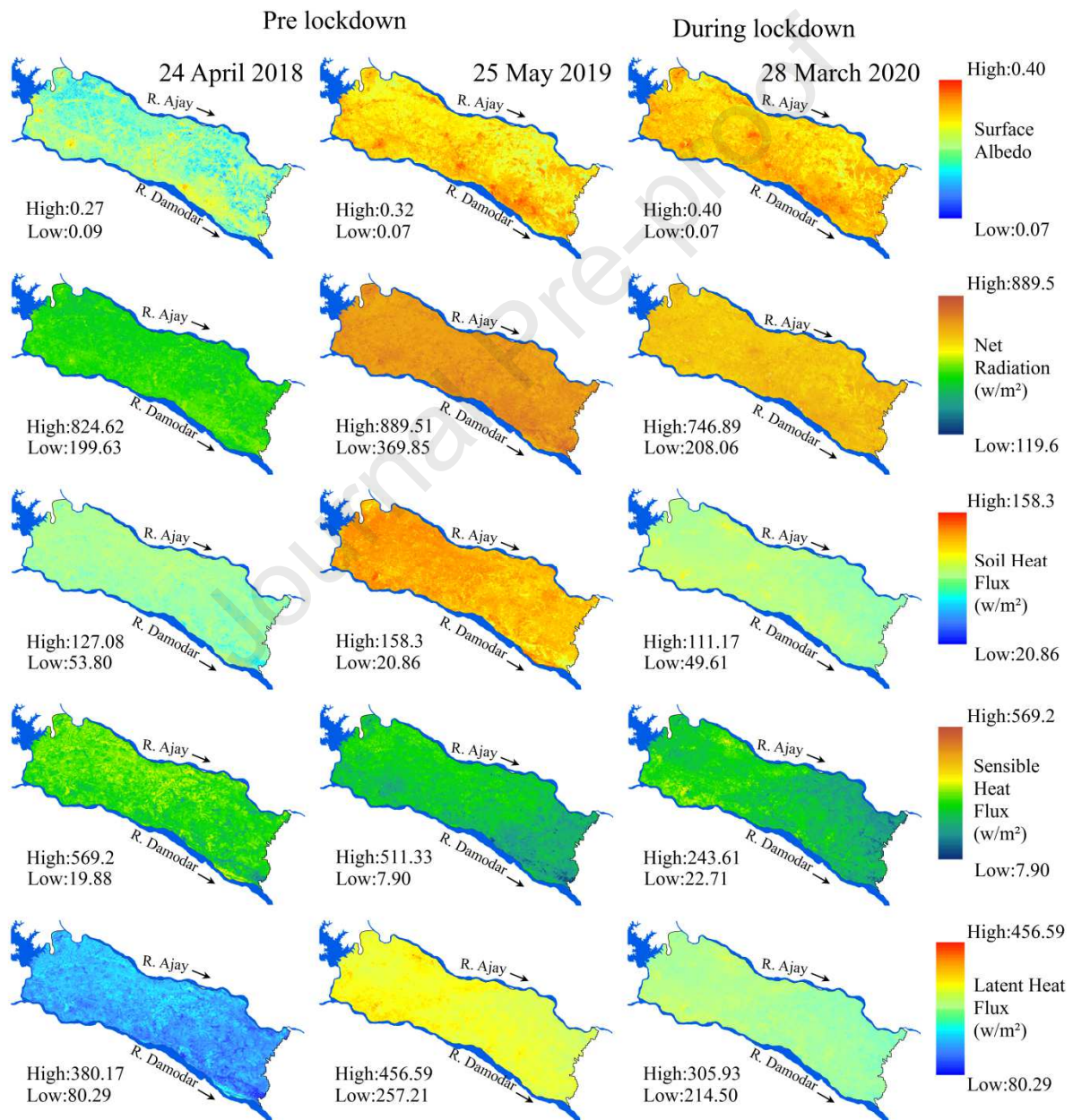
$$245 \quad H_n = R_n - G - LE \quad (\text{Eq. 2})$$

246 The difference between total sensible heat flux ( $H$ ) and  $H_n$  is known as anthropogenic heat  
 247 flux ( $H_{as}$ ) and was estimated by the equation:

$$248 \quad H_{as} = H - H_n \quad (\text{Eq. 3})$$

249 It was only calculated if  $H$  was higher than or equivalent to  $H_n$ . We can use Eq. (3) to  
 250 calculate  $H_{as}$ . If not, it was a substitute for  $H_n$ .

251



252

253 **Fig. 2** Atmospheric parameters used for computing AHF

## 254 Source-specific AHF

255 Major sources of AHF include human metabolism ( $Q_M$ ), industry ( $Q_I$ ), vehicles ( $Q_V$ ), and  
 256 buildings ( $Q_B$ ). Total anthropogenic heat emission ( $Q_F$ ) is the sum of heat from all the  
 257 mentioned sources expressed (Sailor and Lu, 2004). For computing source-specific AHF, day  
 258 time metabolism rate of men, energy consumption rate in residential and commercial units,  
 259 vehicle movement of different kinds were taken into account (Supplementary material 1).  
 260 AHF from different sources were computed for 2018 (pre lockdown) but during lockdown  
 261 extensive field survey was quite difficult. Still based on the information collected from the  
 262 residents living over there regarding vehicle movement, operational state of the industries,  
 263 electricity consumption state of eastern region of India (Source: Power System Operation and  
 264 Cooperation or POSOCO) it was tried to estimate the possible change in AHF.

### 265 2.4 Method for showing change on air quality components

266 For integrating seven air quality parameters, National Air Quality Index (NAQI) of CPCB  
 267 (2014) was used. For these seven air quality components ( $PM_{10}$ ,  $PM_{2.5}$ ,  $NO_2$ ,  $NH_3$ ,  $SO_2$ ,  $CO$ ,  
 268 and  $O_3$ ) were aggregated based on the weighted additive method. Before doing this, sub-  
 269 indices for all the individual components had to be done. A detailed method for developing  
 270 sub-indices and aggregation is given in Supplementary material 1. After computing all the  
 271 sub-indices, the aggregated index was calculated summing up all those sub-indices.

272 The AQI can be interpreted about the six AQI states and their possible health threats, as  
 273 mentioned by CBCB (Table 1). The health exposures consist of minimal impact which is  
 274 denoted as good AQI state, where the concentration all the pollutants lies at the lowest  
 275 category. Breathing discomfort starts when AQI crosses satisfactory state and reaches to  
 276 moderately pollution level. In severe AQI state all pollutants reach to the worst concentration  
 277 level with health impact of respiratory illness and prolonged exposure.

278 **Table 1** Range of air quality components in National AQI classes and health impacts

	Health Impact	$PM_{10}$	$PM_{2.5}$	$SO_2$	$NO_2$	$O_3$	$CO$	$NH_3$
		24 hrs ( $\mu g/m^3$ )	24 hrs ( $\mu g/m^3$ )	24 hrs ( $\mu g/m^3$ )	24hrs ( $\mu g/m^3$ )	8hrs ( $\mu g/m^3$ )	8 hrs ( $mg/m^3$ )	24 hrs ( $\mu g/m^3$ )
		Concentration Range						
Good (0–50)	Minimal Impact	0–50	0–30	0–40	0–40	0–50	0–1	0–200
Satisfactory (51–100)	Minor breathing discomfort to sensitive people	51–100	31–60	41–80	41–80	51–100	1.1 - 2	201– 400

