Reduction in Human Activity can Enhance the Urban Heat Island: Insights from the COVID-19 Lockdown

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Abstract

The COVID-19 lockdowns drastically reduced human activity, emulating a controlled experiment on human-land-atmosphere coupling. Here, using a fusion of satellite and reanalysis products, we examine this coupling during the lockdown in the Indo-Gangetic Basin, one of the world's most populated and polluted regions. During the lockdown, the reduction ($>10\%$) in columnar air pollution, expected to increase incoming solar radiation, was counteracted by a $\sim 30\%$ enhancement in cloud cover, causing little change in available energy at the surface. More importantly, the delay in winter crop harvesting increased surface vegetation cover, causing almost half the regional cooling (of -3.9 K) via evapotranspiration. Since this cooling was higher for rural areas, the daytime surface urban heat island (SUHI) intensity increased (by 0.20 to 0.41 K) during a period of reduced human activity. Our study provides strong observational evidence of the influence of agricultural activity on both urban and rural climate in this region.

1. Introduction

Human-induced changes in the Earth's surface climate have traditionally been difficult to constrain [1, 2], particularly since these changes typically occur at time scales similar to natural decadal perturbations. In contrast, the COVID-19 lockdowns – the restrictions placed by various governing bodies as a response to the COVID-19 pandemic in 2020 – caused unprecedented slowdown in human activity [3], were short in duration, and yet intense enough to produce measurable effects. They can thus serve as natural experiments on the anthropogenic control on surface climate.

An ideal study area to explore the results of this perturbation experiment is the Indo-Gangetic Basin (IGB), one of the most densely populated regions on the planet with high levels of air pollution [4]. Covering the majority of North India, the IGB has a subtropical monsoon climate, and is a global hot spot for land-atmosphere coupling [5]. From late March to end of May, a countrywide lockdown was imposed in India as a response to COVID-19. This lockdown strictly restricted people's movement outside their homes, suspended educational, industrial, and hospitality services, and limited all transportation systems [6].

Being both heavily cultivated and rapidly urbanizing [7, 8], the IGB is strongly influenced by anthropogenic changes in land use and land cover [9, 10]. Human influence on surface climate is distinct for urban and rural areas. Urbanization modifies the biophysical properties of the surface due to replacement of natural vegetation with built-up structures. Consequently, cities are characterized by higher temperatures compared to their surroundings – the urban heat island (UHI) effect [11]. Rural areas are influenced by land use and land management practices, which is primarily due to agriculture in this region.

The reduction in atmospheric aerosols during the lockdown (up to 45% reduction for some Indian states) is well-documented [12] and, all else remaining constant, would increase incoming surface radiation. Since urban and rural areas may have different levels of pollution, this radiative forcing change can impact the UHI intensity [13, 14]. However, the UHI, and surface climate in general, is also modulated by non-radiative pathways [15]. The lockdown restrictions delayed crop harvesting [16], which would maintain high vegetation cover and can enhance latent heat flux (λE), a non-radiative pathway of surface heat

dissipation. Previous studies have noted that the seasonality of the UHI in this region is influenced by the variability in surface vegetation in the rural area [17, 18]. Agricultural influence on surface climate in this region is not well-captured by LSMs due to inaccurate representation of vegetation properties and the poorly constrained influence of irrigation on the hydrological cycle [10, 19]. Thus, beyond the widely studied changes in atmospheric composition [20, 21], the lockdowns provide a unique opportunity to ask broader questions about human-land-atmosphere interactions in the IGB. The role of these interactions in modulating the ensuing South Asian monsoon circulations is critical to the livelihood of over a billion people dependent on this region [22].

Here, we examine the changes in the surface temperature in the IGB during the lockdown with a focus on the UHI, allowing us to separate human influence on urban and rural surface climate, particularly due to air pollution and land use. First, using a suite of satellite observations, we isolate changes in atmospheric and surface properties over urban areas and their rural periphery. Since satellite observations are restricted by the presence of clouds and do not directly provide estimates of the surface energy budget, we use a reanalysis dataset to gain a mechanistic understanding of the observed perturbations in rural surface climate. We find significant regional surface cooling through evapotranspiration during the lockdown, which enhanced the UHI intensity despite decreased human activity.

2. Materials and Methods

2.1 Urban-Rural delineations for region of interest

We only consider the Indian portion of the IGB (Fig. S1a; $\sim 50000 \text{ km}^2$), to avoid uncertainties arising from variations in lockdown periods in other countries. An urban cluster database was developed for this region by generating polygons covering continuous groups of high-density urban pixels from the Global Human Settlement Index (GHSL) for 2015 [23]. The corresponding normalized rural reference (roughly equal to area of urban cluster) for each of these clusters was created using an iterative buffering procedure with a step size of 300 m. Our methodology generates 1420 urban-rural delineations, making it the most comprehensive dataset of this type for the region.