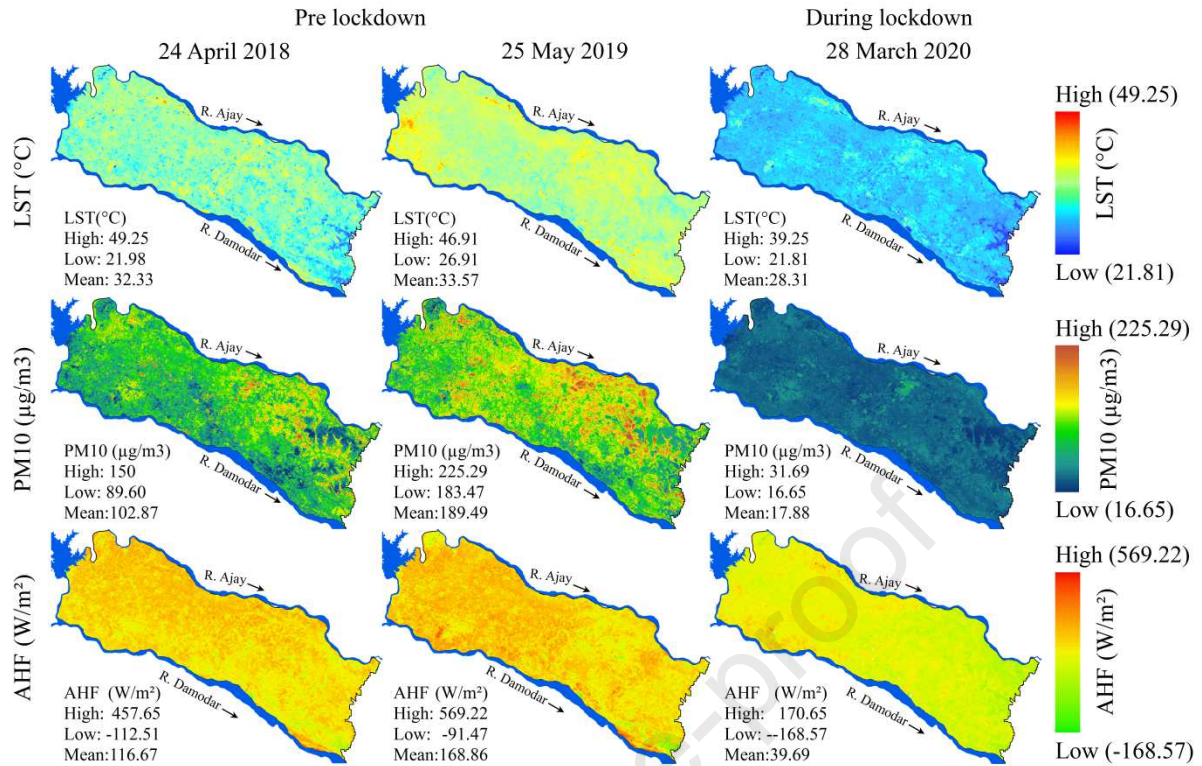
Moderately polluted (101– 200)	Breathing discomfort to the people with lung,	101–250	61–90	81–380	81–180	101–168	2.1–10	401–800
Poor (201– 300)	Breathing discomfort to people on prolonged exposure	251–350	91–120	381–800	181–280	169–208	10–17	801–1200
Very poor (301– 400)	Respiratory illness to the people on prolonged exposure	351–430	121–250	801–1600	281–400	209–748*	17–34	1200–1800
Severe (401–500)	Respiratory illness to the people on prolonged exposure	>430	>250	>1600	>400	>748	>34	>1800

279

### 280 3. Results

#### 281 3.1 Effect on LST, PM<sub>10</sub> concentration and AHF

282 Figure 3 denotes spatial LST, PM<sub>10</sub> and AHF states of the study area in summer seasons of  
 283 2018, 2019 and 2020 representing pre-lockdown and during lockdown periods. The range of  
 284 LST was from 22°C to 49°C in this area with an average of 33°C. However, immediately after  
 285 implementation of lockdown in West Bengal and India, the upper limit of temperature  
 286 reduced to 39°C with much less notable change in lower limit. Average temperature reduced  
 287 by >2.5 °C within one week of lockdown. This reduction was observed over the entire study  
 288 area and the rate of reduction was quite high in the industrial hubs and urban areas. For  
 289 making micro level comparison, LST was classified into three classes and area under these  
 290 classes was computed in pre and during lockdown periods considering study area as a whole,  
 291 municipal area and municipal corporation area individually (Table 2). In the pre-lockdown  
 292 period, 1584 to 1591km<sup>2</sup> (up to 99% of the total area) was under >30 °C LST category, but  
 293 during lockdown about 30% area from this category and shifted to relatively less intensive  
 294 temperature classes. In municipal areas, the effect was almost the same in trend. In Asansol,  
 295 125 km<sup>2</sup> area was under >30°C temperature class before lockdown was implemented and it  
 296 squeezed to 90.51 km<sup>2</sup> amid lockdown implementation. In Durgapur municipal corporation  
 297 area, this change was quite higher than those of the other areas. About 153 km<sup>2</sup> area was  
 298 characterized with 30 °C or higher surface temperature before commencing lockdown, but  
 299 after commencing lockdown area under this temperature class reduced to only 37.17 km<sup>2</sup>  
 300 (Table 2). For validating LST maps derived from image data, field driven data is taken with  
 301 correlation computed. Correlation coefficient varied from 0.61 to 0.73 at 0.01 level of  
 302 significance.



303

304 **Fig. 3** LST (°C), PM<sub>10</sub> (µg/m<sup>3</sup>) and AHF (W/m<sup>2</sup>) states computed from image data for pre and during  
 305 lockdown periods

306 **Table 2:** Area (km<sup>2</sup>) under different LST classes for pre and during lockdown phases

Phase	Month	LST (°C)	ADDA Region	Asansol MC	Durgapur MC	Raniganj (M)	Jamuria (M)	Kulti (M)
Pre Lockdown	24 April (2018)	<25	1.12	0.07	0.35	0	0.10	0
		25-30	17.77	0	0.85	0	0	0.21
		>30	1584.28	124.93	153.00	24.99	79.10	95.79
	25 May (2019)	<25	0.83	0	0.00	0	0	0
		25-30	11.09	0	0.85	0	0	0.11
		>30	1591.25	125	153.35	24.99	79.20	95.89
During lockdown	28 March (2020)	<25	52.04	2.10	40.23	0.55	0.49	16.10
		25-30	600.35	32.39	76.80	14.18	14.36	29.65
		>30	950.78	90.51	37.17	10.26	64.35	50.25

307

308 Particulate matter (PM) concentration above 100µg/m<sup>3</sup> in the atmosphere is hazardous for  
 309 human health (WHO, 2016). When industries were in operational mode and urban sectors  
 310 worked normally, a huge amount of PM emits to the atmosphere with average PM level  
 311 exceeding the WHO defined tolerance limit. Figure 3 shows spatial distribution of PM<sub>10</sub> level  
 312 in pre and during lockdown periods. The range of PM<sub>10</sub> level was from 89.60 to 150 µg/m<sup>3</sup> in

313 April 2018 and from 183.47 to 225.29  $\mu\text{g}/\text{m}^3$  in May 2019 (in pre lockdown period), but this  
 314 range reduced to from 16.65 to 31.69  $\mu\text{g}/\text{m}^3$ . Average  $\text{PM}_{10}$  levels were 102.87 and 189.49  
 315  $\mu\text{g}/\text{m}^3$  in April 2018 and May 2019, respectively, but this is only 17.88  $\mu\text{g}/\text{m}^3$  during  
 316 lockdown period. This significant reduction showed that the critical level of  $\text{PM}_{10}$   
 317 concentration changed to ambient and good for human respiration. Area concentration  
 318 analysis in different  $\text{PM}_{10}$  levels exhibited that in the pre-lockdown period 98.75% area was  
 319 under critical  $\text{PM}_{10}$  level, but after announcing lockdown due to reduction of  $\text{PM}_{10}$  level, all  
 320 parts of the study area were characterized with ambient PM level. In all the municipal areas  
 321 the picture was similar (Table 3). Image derived  $\text{PM}_{10}$  data was correlated with field  
 322 obtained data and correlation coefficient value was achieved between 0.43 and 0.64 at 0.01  
 323 level of significance.

324 **Table 3** Area ( $\text{km}^2$ ) under different  $\text{PM}_{10}$  classes for pre and during lockdown phases

Phase	Month	PM 10 ( $\mu\text{g}/\text{m}^3$ )	ADDA Region	Asansol MC	Durgapur MC	Raniganj (M)	Jamuria (M)	Kulti (M)
Pre Lockdown	24 April (2018)	<100	5.05	0	0	0	0	0
		100-125	12.16	4.8	4.03	0.28	0	0
		>125	1585.96	120.2	150.17	24.71	79.2	96
	25 May (2019)	<100	0	0	0	0	0	0
		100-125	0	0	0	0	0	0
		>125	1603.17	125.00	154.20	24.99	79.20	96.00
During lockdown	28 March (2020)	<100	1603.17	125.00	154.20	24.99	79.20	96.00
		100-125	0	0	0	0	0	0
		>125	0	0	0	0	0	0

325

326 Figure 3 shows the AHF in pre and during lockdown periods. Average AHF of 117 to 169  
 327  $\text{W}/\text{m}^2$  in pre-lockdown reduced to 40  $\text{W}/\text{m}^2$  during lockdown condition. Along with reduction  
 328 of average AHF, spatial variability of AHF also significantly reduced after implementing  
 329 lockdown. Area coverage under different AHF classes also shows that area under higher  
 330 AHF overwhelmingly reduced during lockdown (Table 4). About 203  $\text{km}^2$  area was  
 331 delineated  $\text{AHF} > 100 \text{ W}/\text{m}^2$  in pre-lockdown period, but amid lockdown all parts of the study  
 332 area were recorded with  $\text{AHF} < 100 \text{ W}/\text{m}^2$ . Municipal area specific analysis of the same also  
 333 shows the same trend. The determinants of AHF represented in Fig. 2 shows a significant  
 334 change with the implementation of lockdown. The higher limit of surface increased from 0.32  
 335 to 0.40 during lockdown whereas lower limit remained same as 0.07. Among the other  
 336 factors like net radiation, soil heat flux, sensible heat flux and latent heat flux show sharp

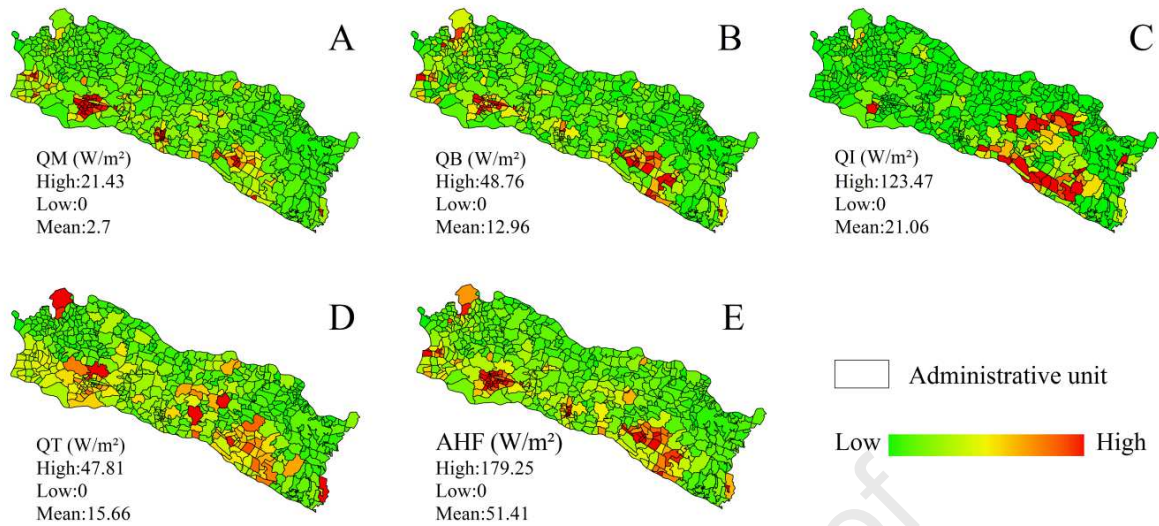
337 decrease. Maximum limits of all three-heat flux reduced up to 50% during lockdown as  
 338 compared to pre lockdown situation.

339 **Table 4:** Area (km<sup>2</sup>) under different AHF classes for pre and during lockdown phases

Year	Pre lockdown						During lockdown		
	24 April (2018)			25 May (2019)			28 March (2020)		
AHF (W/m <sup>2</sup> ) Range	<100	100-200	>200	<100	100-200	>200	<100	100-200	>200
ADPA Region	1400	193.2	9.97	1359.86	232.42	10.89	1602.65	0.52	0
Asansol MC	117.91	7.03	0.06	116.881	8.05	0.07	124.95	0.05	0
Durgapur MC	150.6	3.2	0.4	146.72	6.98	0.5	154	0.2	0
Raniganj (M)	24.01	0.97	0.01	23.75	1.23	0.01	24.99	0	0
Jamuria (M)	67.5	11.53	0.17	65.78	13.23	0.19	79.19	0.01	0
Kulti (M)	87.1	8.83	0.07	86.37	9.54	0.09	96	0	0
Mining area	10.4	7.24	0.5	10.66	6.87	0.61	18.14	0	0

340

341 Figure 4 shows the spatial pattern of source-specific AHF in the pre lockdown period.  
 342 Computed mean AHF from human metabolism, commercial and residential buildings,  
 343 industrial sector, and transport sector were 2.7, 12.96, 21.06, and 15.66 W/m<sup>2</sup>, respectively.  
 344 Precisely to what extent the AHF from the mentioned sources reduced was not explored so  
 345 far, but supporting information can help to understand the possibility of reducing AHF. In the  
 346 eastern region, electricity consumption reduced by 10-20%. Maximum industries were closed  
 347 immediately after announcing lockdown in India. This fact explains the lowering of  
 348 electricity consumption. Due to the stoppage of public and private vehicles, emission from  
 349 transport sectors was reduced by 83%. Hence, AHF from the transport sector was likely to be  
 350 reduced by >80%. AHF from human metabolism will not be influenced by the lockdown  
 351 incident as it is the function of population density. Since 2018 to present, population density  
 352 has increased to some extent, and therefore, there is a possibility to increase AHF from this  
 353 particular source. As the proportion of AHF emission from industrial and transport sectors  
 354 was very high, overall, AHF possibly reduced during the lockdown as estimated from the  
 355 satellite image.