2.2 Satellite observations

Multiple satellite-derived products were used to extract urban-rural differentials in relevant variables (details in Table 1), including Land Surface Temperature (LST) for calculating surface UHI (SUHI) [24], reflectance data from Moderate Resolution Imaging Spectroradiometer (MODIS) to estimate surface vegetation [25], and metrics of air pollution, including aerosol optical depth (AOD) from MODIS [26] and individual pollutant estimates from the Sentinel-5p TROPospheric Monitoring Instrument (TROPOMI) sensor [27]. We also extract cloud fraction (CF) from Sentinel since clouds strongly affect the radiative budget. Finally, the Black-Sky Albedo (BSA) and White-Sky Albedo (WSA), the reflectivity of the surface for direct beam and diffuse radiation, respectively, were extracted from MODIS [28]. These can be combined to derive total surface albedo (α ; see Section 2.3), which is known to vary between urban and rural areas [29]. Although the MODIS observations are daily, the multi-day composites are used to reduce cloud contamination [30].

The normalized difference vegetation index (NDVI) is a proxy for green vegetation [31] and used here to estimate the impact of the lockdown on surface vegetation cover. We calculate NDVI from the NIR (near infra-red) and RED bands of the 8-day composite MODIS surface reflectance product, available for 1 km x 1 km grids (Table 1), as:

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (1)$$

The lockdown in India started from midnight March 24th and continued in a limited capacity till June 7th. To remove the noise from the transition periods, we considered April 1st to May 15th, 2020 to be the lockdown case. The 5-year (2015-2019) mean of the data from April 1st to May 15th was treated as the baseline (only April 1st to May 15th, 2019 for TROPOMI due to data unavailability). Since the satellite observations are relatively coarse, only urban clusters with an area of above 10 km² were considered. This threshold, along with cloud screening, leaves 382 clusters for the MODIS and Sentinel-derived CF data (Fig. S2) and 302 clusters for the Sentinel-derived air pollutant data.

110 **Table 1:** Summary of satellite products used in the present study.

Satellite product	Time of Interest	Variable(s) of interest	Temporal resolution	Spatial resolution	Reference
MODIS Land Surface Temperature (LST) product (MYD11A2 v006)	2015-2020	Daytime and nighttime LST from Aqua	8-day	1000 m	[24]
MODIS surface reflectance product (MYD09A1 v006)	2015-2020	Reflectances in the near-infrared and red bands	8-day	500 m	[25]
MODIS global albedo (α) product (MCD43A3 v006)	2015-2020	Black Sky Albedo (BSA) and White Sky Albedo (WSA)	16-day	500 m	[28]
MODIS Aerosol Optical Depth (AOD) product	2015-2020	AOD	Daily	1000 m	[26]
Sentinel-5P TROPOMI	2019-2020	Nitrogen Dioxide (NO ₂), Sulphur Dioxide (SO ₂), Ozone (O ₃), Carbon Monoxide (CO), Formaldehyde (HCHO), Methane (CH ₄), and Cloud Fraction (CF)	2-day	1000 m (downscaled)	[27]
European Space Agency Climate Change Initiative (ESA CCI) land cover data	2018	Land cover	Yearly	300 m	[33]

111 Urban and rural means of all the variables of interest were extracted using the Google Earth
112 Engine platform [32]. The urban values were calculated as the spatial means of all the urban
113 pixels, as defined by the European Space Agency Climate Change Initiative (ESA CCI) land
114 cover data [33], within an urban cluster. The corresponding rural values are the spatial means

of the non-urban, non-water pixels (from the ESA data) in the rural references. Each urban cluster is treated as one sample and we do not examine intra-urban distributions since they are not fully captured by the resolution of the satellite observations. We also calculate the averages of each variable weighted by the urban cluster areas. The urban-rural differential in LST is the SUHI, while for the other variables, we use the subscript _{urb-rur}.

2.3 Reanalysis data

We used two reanalysis products - the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5 (ERA5) [34] and the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) [35]. The 5-year (2015-2019) mean of the diffuse fraction (k_d) of the ERA5 reanalysis was used to calculate α from BSA and WSA [36] using the equation:

$$\alpha = k_d \text{WSA} + (1 - k_d) \text{BSA} \quad (2)$$

For each case, the centroid of the urban and rural polygons was located and k_d was extracted for the ERA5 grid containing it, similar to [37].

The MERRA-2 reanalysis assimilates bias-corrected satellite observations of aerosols and provides estimates of the aerosol direct radiative effect, making it ideal for studying the impacts of the COVID-19 lockdowns. Though MERRA-2 also includes estimates of k_d , inter-reanalysis evaluations show that it significantly underestimates k_d compared to other products [38]. Thus, MERRA-2 data were not used to calculate α . Instead, MERRA-2 was used to get all-sky estimates of perturbations in the surface and atmospheric variables (since satellites only provide clear-sky estimates) and to diagnose reasons for perturbations in the rural LST. The MERRA-2 variables were based on hourly data from 12:30 pm to 2:30 pm local time, corresponding to the 1:30 pm MODIS Aqua overpass.

2.4 Statistical analysis

To examine reasons for any potential SUHI change, we considered the temporal changes (Δ , variable value during the lockdown minus value of the reference period) in $\text{AOD}_{\text{urb-rur}}$, $\text{NDVI}_{\text{urb-rur}}$, $\alpha_{\text{urb-rur}}$, and $\text{CF}_{\text{urb-rur}}$ as the predictors. For robustness, we used two methods – linear regressions and random forest (RF) regression. For the linear regressions, we considered each of these four predictors ($\Delta\text{AOD}_{\text{urb-rur}}$, $\Delta\text{NDVI}_{\text{urb-rur}}$, $\Delta\alpha_{\text{urb-rur}}$, and $\Delta\text{CF}_{\text{urb-rur}}$)

and all their combinations and subsets. Since the relationships between the predictors and ΔSUHI are not necessarily linear, we also checked the consistency of our results using RF regressions. RF regressions use ensembles of decision trees to detect non-linear relationships and are less sensitive to outliers than parametric linear models [39]. To prevent overfitting, we trained the models using 70% of the data and checked the model accuracy using the remaining data. The training and accuracy assessment were repeated 50 times with different random splits of training and validation data [40].

2.5 Intrinsic Biophysical Mechanism

Since the statistical analyses do not reveal the physical mechanisms for the SUHI increase, we employed the theory of Intrinsic Biophysical Mechanism (IBPM) [14, 15, 41, 42], implemented using the MERRA-2 variables [42], to diagnose the reasons for the change in the LST_{rur} in the region. Conceptually, the total LST change (ΔLST) due to a forcing agent is the sum of the changes in the blending height temperature (ΔBHT) and the local temperature response (ΔT):

$$\Delta\text{LST} = \Delta T + \Delta\text{BHT} \quad (3)$$

According to the IBPM theory, the local temperature response is:

$$\Delta T = \frac{\lambda_0}{1+f} \Delta K_{\downarrow} (1 - a) + \frac{\lambda_0}{1+f} \Delta L + \frac{-\lambda_0}{(1+f)^2} (R_n^* - G) \Delta f_1 + \frac{-\lambda_0}{(1+f)^2} (R_n^* - G) \Delta f_2 + \frac{\lambda_0}{1+f} \Delta G \quad (4)$$

The terms on the right-hand side of Eq. 4, from left to right, are the contributions to ΔT from shortwave radiative forcing, longwave radiative forcing, energy redistribution through evaporation, energy redistribution through convection, and change in ground heat flux. Here, $\Delta K_{\downarrow}$ is the change in incoming shortwave radiation, ΔL is the change in absorbed longwave radiation, ΔG is the change in ground heat flux, and R_n^* is the apparent net radiation. The intrinsic climate sensitivity is given by λ_0 , f is the energy redistribution factor and Δf_1 and Δf_2 are the changes in f due to evaporation and convection, respectively. Check supplementary material for more details.

3. Results

3.1 Changes in urban-rural differentials during lockdown

The daytime SUHI increased (non-weighted mean from 0.23 K to 0.43 K; area-weighted mean from 0.56 K to 0.97 K) during the COVID-19 lockdown period compared to the 5-year baseline (Fig. 1 and Fig. S3), with 67% or 257 of the 382 urban clusters showing an increase. In contrast, the nighttime Δ SUHI was statistically insignificant (p -value > 0.01). Daytime LST decreased during the lockdown, though the mean decrease over rural locations was greater (-1.96 K non-weighted; -1.55 K weighted) compared to that over urban regions (-1.76 K non-weighted; -1.14 K weighted).

Figure 1: Perturbations to land surface temperature (LST) and surface urban heat island (SUHI) intensity. Sub-figures (a) and (b) show the mean (not weighted by urban cluster area) land surface temperature (LST) and surface urban heat island (SUHI) for urban clusters and their rural references for the baseline period, as well as their perturbed values during the lockdown period, for daytime and nighttime, respectively. The values above the bars show the mean values (percentage change during lockdown period for SUHI) and the error bars represent the 95% confidence interval of the mean. Sub-figure (c) shows a map of the urban

clusters in the region of interest and the change in their spatial mean daytime SUHI during the lockdown compared to the 5-year baseline.

To explain this differential perturbation in daytime LST_{urb} and LST_{rur} , we consider major atmospheric (CF and AOD) and surface (NDVI and α) factors that impact the SUHI. Unsurprisingly, the air quality over both urban and rural locations improved during the lockdown. This reduced air pollution is evident from both MODIS-derived AOD ($\sim 5\text{-}6\%$ decrease; Figs 2a and S4a) and individual air pollutants measured by TROPOMI ($\sim 14\%$ and $\sim 19\%$ decrease in urban NO_2 and SO_2 , respectively; Fig. S5). AOD decreases in roughly 67% of the urban clusters and for most non-urban grids in the IGB (Fig S6a). The small magnitude of MODIS-derived $AOD_{urb-rur}$ could be due to the large contributions from natural dust and biomass burning aerosols, as well as occurrence of turbulently mixed deep boundary layers, in this region during this period [43]. Moreover, there was a surprisingly large ($>36\%$ for non-weighted; $>43\%$ for weighted) increase in CF during the lockdown (Fig. 2d and Fig S4d), though some regions show a decrease (Fig. S6b).