356

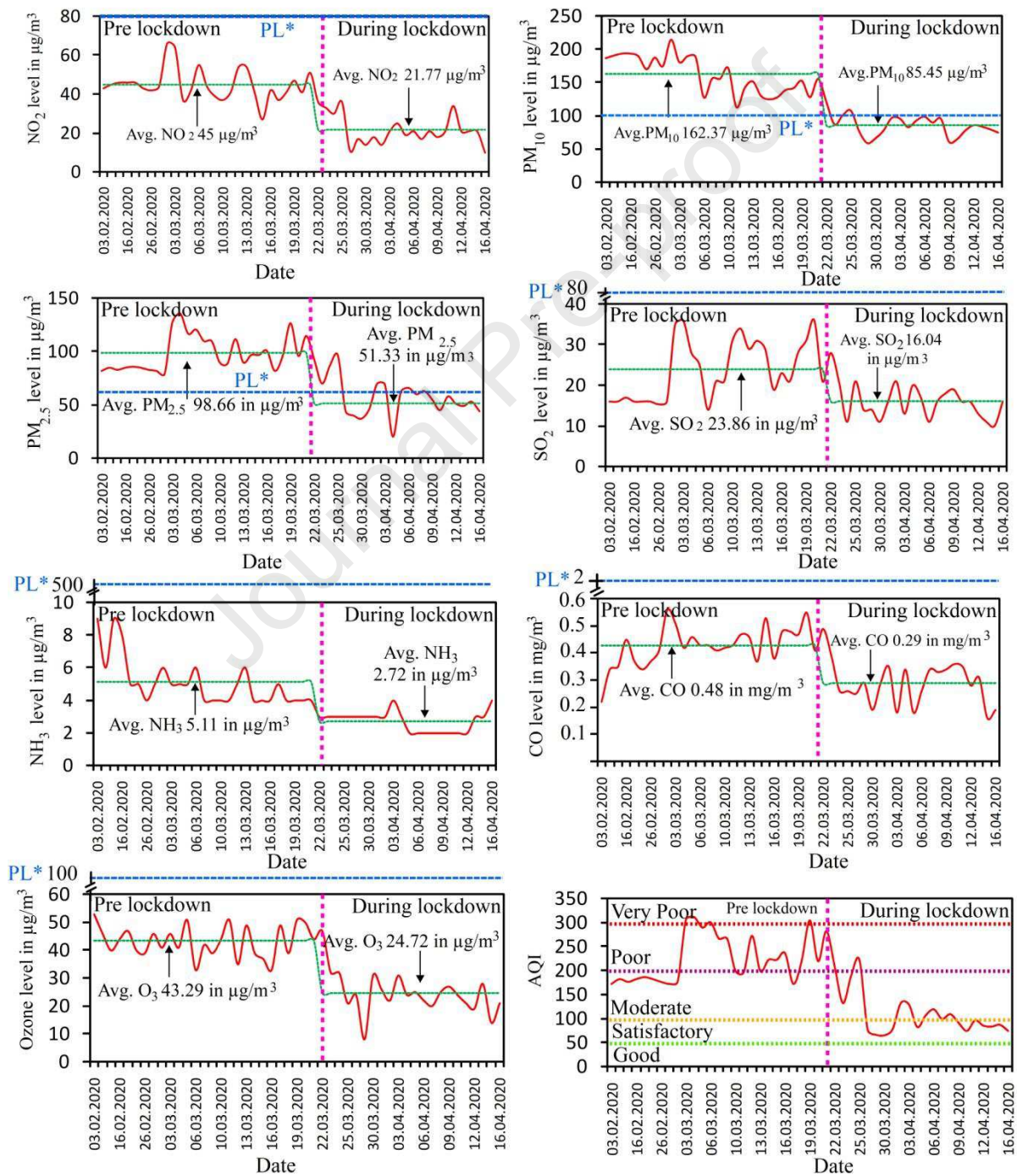
357 **Fig.4** Heat release from (A) Human Metabolism, (B) Commercial and Residential buildings,  
 358 (C) Industrial sector, (D) Transport sector and (E) Total AHF in the year of 2018

359 If it was focused on how far the LST and  $PM_{10}$  states of industrial and urban areas were  
 360 different from the non-industrial areas, some inference could be drawn. In the pre-lockdown  
 361 period, rich economic activity units including most parts of urban areas and industrial sites  
 362 showed positive departure of LST from mean, but in the lockdown period most parts came  
 363 under negative departure. More specifically, in the mining areas, 4.17% area was of negative  
 364 departure in the pre-lockdown period, but in the lockdown period, about 84% area registered  
 365 negative departure showing significant reduction of LST. When the same analysis was  
 366 conducted with respect to steel plants and power plant sites, an almost same trend of result  
 367 was identified. In this same line of thinking, when this departure analysis was carried out in  
 368 respect to  $PM_{10}$  level, >85% areas reported negative deviation in the study region. With  
 369 regards to the thermal power plants, all parts of the study area were under positive  $PM_{10}$   
 370 departure, but the entire region was found under negative departure from mean of all the  
 371 considered phases. This result shows that an industrial and urban site has responded  
 372 sensitively by significantly reducing the thermal intensity and pollutant level than non-urban  
 373 and non-industrial counterparts indicating the role of anthropogenic activities.

### 374 **3.2 Effect on air quality components**

375 Figure 5 portrays the air quality components and air quality index (AQI) of the study region  
 376 from February to April 2020, representing both pre and during lockdown conditions. All the  
 377 quality components show that after implementation of lockdown pollutant level reduced to

378 moderate or satisfactory condition from poor or very poor quality. For example,  $PM_{2.5}$   
 379 reduced from  $98.66 \mu\text{g}/\text{m}^3$  to  $51.3 \mu\text{g}/\text{m}^3$  signifying improvement of quality from poor to  
 380 satisfactory. CP level reduced from 47 to  $29 \mu\text{g}/\text{m}^3$  showing improvement of quality from  
 381 severe to very poor category. As the lockdown will be continued till the 3<sup>rd</sup> May 2020 or  
 382 more, the quality will further be improved. In effect of the positive response of the air quality  
 383 components, AQI s also improved from poor or very poor condition to moderate or  
 384 satisfactory condition (Fig. 5).



PL\* Permissible limit (CPCB)

385

386 **Fig. 5** Change of air quality components and AQI between pre and during lockdown periods

#### 387 **4. Discussion**

388 From the results, it was very evident that lockdown has exerted a positive impact on air  
389 quality and climatic components in the highly industrialized and urbanized study area. Since  
390 implementation of complete lockdown in this region along with entire country all the major  
391 economic activities like industry, transportation, mining, public mobility, other services were  
392 completely prohibited. Almost all these activities are pollution intensive therefore, lockdown  
393 principle was able to restrict pollution generation and release. From the environmental  
394 perspective such measures were amicable to the qualitative improvement of environment in  
395 this region. The environmental compensation of lockdown was not distinctively observed in  
396 this region, as several studies carried out in different regions of world along with the satellite  
397 images of ESA and NASA categorically reported sort of similar results especially remarkable  
398 improvement of air quality (Sathe et al. 2021; Naqvi et al. 2021; Mele and Magazzino 2021;  
399 Das et al. 2021; Mor et al. 2021). In this study, it was seen that upper limit of surface  
400 temperature reduced by 20% after implementation of lockdown without having any notable  
401 change in lower limit, which signifies lowering of surface temperature in spite of having  
402 almost similar amount of solar radiation. It was witnessed in all urban-industrial centers, as  
403 the area under very hot ground surface squeezed in the municipalities. This incident clarifies  
404 the fact that industrial functioning, mining activities were the major contributors of heat  
405 source. Mixing of black aerosols ejected from the coal mining sites not only supplies a bulk  
406 amount to the concentration of particulate matter in the atmosphere, but the absorbed heat by  
407 these black particles contribute a lot to enhance atmospheric temperature. Moreover, coating  
408 of surface with these black dusts also increase the capacities of the surface to retain surface  
409 temperature, which are responsible for increasing temperature in this region. During  
410 lockdown, electricity consumption was reduced by about 20% in major industrial region. It  
411 also decelerated the fossil fuel combustion. Moreover, mining activities was almost closed in  
412 this time along with the industries. It does mean that dust admixing process was quite  
413 stopped. All these were responsible for lowering temperature condition of the study area.  
414 These processes also explain the reasons behind lowering of aerosol concentration in the  
415 atmosphere.

416 This study identified a decreasing trend of AHF in this area. Fossil fuel combustion is a major  
417 driver of increasing AHF (Zhang et al., 2019) which was largely stopped due the abundance

418 of large industrial and commercial manufacturing units. Traffic exhaust is another recognized  
419 cause behind this (Veena et al., 2020) which was noticeably restricted due to prohibition of  
420 public mobility. AHF was noticeably low in the rural areas with no signature of heavy  
421 industries. In these areas, the rate of reduction of AHF was significantly low during  
422 lockdown. It is because of non existence of heavy traffic and industry since before lockdown.  
423 Even the energy foot print of the rural India is far lower than urban and industrial  
424 counterparts.