Figure 2: Changes in major surface and atmospheric factors. Sub-figures (a), (b), (c), and (d)

show the mean (not weighted by urban cluster area) Aerosol Optical Depth (AOD), normalized difference vegetation index (NDVI), surface albedo (α), and cloud fraction (CF) for urban clusters and their rural references for the baseline period, as well as their perturbed values during the lockdown. The values above the bars show the mean values for the baseline period (2015-2019 baseline for everything other than CF; 2019 baseline for CF) and the percentage change from that value. The error bars represent the 95% confidence interval of the mean.

We find large ($>12\%$) increases in NDVI during the lockdown period. These increases are generally higher in rural areas (13.3% or 0.043) than in urban areas (12.8% or 0.038; Fig. 2b), with $\Delta\text{NDVI}_{\text{urb-rur}}$ being negative in $\sim 59\%$ of the urban clusters. The positive $\Delta\text{NDVI}_{\text{rur}}$ is consistent with the impact of the lockdown on agricultural activity, which is the predominant land use for $\sim 88\%$ of this area according to the ESA CCI data (Fig. S2b). The lockdown overlapped with the harvesting season for rabi (winter) crops, which, together with the drier conditions during this period, reduces surface vegetation during regular years, as can be seen from the moving average of MODIS-derived 8-day NDVI in Figure 3c. The delay in harvesting activity [16] temporally shifted this normal drop in NDVI, contributing to surface greening compared to the baseline (Fig. 3c). Most of IGB shows this surface greening, as well as a reduction in LST_{rur} (Figs 3a and 3b), with the SUHI increasing compared to baseline (Fig. 3d). Simultaneously, α decreased in both urban (-2.6%) and rural (-2.9%) areas (Figs 2c and S4c). Paired two-sample t-tests confirm that all the satellite-observed changes in the variables, other than that for nighttime SUHI, are statistically significant ($p\text{-value} < 0.01$). The 95% confidence intervals for the mean of each variable are in Table S1.

Figure 3: Regional changes in vegetation cover and land surface temperature (LST). Sub-figures (a) and (b) show maps of the changes in rural normalized difference vegetation index (NDVI_{rur}) and daytime rural land surface temperature (LST_{rur}) during the lockdown compared to the 5-year baseline. Sub-figure (c) shows the seasonal change in NDVI for baseline period (2015-2019; in red) and from January to June 2020 (in blue) over all rural pixels in the study area. The percentage change in NDVI_{rur} between the baseline and lockdown for each 8-day period is shown in orange. The red shaded region shows the standard deviation of the baseline value across years, while the grey shaded region shows the overall lockdown period. To reduce noise, the moving average of three points is used to compute the 2020 values. Sub-figure (d) is similar to sub-figure (c), but for seasonal variability of daytime surface urban heat island (SUHI) intensity. Percentage changes are not shown for (d) since the baseline daytime SUHI values can be close to zero in some cases.

3.2 Attribution of daytime SUHI enhancement

Previous studies have shown relationships between AOD_{urb-rur} and SUHI [13, 14]. Here, we find almost no associations between the perturbations in the two during the lockdown period (Fig. 4a). Similarly, AOD_{urb-rur} and daytime SUHI are not well-correlated during the baseline and lockdown periods (Fig. S7b). However, Δ NDVI_{urb-rur} shows a relatively strong inverse relationship with Δ SUHI (Fig. 4b). Given the generally higher Δ NDVI_{rur}, the pause in human activity in the rural area may have contributed to the enhanced daytime SUHI. This impact of urban-rural vegetation differentials on SUHI is consistent with previous studies [44, 45] and

is corroborated by the relatively strong associations between $\text{NDVI}_{\text{urb-rur}}$ and daytime SUHI for the two periods (Fig. S7a). Although $\Delta\alpha_{\text{urb-rur}}$ shows a weak positive relationship with ΔSUHI , this relationship is not physically possible in isolation, since a higher α implies lower absorption of solar insolation by the surface, and thus, lower ΔSUHI . Since α and NDVI are correlated (Fig. S8), the positive relationship between $\Delta\alpha_{\text{urb-rur}}$ and ΔSUHI may be a statistical artifact of the relatively higher NDVI_{rur} . Neither $\text{CF}_{\text{urb-rur}}$ and daytime SUHI intensity, nor their perturbations from the baseline to the lockdown, are correlated (Fig. 4d and S7c).

We use multiple linear and RF regressions to provide further statistical robustness to our findings (Table S2). In general, $\Delta\text{NDVI}_{\text{urb-rur}}$ explains the largest portion of the variability in ΔSUHI , followed by $\Delta\alpha_{\text{urb-rur}}$, $\Delta\text{AOD}_{\text{urb-rur}}$, and $\text{CF}_{\text{urb-rur}}$. The permutation importance scores from the RF models also support the primary control of $\Delta\text{NDVI}_{\text{urb-rur}}$ on ΔSUHI (Table S2).

The percentage changes in the atmospheric variables (AOD and CF) are higher over urban areas compared to the rural areas during the lockdown period and the surface properties (NDVI and α) change more for rural areas (Figs 2 and S4). The lower AOD_{urb} is a direct consequence of reduced human activity in cities. Although 2020 was already wetter than regular years [18], a further reduction in AOD over the study area may have perturbed the regional circulation and thermodynamics [46, 47], creating an environment conducive to more cloud formation. It may also be possible that the lower aerosol loading reduced the cloud-burning effect [48], thus increasing CF. Finally, the surface greening could also enhance CF [49]. We expect a greater decrease in AOD over urban clusters to correspond to an increase in $K_{\downarrow}$, which can enhance SUHI intensity. However, we find that the effect of reduced AOD and that of increased CF mostly cancel each other out. Instead, the observed positive ΔSUHI is associated with the higher vegetation cover over rural areas. This control of vegetation cover on LST is further corroborated by the negative correlations between LST and NDVI for the urban and rural units (Fig. S9). The relatively weaker correlations in Fig. 4b compared to Figs S7a and S9 (and previous studies [44, 45, 50]) is because we are dealing with differences of differences in Fig. 4b during a time of the year with low expected SUHI intensities (Fig. 3d), making the signal hard to isolate from the noise.

Figure 4: Statistical examination of daytime surface urban heat island (SUHI) enhancement. Sub-figures (a), (b), (c), and (d) show the correlations between daytime change in surface urban heat island (SUHI) (Δ SUHI) during the lockdown compared to the 5-year baseline and the respective change in urban-rural differential in Aerosol Optical Depth (Δ AOD_{urb-rur}), normalized difference vegetation index (Δ NDVI_{urb-rur}), surface albedo ($\Delta\alpha_{urb-rur}$), and cloud fraction (Δ CF_{urb-rur}), respectively. Each data point corresponds to an urban cluster. The lines of best fit are shown, and their corresponding equations (along with their sample sizes and p-values) are annotated. Values that are outside the 1 to 99 percentiles of the change in the predictor variables are considered outliers and not shown in the scatter plots.

3.3 Perturbations to rural background surface climate

The lack of large-scale continuous observations of meteorological variables in urban areas makes diagnosing these patterns for all-sky conditions difficult using in-situ observations. Instead, we use the MERRA-2 reanalysis, which is observationally constrained by ground-level measurements of surface meteorology and satellite measurements of columnar AOD,

and physically constrained by the model components [35]. MERRA-2 primarily represents the rural background since it does not incorporate urban land cover. Since, as also suggested by the satellite-derived NDVI and α (Fig. 2), urban surfaces changed less than rural surfaces during the lockdown, the reanalysis data can be used to generate insights about the mechanism behind the SUHI enhancement.

The MERRA-2 reanalysis captures the direction of the changes in the region during the lockdown compared to satellite observations (Table S3). Although the midday aerosol direct radiative effect in MERRA-2 decreases by almost 25% (from $-78.4 \pm 12.6 \text{ W m}^{-2}$ to $-58.7 \pm 13.3 \text{ W m}^{-2}$) during the lockdown, with the potential to increase $K_{\downarrow}$ by $19.8 \pm 5.1 \text{ W m}^{-2}$, we find an overall reduction in $K_{\downarrow}$ ($-10.5 \pm 39.8 \text{ W m}^{-2}$). This decrease in $K_{\downarrow}$ is due to the compensating effect of increased cloudiness during the lockdown, as well as the higher water vapor content in the atmospheric column, as seen from the higher near-surface relative humidity (Table S3). Overall, the total absorbed energy by the surface decreases slightly ($-10.4 \pm 32 \text{ W m}^{-2}$) during the lockdown despite the negative $\Delta \text{AOD}_{\text{rur}}$.

Separating the contributions from both radiative and non-radiative pathways that can change LST reveals large evaporative cooling ($-1.79 \pm 0.05 \text{ K}$) during this period (Fig. 5a); expected if vegetation cover increased. The diagnosed and MERRA-2 calculated ΔT are similar in magnitude (-1.29 K versus -1.22 K) and in spatial distribution (Fig. 5b), though the MODIS observed clear-sky ΔLST is lower than the MERRA-2 ΔLST (-2.01 K versus -3.92 K ; Table S3). MERRA-2 uses prescribed vegetation, with identical leaf area index (LAI; regional mean = ~ 0.79) for the two periods. However, since it is constrained by observed surface meteorology, it captures the decrease in Bowen ratio – the ratio of sensible heat flux (H) and λE – during midday (from 2.87 ± 3.02 for baseline to 1.24 ± 0.76 during the lockdown; Table S3), which is an expected impact of surface greening. The higher precipitation, latent heat, cloud cover, and relative humidity point to a more intense hydrological cycle during the lockdown compared to regular years (Table S3).

The satellite-observed negative $\Delta \text{NDVI}_{\text{urb-rur}}$ suggests that the increase in evaporative cooling during the lockdown was more for rural areas compared to urban areas. This would be true even if NDVI_{urb} and NDVI_{rur} had changed identically, since urban areas are generally more

moisture-limited. Figure 5b shows the correlations of ΔT from MERRA-2, the IBPM calculations, and contributions due to evaporation and convection with LAI. The negative correlations between LAI and ΔT demonstrate a stronger cooling response during the lockdown over more densely vegetated surfaces. Here, the lowest LAI grids represent relatively urbanized areas. The increasing positive temperature response through the convective pathway with LAI suggests that this is a negative feedback to the evaporative cooling [51]. This convective feedback can be understood either in terms of energy conservation or through evaporation-induced near-surface stability. A relative increase in λE under similar (or reduced) available energy requires a corresponding decrease in H . Alternatively, the additional evaporative cooling of the surface compared to the blending height renders the lower atmosphere relatively stable compared to the baseline period, impeding the dissipation of available energy via H .