425 Chen and Hu (2017) found significantly higher AHF in urban areas than the suburb areas in  
426 Beijing-Tianjin-Hebei region of northern China where they recognized vehicular traffic,  
427 industry and residential buildings as the main contributors of AHF. In present study,  
428 attenuation of heat released from two major sources namely industry and traffic largely  
429 helped to decrease the positive components of AHF like soil heat flux, sensible heat flux and  
430 latent heat flux. Temperature rise was a very well explored fact in the world due to increasing  
431 energy footprint (Aydin and Turan, 2020), but the lockdown incident adversely produced  
432 amicable results. Not only the reduction of AHF but also the disappearance of urban heat  
433 island effect was also observed in this study. The area under highest AHF category (more  
434 than  $200 \text{ W/m}^2$ ) became nil in all the municipalities after commencement of lockdown. Meng  
435 et al. (2020) showed the capacity of anthropogenic heat to increase the surface temperature  
436 by simulating LST data in Beijing city and such effect can also be seen in present study area  
437 where reduction of anthropogenic heat release helped to some extent to reduce the surface  
438 temperature of industrial asphalt area. As the previous literature explored remarkable  
439 improvement of air standard during lockdown, which was also examined in this study and a  
440 promising result is observed with consideration of all parts of the study region. With the  
441 stoppage of mining sector, concentration level  $\text{PM}_{10}$  in air has started to fall with  
442 disappearance of dust emerged from the traffic greatly attributed to this fall. The same kind of  
443 result was also reported by Mandal and Pal (2020) studying stone quarrying and crushing  
444 dominated study area from Eastern India. The Sulphur containing invisible gas  $\text{SO}_2$  released  
445 from the industries and fossil fuel driven vehicles was significantly attenuated during the  
446 progression of lockdown. As a result, overall AQI of the region shifted from very poor or  
447 poor state of pre lockdown to moderate to even satisfactory state. The reduction of power  
448 generation from power plants also attenuated the emission of  $\text{NO}_2$  level. All these resulted in  
449 air quality improvement in pursuance of lockdown.

450 The rate of air quality improvement was not uniform all over the world because of the  
451 difference in land use and land cover, and different economic activity with varying intensity.  
452 This was also seen in the present study. Varying spatial PM<sub>10</sub>, LST, AHF, and AQI can be  
453 explained by the existing land use and economic set up. Concentration of PM<sub>10</sub> and other  
454 pollutants were usually high near the industrial units and traffic congestion area, whereas  
455 concrete ground, industrial hubs and densely populated urban settlement sites showed greater  
456 heat flux and surface temperature. In such context, another dimension of lockdown is seen in  
457 this study. The dichotomy of heat discomfort and pollution level between the area having  
458 intensive economic activity like industry, transport service and mining and the area belonging  
459 to interior countryside region reduced reasonably. It was observed in temperature as well as  
460 pollutant components. Average surface temperature of the far countryside parts of the study  
461 area was around 28°C before lockdown started, and reduced to 27°C amid lockdown. In  
462 intensive industry dominated and urban areas, this change was from 33°C to 28°C. The  
463 temperature gap between non-industrial rural areas, and urban and industrial areas was about  
464 5°C before lockdown, but this gap was narrowed down in lockdown (1°C). Therefore, it  
465 clearly proves that anthropogenic activities and industrial functioning were highly responsible  
466 for higher temperature (4°C) in the industrial and urban sectors. Consequently, it should not  
467 be conceived that 4°C temperature was contributed from human activities. Land use  
468 transformation was another important aspect that also caused changing of thermal condition.  
469 Natural land already transformed into urban scape stimulated the thermal environment since  
470 well before lockdown. It signifies that temperature preexisting before lockdown in urban-  
471 industrial area was also partly contributed by human activities. Many studies relating to the  
472 impact of land use/land cover transformation on temperature clearly revealed that  
473 temperature in the built-up areas was 2-5°C higher than natural ecosystem (Ziaul and Pal,  
474 2017). Similarly, in countryside, pre-lockdown AHF was reduced from 48 to 29 W/m<sup>2</sup> amid  
475 lockdown and in urban-industrial area it reduced from 82 to 40 W/m<sup>2</sup>. Here also the area  
476 specific gap was reduced by 67%. As for pollutant level, an identical trend was observed in  
477 PM<sub>10</sub> concentration with concentration reduced by 75% between countryside and urban-  
478 industrial areas. These facts show the healing effect of lockdown clearly improved the  
479 environment alike the countryside region which was recognized for having healthy  
480 environment by DaSilva et al. (2017). Behind this scenario, the socio-economic parameters  
481 were found to be vital. The major economic activities of the urban-industrial areas like  
482 Asansol, Durgapur, as mentioned earlier are mainly pollution generating or heat releasing  
483 industrial production or transportation. Eventually the level of pollutants in the air and the

484 heat island effect remain high even in normal situation of the year. On the other hand, mainly  
485 agro or household manufacturing based economic activity and small scale transportation of  
486 the countryside release lesser pollutants or create lesser heat effect. Therefore, there was  
487 greater scope of improvement as compared to countryside. In urban-industrial area the AHF  
488 reduced to some extent due to some other socio-economic factors like complete shutdown of  
489 air-conditioned offices, hotels, malls and marts some recreational centers like auditoriums,  
490 multiplexes, restaurants etc. the commercial air-conditioned system of these places release a  
491 considerable anthropogenic heat to the surrounding. These causes were recognized by Ziaul  
492 and Pal, (2018) behind the AHF creation in another business town of eastern India. Few  
493 social festivals like several pujas (worshiping rituals), marriages, social gathering were  
494 completely prohibited amid lockdown which helped to reduce energy consumption.  
495 POSOCO data shows almost 20% reductions in average daily electricity consumption in the  
496 country during first month of lockdown implementation which was a major source of AHF  
497 release (Zhang et al., 2019).

498 Spatial  $PM_{10}$  concentration and AHF state were not always figured out high over all the  
499 industrial sites. Theoretically, it is not expected, but it is to be remembered that the map  
500 shows a condition of particular time. Wind may be a factor that can also play a significant  
501 role for transporting them to the other areas. This issue was not addressed in this paper due to  
502 lack of spatial level data scarcity of wind direction and speed. If all such influencing  
503 parameters could be considered, the result would be more prominent. LST,  $PM_{10}$ , AHF and  
504 AQI simulation at different degree of urbanization, built-up density, built-up materials, green  
505 space, blue space, industrialization, emission of pollution can help us find out the threshold  
506 anthropogenic activities that could be ecologically and physiologically permissible. This  
507 could help us set a goal for pollution abatement strategies. Computation of emission level,  
508 pollution level, AHF in green technology, and efficient energy use technology used is another  
509 scope of future work that can inspire strategists and encourage a common man to rethink  
510 about the alternative option of energy use.

## 511 **5. Conclusion**

512 The present study contributed to articulate the response of a regional unit dominated by the  
513 industrial sector and densely populated urban sector in comparison to non-industrial rural  
514 parts in effects of lockdown. Moreover, most of the previous studies considered pollution  
515 parameters for showing the impact of lockdown in chiefly in urban areas, while the present

516 work focused on the impact of lockdown on PM<sub>10</sub>, LST, and AQI along with AHF using  
517 satellite images and daily CBCB data. How far heat island effect was diluted due to stoppage  
518 of anthropogenic activities is well explained. The study explained that AHF was a noticeable  
519 contributor of urban heat and how the reduction of AHF attributed to reduced heat island  
520 effect in terms of both spatial extent and intensity. Here is the novelty of the worklies. Results  
521 exhibited reduction of LST by 4.02°C, PM<sub>10</sub> level from 102 to 18 µg/m<sup>3</sup>, and AHF from 116  
522 to 40 W/m<sup>2</sup> during lockdown period. AQI level was improved from *poor to very poor* state to  
523 *moderate to satisfactory* state. Due to lack of data source, specific AHF was not spatially  
524 estimated in lockdown condition, but change in input data for AHF computation showed the  
525 possibility of reducing AHF during lockdown. This lockdown situation is against economic  
526 production and growth of gross domestic product, and it can bring hardship among the  
527 marginal people. Therefore, lockdown is denied to be a permanent solution for checking the  
528 pollution level, while this lockdown gave a unique scope to realize how far we are  
529 responsible for changing the thermal state, pollution ambience of this region and beyond.  
530 Here is the relevance of this study. Increasing temperature in the industrial and urban  
531 environments is caused for growing thermal disconformities; increasing pollution level is  
532 caused for different predictable and unpredictable diseases. Therefore, posing control on  
533 temperature state and pollution state is highly required for our health and long life in  
534 particular and ecosystem health in general. This study clearly gives a lesson that heat and  
535 pollution emission from different anthropogenic stimulated sources is the major culprit that  
536 we must have to check for the sake of socio-economic and environmental sustainability. In  
537 this connection, prioritizing green energy, advance and efficient techniques of energy use,  
538 increase conscience and effective energy users to reduce waste are the alternatives. Optimum  
539 and economic use of energy may reduce the pollution level. To reduce heat island effect and  
540 associated human disconformities, emphasis on green space management, blue space  
541 management are some effective steps in the industrial and urban sectors. Some previous  
542 studies reported that through these steps thermal extremities could be reduced to some extent.  
543 Plantation of vegetation along road side, railways, fallow lands, roof top gardening, kitchen  
544 gardening all these are some small initiatives that could be taken for reducing heat island  
545 effect as well as pollution intensity. These steps could be partly capable to keep a balance  
546 between economic growth and environmental sustainability.

547

548 **Acknowledgments:**

549 Authors would like to thank the handling editor and anonymous reviewers for their  
550 constructive comments and suggestions to manuscript improvement.

### 551 **Conflict of Interest**

552 None

### 553 **References**

554 Ayanlade, A. and Howard, M.T., 2019. Land surface temperature and heat fluxes over three  
555 cities in Niger Delta. *Journal of African Earth Sciences*, 151, pp.54-66.  
556 <https://doi.org/10.1016/j.jafrearsci.2018.11.027>

557 Aydin, M. and Turan, Y.E., 2020. The influence of financial openness, trade openness, and  
558 energy intensity on ecological footprint: revisiting the environmental Kuznets curve  
559 hypothesis for BRICS countries. *Environmental Science and Pollution Research*, 27(34),  
560 pp.43233-43245. <https://doi.org/10.1007/s11356-020-10238-9>

561 Bashir, M.F., Ma, B., Komal, B., Bashir, M.A., Tan, D. and Bashir, M., 2020. Correlation  
562 between climate indicators and COVID-19 pandemic in New York, USA. *Science of The*  
563 *Total Environment*, p.138835. <https://doi.org/10.1016/j.scitotenv.2020.138835>

564 Chakraborty, S.D., Kant, Y. and Mitra, D., 2015. Assessment of land surface temperature and  
565 heat fluxes over Delhi using remote sensing data. *Journal of Environmental*  
566 *Management*, 148, pp.143-152. <https://doi.org/10.1016/j.jenvman.2013.11.034>

567 Chen, S. and Hu, D., 2017. Parameterizing anthropogenic heat flux with an energy-  
568 consumption inventory and multi-source remote sensing data. *Remote Sensing*, 9(11), p.1165.  
569 <https://doi.org/10.3390/rs9111165>

570 Chen, Z., Hao, X., Zhang, X. and Chen, F., 2020. Have traffic restrictions improved air  
571 quality? A shock from COVID-19. *Journal of Cleaner Production*, 279, p.123622.  
572 <https://doi.org/10.1016/j.jclepro.2020.123622>

573 Choudhury, D., Das, K. and Das, A., 2019. Assessment of land use land cover changes and  
574 its impact on variations of land surface temperature in Asansol-Durgapur Development  
575 Region. *The Egyptian Journal of Remote Sensing and Space Science*, 22(2), pp.203-218.

576 CPCB (Central Pollution Control Board), 2014. Central Pollution Control Board Continuous  
577 Ambient Air Quality. <http://www.cpcb.gov.in/CAAQM/frmUserAvgReportCriteria.aspx>,  
578 accessed in March 2014.

579 Da Silva, F.B.V., do Nascimento, C.W.A., Araújo, P.R.M., da Silva, F.L. and Lima, L.H.V.,  
580 2017. Soil contamination by metals with high ecological risk in urban and rural  
581 areas. *International Journal of Environmental Science and Technology*, 14(3), pp.553-562.

582 Das, P., Mandal, I., Debanshi, S., Mahato, S., Talukdar, S., Giri, B. and Pal, S., 2021. Short  
583 term unwinding lockdown effects on air pollution. *Journal of Cleaner Production*, p. 126514.  
584 <https://doi.org/10.1016/j.jclepro.2021.126514>

- 585 Deyong, H., Shanshan, C. and Fuzhou, D., 2017. July. Estimation of the anthropogenic heat  
 586 flux distribution in Beijing-Tianjin-Hebei region based on Suomi-NPP/VIIRS nighttime light  
 587 image. In *2017 IEEE International Geoscience and Remote Sensing Symposium*  
 588 (*IGARSS*) (pp. 4012-4015). <https://doi.org/10.1109/IGARSS.2017.8127880>
- 589 Du, J., Park, K., Yu, X., Zhang, Y.J. and Ye, F., 2020. Massive pollutants released to  
 590 Galveston Bay during Hurricane Harvey: Understanding their retention and pathway using  
 591 Lagrangian numerical simulations. *Science of The Total Environment*, 704, p.135364.  
 592 <https://doi.org/10.1016/j.scitotenv.2019.135364>
- 593 Dutta, D. and Gupta, S., 2021. Rising Trend of Air Pollution and Its Decadal Consequences  
 594 on Meteorology and Thermal Comfort Over Gangetic West Bengal, India. In *Spatial*  
 595 *Modeling and Assessment of Environmental Contaminants* (pp. 689-720). Springer, Cham.  
 596 [https://doi.org/10.1007/978-3-030-63422-3\\_32](https://doi.org/10.1007/978-3-030-63422-3_32)
- 597 European Space Agency, 2020. COVID-19: nitrogen dioxide over China.  
 598 [https://www.esa.int/Applications/Observing\\_the\\_Earth/Copernicus/Sentinel-5](https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5_P/COVID_19_nitrogen_dioxide_over_China)  
 599 [P/COVID](https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5_P/COVID_19_nitrogen_dioxide_over_China)  
 19\_nitrogen\_dioxide\_over\_China.
- 600 Ficetola, G.F. and Rubolini, D., 2020. Climate affects global patterns of COVID-19 early  
 601 outbreak dynamics. *medRxiv*. <https://doi.org/10.1101/2020.03.23.20040501>
- 602 Firozjaei, M.K., Weng, Q., Zhao, C., Kiavarz, M., Lu, L. and Alavipanah, S.K., 2020.  
 603 Surface anthropogenic heat islands in six megacities: An assessment based on a triple-source  
 604 surface energy balance model. *Remote Sensing of Environment*, 242,  
 605 p.111751. <https://doi.org/10.1016/j.rse.2020.111751>
- 606 García-Santos, V., Cuxart, J., Martínez-Villagrasa, D., Jiménez, M.A. and Simó, G., 2018.  
 607 Comparison of three methods for estimating land surface temperature from landsat 8-tirs  
 608 sensor data. *Remote Sensing*, 10(9), p.1450. <https://doi.org/10.3390/rs10091450>
- 609 Ghosh, S., Chatterjee, N.D. and Dinda, S., 2019. Relation between urban biophysical  
 610 composition and dynamics of land surface temperature in the Kolkata metropolitan area: a  
 611 GIS and statistical based analysis for sustainable planning. *Modeling Earth Systems and*  
 612 *Environment*, 5(1), pp.307-329. <https://doi.org/10.1007/s40808-018-0535-9>
- 613 Griffiths J, and Woodyatt A., 2020. 780 million people in China are living under travel  
 614 restrictions due to the coronavirus outbreak.  
 615 [https://www.cnn.com/2020/02/16/asia/coronavirus-covid-19-death-toll-updateintl-](https://www.cnn.com/2020/02/16/asia/coronavirus-covid-19-death-toll-updateintl-hnk/index.html)  
 616 [hnk/index.html](https://www.cnn.com/2020/02/16/asia/coronavirus-covid-19-death-toll-updateintl-hnk/index.html)
- 617 <https://doi.org/10.1016/j.scitotenv.2020.139281>
- 618 Jin, K., Wang, F. and Wang, S., 2020. Assessing the spatiotemporal variation in  
 619 anthropogenic heat and its impact on the surface thermal environment over global land areas.  
 620 *Sustainable Cities and Society*, 63, p.102488. <https://doi.org/10.1016/j.scs.2020.102488>
- 621 Ju, M.J., Oh, J. and Choi, Y.H., 2021. Changes in air pollution levels after COVID-19  
 622 outbreak in Korea. *Science of The Total Environment*, 750, p.141521.  
 623 <https://doi.org/10.1016/j.scitotenv.2020.141521>