Overall, ΔT is almost a third of ΔLST , with the other two-third attributable to atmospheric factors, including AOD and CF (Fig. 5a). The IBPM results show that the sum of the evaporative cooling and its convective feedback accounted for roughly 79% of the midday ΔT , while the evaporative cooling alone accounted for roughly 46% of the corresponding ΔLST . The land contribution to ΔLST found here is probably a lower bound estimate since there is strong coupling between the land and the atmosphere. For instance, enhanced surface evaporation due to the increase in vegetation cover would also increase low level cloudiness through condensation feedback [52], lowering both BHT and LST. A similar theoretical diagnosis is not possible for the urban surfaces explicitly since the MERRA-2 land cover dataset does not consider urban areas. Nonetheless, these results can explain the SUHI increase, as the implicit assumption is that the surface characteristics of the rural areas changed more than those of the urban areas during the lockdown period, which is reasonable given the time scale.

Figure 5: Contributions of different pathways to regional land surface temperature (LST) change. Sub-figure (a) shows contributions of all pathways, namely shortwave radiative forcing, longwave radiative forcing, evaporation, convection, and ground heat storage to the total calculated local temperature change (ΔT) in the Indo-Gangetic Basin during the lockdown compared to the 5-year baseline. The corresponding ΔT , ΔLST , and change in blending height temperature (ΔBHT) in MERRA-2, as well as the clear-sky ΔLST as derived from MODIS observations, are also shown. The standard errors are displayed in all cases. Sub-figure (b) shows the correlations between the MERRA-2 grid-averaged leaf area index (LAI) and the corresponding ΔT from MERRA-2, the calculated ΔT using the IBPM framework, and the contributions to ΔT through the evaporative pathway and convective pathways. Each data point corresponds to a grid cell average. The lines of best fit are shown and the corresponding equations (including confidence bounds for the slopes of the lines, sample sizes, and p-values) are annotated. Values that are outside the 1 to 99 percentile of the total diagnosed local temperature change are considered outliers and not shown in the scatter plot.

4. Discussion and Conclusions

The UHI effect is traditionally viewed as an outcome of the replacement of the natural landscape by built-up structures. The consequences of this land cover change are simpler to define in the abstract than to measure in practice. While cities modify their local climate as they expand, the UHI intensity is usually quantified using snapshot measurements in the urban area and for some rural reference. For the SUHI, how to define this rural reference remains a contentious issue [45, 53, 54, 55]. Generally, the urban-rural delineations are more clearly constructed for less sprawling cities with very little land management surrounding the city centers. Here, we show an example of a region of the world with high human intervention in both urban and rural areas, the interruption of which leads to the seemingly counter-intuitive enhancement of the SUHI during a period of low human activity. Thus, the COVID-19 lockdown period illustrates the importance of the rural reference on the SUHI intensity during a perturbation scenario, the relevance of which has previously only been examined for the mean climate state in this region [17, 18, 56].

Our results can help contextualize a larger current discussion in the urban climate community on the utility of the UHI as a metric to examine urban public health [57, 58, 59]. The UHI intensity is the impact of urbanization on local temperature [60]. However, urban heat stress is dependent on the absolute temperature, or more accurately, a combination of temperature, humidity, and other factors [61]. As such, the relevance of UHI for urban public health can be misleading during certain times because enhancement in UHI intensity does not necessarily imply similar enhancement in heat stress in urban areas. In agreement, [62] argues that mitigating the UHI should not be the goal when addressing the public health consequences of urbanization. In theory, one can reduce the UHI intensity by increasing the rural temperature, which does not change the potential heat stress in the urban area. Here, we see something similar occurring, with the SUHI increasing due to rural areas cooling down more than the urban core between the baseline and the lockdown periods, rather than due to an increase in urban temperature. However, this is only the temporal perspective. From the spatial perspective, it is also true that residents moving from rural to urban regions in the IGB were exposed to higher temperatures than they would have had they remained in rural areas. This separation of the temporal and spatial perspectives is critical to reconciling the debate in the community. The criticisms of UHI as a metric primarily pertain to the total

393 impact of temperature on human health in urban areas. In contrast, since the UHI is an
394 abstract isolation of the contribution to that temperature from urbanization, it remains
395 theoretically important, assuming we establish a more consistent definition of the rural
396 reference to facilitate accurate inter-urban comparisons.

397 Lastly, our finding demonstrates the importance of human-land-atmosphere coupling on the
398 regional climate over South Asia as a whole. Agricultural practices are less mechanized and
399 more human-labor intensive in this region, and thus strongly control the vegetation
400 phenology of the croplands, modulating how energy is partitioned and dissipated from the
401 surface through non-radiative means (Fig. 3c). As seen here, the importance of these non-
402 radiative components on the LST is apparent, even when input energy to the system is
403 relatively stable, providing large-scale observational evidence of previously modeled results
404 [52]. Over 88% of the landmass in North India is agricultural (Fig S1b). Therefore, an
405 increase in surface vegetation due to agriculture can lead to large regional cooling, modify
406 cloud formation, and lower tropospheric stability. Moreover, enhanced evaporative cooling
407 over the Indian landmass during the monsoon onset period (as seen here) can also perturb the
408 land-sea thermal gradient - a major driver of monsoonal wind circulation [63]. Our study
409 puts forth important observational evidence of human-induced control on surface climate,
410 which strengthens the need for the ongoing efforts to explicitly include these in earth system
411 models to better predict long-term climate change [64, 65]. For the UHI, the inclusion of
412 human dynamics can help constrain its future estimates, since urban and rural areas are
413 expected to change differently in future scenarios [66].

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Supplementary Materials

The Intrinsic Biophysical Mechanism

Since satellite-derived observations are only valid for clear-sky conditions, we employ the Intrinsic Biophysical Mechanism (IBPM) [41] to diagnose the reasons for the change in the rural surface climate in the region for all-sky conditions. The IBPM theory solves the surface energy budget to isolate the different drivers of ΔLST . The surface energy budget is given by:

$$K_{\downarrow} + L_{\downarrow} - K_{\uparrow} - L_{\uparrow} = H + \lambda E + G \quad (1)$$

Here, $K_{\downarrow}$ is the incoming shortwave radiative flux, $L_{\downarrow}$ is the incoming longwave radiative flux, $K_{\uparrow}$ is the surface reflected shortwave radiation flux, $L_{\uparrow}$ is the surface emitted longwave radiative flux, H is the sensible heat flux, λE is the latent heat flux, and G is the ground flux. The left-hand side of Eq 1 represent the surface net radiation (R_n).

The perturbation in LST can be due to either a change in the energy input to the system ($K_{\downarrow}$ and $L_{\downarrow}$) or a redistribution of the energy through convection (H) and/or evaporation (λE).

The total LST change (ΔLST) due to a forcing agent is the sum of the changes in the blending height temperature (ΔBHT) and the local temperature response (ΔT):

$$\Delta\text{LST} = \Delta T + \Delta\text{BHT} \quad (2)$$

Here the blending height is the height at which the vertical profiles of atmospheric variables are horizontally blended and no longer influenced by surface heterogeneity. For this study, the blending height is derived from the lowest model level in MERRA-2 (985 hPa) [42]. The conceptual assumption follows that, ignoring larger-scale feedback, changes in ΔBHT are due to atmospheric processes, while changes in ΔT are controlled by the Earth's land surface processes.

The local temperature response due to these surface processes is given by:

$$\Delta T = \frac{\lambda_0}{1+f} \Delta K_{\downarrow} (1 - a) + \frac{\lambda_0}{1+f} \Delta L_{\downarrow} + \frac{-\lambda_0}{(1+f)^2} (R_n^* - G) \Delta f_1 + \frac{-\lambda_0}{(1+f)^2} (R_n^* - G) \Delta f_2 + \frac{\lambda_0}{1+f} \Delta G \quad (3)$$

The terms on the right-hand side of Eq. 3 represent these pathways, and from left to right, are the temperature response due to the shortwave radiative forcing, the longwave radiative forcing, energy redistribution through evaporation, energy redistribution through convection, and change in ground heat flux. Here, $\Delta K_{\downarrow}$ is the change in incoming shortwave radiation, ΔL is the change in absorbed longwave radiation, and ΔG is the change in ground heat flux. Since R_n is dependent on LST (through the $L \uparrow$ term), we define an apparent net radiation (R_n^*) that is not a function of the land surface temperature by replacing LST with BHT.

$$R_n^* = K_{\downarrow}(1 - a) + L_{\downarrow} - \varepsilon \sigma BHT^4 \quad (4)$$

where ε is the surface emissivity and σ is the Stefan Boltzmann constant ($5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$). λ_0 is the temperature sensitivity due to longwave feedback, derived by differentiating the Stefan-Boltzmann law, and given by:

$$\lambda_0 = \frac{1}{4\sigma LST^3} \quad (5)$$

and f is a factor denoting energy redistribution through non-radiative pathways, calculated using:

$$f = \frac{\lambda_0}{LST - BHT} (R_n^* - G) - 1 \quad (6)$$

The change in f due to evaporative (Δf_1) and convection (Δf_2) can be calculated from:

$$\Delta f_1 = -f \frac{\Delta \beta}{\beta(1+\beta)} \quad (7)$$

$$\Delta f_2 = -f \frac{\Delta r_a}{r_a} \quad (8)$$

where β is the Bowen ratio, the ratio of H and λE , and r_a is the aerodynamic resistance, formulated by inverting the equation for H as:

$$r_a = \frac{\rho C_p (LST - BHT)}{H} \quad (9)$$

Here, ρ is the air density, and C_p is the specific heat capacity of air at constant pressure. All the perturbation terms were calculated from the MERRA-2 reanalysis as the difference between the 5-year baseline and the lockdown period. f and λ_0 were calculated for the baseline period, while β , r_a , and λ_0 are the averages of the two periods. Since f cannot physically have a negative value, the grids with $f < 0$ are excluded from the analysis.