- 624 Kato, S. and Yamaguchi, Y., 2005. Analysis of urban heat-island effect using ASTER and  
 625 ETM+ Data: Separation of anthropogenic heat discharge and natural heat radiation from  
 626 sensible heat flux. *Remote Sensing of Environment*, 99(1-2), pp.44-54.
- 627 Kotthaus, S. and Grimmond, C.S.B., 2014. Energy exchange in a dense urban environment–  
 628 Part I: Temporal variability of long-term observations in central London. *Urban Climate*, 10,  
 629 pp.261-280. <https://doi.org/10.1016/j.uclim.2013.10.002>
- 630 Landsat Project Science Office, 2002. Landsat 7 Science Data User's Handbook. Goddard  
 631 Space FlightCenter, NASA, Washington, DC  
 632 [http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook\\_toc.html](http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_toc.html)
- 633 Liou, Y.-A., Nguyen, K.A. and Ho, L.T., 2021. Altering urban greenspace patterns and heat  
 634 stress risk in Hanoi City during Master Plan 2030 implementation. *Land Use Policy*, in press,  
 635 2021.
- 636 Mahato, S. and Ghosh, K.G., 2020. Short-term exposure to ambient air quality of the most  
 637 polluted Indian cities due to lockdown amid SARS-CoV-2. *Environmental Research*, 188,  
 638 p.109835.
- 639 Mahato, S. and Pal, S., 2018. Changing land surface temperature of a rural Rarh tract river  
 640 basin of India. *Remote Sensing Applications: Society and Environment*, 10, pp.209-223.  
 641 <https://doi.org/10.1016/j.rsase.2018.04.005>
- 642 Mahato, S. and Pal, S., 2019. Influence of land surface parameters on the spatio-seasonal land  
 643 surface temperature regime in rural West Bengal, India. *Advances in Space Research*, 63(1),  
 644 pp.172-189. <https://doi.org/10.1016/j.asr.2018.09.014>
- 645 Mahato, S., Pal, S. and Ghosh, K.G., 2020. Effect of lockdown amid COVID-19 pandemic on  
 646 air quality of the megacity Delhi, India, *Science of the Total Environment*,  
 647 <https://doi.org/10.1016/j.scitotenv.2020.139086>.
- 648 Mandal, I. and Pal, S., 2020. COVID-19 pandemic persuaded lockdown effects on  
 649 environment over stone quarrying and crushing areas. *Science of The Total Environment*,  
 650 p.139281.
- 651 Mandal, S., Madhipatla, K.K., Guttikunda, S., Kloog, I., Prabhakaran, D., Schwartz, J.D. and  
 652 Team, G.H.I., 2020. Ensemble averaging based assessment of spatiotemporal variations in  
 653 ambient PM<sub>2.5</sub> concentrations over Delhi, India, during 2010–2016. *Atmospheric  
 654 Environment*, 224, p.117309. <https://doi.org/10.1016/j.atmosenv.2020.117309>
- 655 Mele, M. and Magazzino, C., 2021. Pollution, economic growth, and COVID-19 deaths in  
 656 India: a machine learning evidence. *Environmental Science and Pollution Research*, 28(3),  
 657 pp.2669-2677. <https://doi.org/10.1007/s11356-020-10689-0>
- 658 Meng, C., Jiang, L., Jin, H., Ren, L. and Chen, T., 2020. Impact of Anthropogenic Heat on  
 659 Surface Balance of Energy and Water in Beijing. *Russian Meteorology and  
 660 Hydrology*, 45(6), pp.438-446. <https://doi.org/10.3103/S1068373920060072>
- 661 Mor, S., Kumar, S., Singh, T., Dogra, S., Pandey, V. and Ravindra, K., 2021. Impact of  
 662 COVID-19 lockdown on air quality in Chandigarh, India: understanding the emission sources  
 663 during controlled anthropogenic activities. *Chemosphere*, 263, p.127978.  
 664 <https://doi.org/10.1016/j.chemosphere.2020.127978>

- 665 Muhammad, S., Long, X., Salman, M., 2020. COVID-19 pandemic and environmental  
 666 pollution: a blessing in disguise? *Science of The Total Environment*, 138820  
 667 <https://doi.org/10.1016/j.scitotenv.2020.138820>
- 668 Naqvi, H.R., Datta, M., Mutreja, G., Siddiqui, M.A., Naqvi, D.F. and Naqvi, A.R., 2021.  
 669 Improved air quality and associated mortalities in India under COVID-19 lockdown.  
 670 *Environmental Pollution*, 268, p.115691. <https://doi.org/10.1016/j.envpol.2020.115691>
- 671 Nguyen, K.A. and Liou, Y.A., 2019a. Global mapping of eco-environmental vulnerability  
 672 from human and nature disturbances. *Science of The Total Environment*, 664, pp.995-1004.  
 673 <https://doi.org/10.1016/j.scitotenv.2019.01.407>
- 674 Nguyen, K.A. and Liou, Y.A., 2019b. Mapping global eco-environment vulnerability due to  
 675 human and nature disturbances. *MethodsX*, 6, pp.862-875.  
 676 <https://doi.org/10.1016/j.mex.2019.03.023>
- 677 Nguyen, T. H., Liou, Y.A., Nguyen, A. K., Sharma, R.C., Phien, T. D., Liou, C.-L., and Cham,  
 678 D. D., 2018. Assessing the effects of land-use types in surface urban heat islands for  
 679 developing comfortable living in Hanoi City. *Remote Sensing*, 10(12), 1965, doi:  
 680 10.3390/rs10121965.
- 681 Ogunjobi, K.O., Daramola, M.T. and Akinsanola, A.A., 2018. Estimation of surface energy  
 682 fluxes from remotely sensed data over Akure, Nigeria. *Spatial Information Research*, 26(1),  
 683 pp.77-89. <https://doi.org/10.1007/s41324-017-0149-8>
- 684 Oke, T.R. and Cleugh, H.A., 1987. Urban heat storage derived as energy balance  
 685 residuals. *Boundary-Layer Meteorology*, 39(3), pp.233-245.
- 686 Pal, S. and Ziaul, S.K., 2017. Detection of land use and land cover change and land surface  
 687 temperature in English Bazar urban centre. *The Egyptian Journal of Remote Sensing and*  
 688 *Space Science*, 20(1), pp.125-145. <https://doi.org/10.1016/j.ejrs.2016.11.003>
- 689 Plocoste, T., Calif, R., Euphrasie-Clotilde, L. and Brute, F.N., 2020. Investigation of local  
 690 correlations between particulate matter (PM10) and air temperature in the Caribbean basin  
 691 using Ensemble Empirical Mode Decomposition. *Atmospheric Pollution Research*, 11(10),  
 692 pp.1692-1704. <https://doi.org/10.1016/j.apr.2020.06.031>
- 693 Raj, S., Paul, S.K., Chakraborty, A. and Kuttippurath, J., 2020. Anthropogenic forcing  
 694 exacerbating the urban heat islands in India. *Journal of Environmental Management*, 257,  
 695 p.110006.
- 696 Saadat, S., Rawtani, D. and Hussain, C.M., 2020. Environmental perspective of COVID-  
 697 19. *Science of The Total Environment*, p.138870.  
 698 <https://doi.org/10.1016/j.scitotenv.2020.138870>
- 699 Sailor, D.J. and Lu, L., 2004. A top-down methodology for developing diurnal and seasonal  
 700 anthropogenic heating profiles for urban areas. *Atmospheric environment*, 38(17), pp.2737-  
 701 2748. <https://doi.org/10.1016/j.atmosenv.2004.01.034>
- 702 Saraswat, I., Mishra, R.K. and Kumar, A., 2017. Estimation of PM10 concentration from  
 703 Landsat 8 OLI satellite imagery over Delhi, India. *Remote Sensing Applications: Society and*  
 704 *Environment*, 8, pp.251-257. <https://doi.org/10.1016/j.rsase.2017.10.006>
- 705 Sathe, Y., Gupta, P., Bawase, M., Lamsal, L., Patadia, F. and Thipse, S., 2021. Surface and  
 706 satellite observations of air pollution in India during COVID-19 lockdown: Implication to air

- 707 quality. *Sustainable cities and society*, 66, p.102688.  
 708 <https://doi.org/10.1016/j.scs.2020.102688>
- 709 Sharma, S., Zhang, M., Gao, J., Zhang, H. and Kota, S.H., 2020. Effect of restricted  
 710 emissions during COVID-19 on air quality in India. *Science of The Total Environment*, 728,  
 711 p.138878. <https://doi.org/10.1016/j.scitotenv.2020.138878>
- 712 Shenoy, M., 2016. Industrial ecology in developing countries. In *Taking stock of industrial*  
 713 *ecology* (pp. 229-245). Springer, Cham.
- 714 Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M.C., Alastuey, A.  
 715 and Querol, X., 2020. Changes in air quality during the lockdown in Barcelona (Spain) one  
 716 month into the SARS-CoV-2 epidemic. *Science of The Total Environment*, p.138540.  
 717 <https://doi.org/10.1016/j.scitotenv.2020.138540>
- 718 Travaglio, M., Yu, Y., Popovic, R., Selley, L., Leal, N.S. and Martins, L.M., 2021. Links  
 719 between air pollution and COVID-19 in England. *Environmental Pollution*, 268, p.115859.  
 720 <https://doi.org/10.1016/j.envpol.2020.115859>
- 721 Varquez, A.C.G., Kiyomoto, S. and Kanda, M., 2021. Global 1-km present and future hourly  
 722 anthropogenic heat flux. *Scientific Data*, 8(1), pp.1-14.  
 723 <https://doi.org/10.6084/m9.figshare.13647935>
- 724 Veena, K., Parammasivam, K.M. and Venkatesh, T.N., 2020. Urban Heat Island studies:  
 725 Current status in India and a comparison with the International studies. *Journal of Earth*  
 726 *System Science*, 129(1), pp.1-15. <https://doi.org/10.1007/s12040-020-1351-y>
- 727 Wang, Q. and Su, M., 2020. A preliminary assessment of the impact of COVID-19 on  
 728 environment—A case study of China. *Science of The Total Environment*, p.138915.  
 729 <https://doi.org/10.1016/j.scitotenv.2020.138915>
- 730 Wang, S., Hu, D., Yu, C., Chen, S. and Di, Y., 2020. Mapping China's time-series  
 731 anthropogenic heat flux with inventory method and multi-source remotely sensed data.  
 732 *Science of The Total Environment*, 734, p.139457.  
 733 <https://doi.org/10.1016/j.scitotenv.2020.139457>
- 734 Ward, H.C., Kotthaus, S., Järvi, L. and Grimmond, C.S.B., 2016. Surface Urban Energy and  
 735 Water Balance Scheme (SUEWS): development and evaluation at two UK sites. *Urban*  
 736 *Climate*, 18, pp.1-32. <https://doi.org/10.1016/j.uclim.2017.05.001>
- 737 World Health Organization, 2016. Ambient Air Pollution: A Global Assessment of Exposure  
 738 and Burden of Disease. World Health Organization (ISBN: 9789241511353)
- 739 Xie, X., Ai, H. and Deng, Z., 2020. Impacts of the scattered coal consumption on PM2. 5  
 740 pollution in China. *Journal of Cleaner Production*, 245, p.118922.  
 741 <https://doi.org/10.1016/j.scitotenv.2020.140963>
- 742 Xu, Y. and Cui, G., 2021. Influence of spectral characteristics of the Earth's surface radiation  
 743 on the greenhouse effect: Principles and mechanisms. *Atmospheric Environment*, 244,  
 744 p.117908. <https://doi.org/10.1016/j.atmosenv.2020.117908>

- 745 Yu, C., Hu, D., Wang, S., Chen, S. and Wang, Y., 2021. Estimation of anthropogenic heat  
746 flux and its coupling analysis with urban building characteristics--A case study of typical  
747 cities in the Yangtze River Delta, China. *Science of The Total Environment*, p.145805.  
748 <https://doi.org/10.1016/j.scitotenv.2021.145805>
- 749 Zhang, G., Luo, Y. and Zhu, S., 2019. Estimation of the Spatio-Temporal Characteristics of  
750 Anthropogenic Heat Emission in the Qinhuai District of Nanjing Using the Inventory Survey  
751 Method. *Asia-Pacific Journal of Atmospheric Sciences*, pp.1-14.  
752 <https://doi.org/10.1007/s13143-019-00142-9>
- 753 Zhang, X., Tang, M., Guo, F., Wei, F., Yu, Z., Gao, K., Jin, M., Wang, J. and Chen, K., 2021.  
754 Associations between air pollution and COVID-19 epidemic during quarantine period in  
755 China. *Environmental Pollution*, 268, p.115897.  
756 <https://doi.org/10.1016/j.envpol.2020.115897>
- 757 Zhang, Y., Balzter, H. and Wu, X., 2013. Spatial-temporal patterns of urban anthropogenic  
758 heat discharge in Fuzhou, China, observed from sensible heat flux using Landsat TM/ETM+  
759 data. *International Journal of Remote Sensing*, 34(4), pp.1459-1477.  
760 <https://doi.org/10.1080/01431161.2012.718465>
- 761 Zhang, Z., Zeng, Y., Zheng, N., Luo, L., Xiao, H. and Xiao, H., 2020. Fossil fuel-related  
762 emissions were the major source of NH<sub>3</sub> pollution in urban cities of northern China in the  
763 autumn of 2017. *Environmental Pollution*, 256,  
764 p.113428.<https://doi.org/10.1016/j.envpol.2019.113428>
- 765 Zheng, Y., Huang, L. and Zhai, J., 2021. Divergent trends of urban thermal environmental  
766 characteristics in China. *Journal of Cleaner Production*, 287, p.125053.  
767 <https://doi.org/10.1016/j.jclepro.2020.125053>
- 768 Zhou, Y., Weng, Q., Gurney, K.R., Shuai, Y. and Hu, X., 2012. Estimation of the relationship  
769 between remotely sensed anthropogenic heat discharge and building energy use. *ISPRS*  
770 *Journal of Photogrammetry and Remote Sensing*, 67, pp.65-72.  
771 <https://doi.org/10.1016/j.isprsjprs.2011.10.007>
- 772

## **Effects of lockdown due to COVID 19 outbreak on air quality and anthropogenic heat in an Industrial belt of India**

### **Highlights**

- Imposition of lockdown has reduced land surface temperature by 5 °C
- Concentration of particulate matter  $PM_{10}$  is decreased from 102 to 18  $\mu\text{g}/\text{m}^3$
- Anthropogenic heat flux is reduced from 116 to 40  $\text{W}/\text{m}^2$
- Air quality standard has improved from poor to satisfactory conditions

Journal Pre-proof

16 July 2020

### **Statement of Conflict of Interest**

The authors declare that there is no conflict of interest for the manuscript entitled **“Effects of lockdown due to COVID-19 outbreak on air quality and anthropogenic heat in an industrial belt of India”** by Pal et al. submitted to the journal *Journal of Cleaner Production* for consideration of publication.

With Regards

Swades Pal, Priyanka Das, Rajesh Sarda, Indrajit Mandal, Susanta Mahato, Kim-Anh Nguyen, Yuei-An Liou, Swapan Talukdar, Tamal Kanti Saha, Sandipta Debanshi