Figure S1: Map of study area. The black polygon in sub-figure (a) show the Indo-Gangetic Basin (IGB). The generated urban clusters are in red, while their corresponding normalized rural buffers are shown in blue. Sub-figure (b) shows the distribution of three relevant land cover categories for the IGB from the European Space Agency Climate Change Initiative land cover dataset for 2018.

Figure S2: Distribution of urban and rural units of calculations used in the study. Sub-figure (a) shows the density plot of the urban clusters with areas greater than 1 km² used in the study after cloud screening of the data. Sub-figure (b) shows the distribution of the buffer widths used to calculate the rural references following the integration procedure used to minimize area difference between urban areas and their references.

Figure S3: Perturbations to land surface temperature (LST) and surface urban heat island (SUHI) intensity. Sub-figures (a) and (b) show the mean (weighted by urban cluster area) land surface temperature (LST) and surface urban heat island (SUHI for urban clusters and their rural references for the baseline period, as well as their perturbed values during the lockdown period, for daytime and nighttime, respectively. The values above the bars show the mean values (percentage change during lockdown period for SUHI) and the error bars represent the 95% confidence interval of the area-weighted mean.

Figure S4: Changes in major surface and atmospheric factors. Sub-figures (a), (b), (c), and (d) show the mean (weighted by urban cluster area) Aerosol Optical Depth (AOD), normalized difference vegetation index (NDVI), surface albedo (α), and cloud fraction (CF) for urban clusters and their rural references for the baseline period, as well as their perturbed values during the lockdown. The values above the bars show the mean values for the baseline period (2015-2019 baseline for everything other than CF; 2019 baseline for CF) and the percentage change from that value. The error bars represent the 95% confidence interval of the area-weighted mean.

Figure S5: Sub-figures (a), (b), (c), (d), (e), and (f) show the mean (weighted by urban cluster area) Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), Ozone (O_3), Carbon Monoxide (CO), Formaldehyde (HCHO), and Methane (CH_4) concentrations for urban clusters and their rural references for the 2019 baseline, as well as their perturbed values during the lockdown. The values above the bars show the mean values for the baseline period and the percentage change from that value. The error bars represent the 95% confidence interval of the mean.

Figure S6: Regional changes in aerosols and clouds. Sub-figures (a) and (b) show maps of the changes in rural aerosol optical depth (AOD_{rur}) and cloud fraction (CF_{rur}) during the lockdown compared to the baseline (5-year for AOD and 1-year for CF).

Figure S7: Correlations between surface urban heat islands (SUHI) and the urban-rural differentials in (a) normalized difference vegetation index (NDVI_{urb-rur}), (b) Aerosol Optical Depth (AOD_{urb-rur}), (c) cloud fraction (CF_{urb-rur}), and (d) surface albedo ($\alpha_{urb-rur}$) respectively, for all urban clusters during the lockdown (in blue) and 5-year baseline period (in red). The lines of best fit and coefficients of correlation are shown.

Figure S8: Correlations between surface albedo (α) and normalized difference vegetation index (NDVI), for rural references during the lockdown (in blue) and for the 5-year baseline period (in red). The lines of best fit and coefficients of correlation are shown.

Figure S9: Correlations between land surface temperature (LST) and normalized difference vegetation index (NDVI), for (a) urban clusters and (b) rural references during the lockdown (in blue) and for the 5-year baseline period (in red). The lines of best fit and coefficients of correlation are shown.

Table S1: Summary (mean, 95% confidence intervals of mean) of satellite-derived estimates of the main variables of interest for urban clusters and their rural references. The spatial mean of each urban (and corresponding rural) polygon is treated as a sample point.

Variable (unit)	Satellite Observations	
	Baseline	Lockdown
Daytime surface urban heat island (K)	(0.23, 0.14, 0.32)	(0.43, 0.34, 0.52)
Nighttime surface urban heat island (K)	(0.88, 0.8, 0.97)	(0.86, 0.78, 0.94)
Urban normalized difference vegetation index	(0.3, 0.29, 0.31)	(0.34, 0.33, 0.34)
Rural normalized difference vegetation index	(0.32, 0.31, 0.33)	(0.37, 0.36, 0.38)
Urban aerosol optical depth	(0.53, 0.53, 0.54)	(0.5, 0.49, 0.51)
Rural aerosol optical depth	(0.54, 0.53, 0.55)	(0.51, 0.5, 0.52)
Urban surface albedo	(0.155, 0.154, 0.157)	(0.151, 0.15, 0.153)
Rural surface albedo	(0.164, 0.162, 0.165)	(0.159, 0.158, 0.16)
Urban cloud fraction	(0.107, 0.102, 0.111)	(0.146, 0.14, 0.151)
Rural cloud fraction	(0.106, 0.102, 0.111)	(0.145, 0.14, 0.15)
Urban daytime surface temperature (K)	(312.9, 312.6, 313.2)	(311.2, 310.8, 311.5)
Rural daytime surface temperature (K)	(312.7, 312.4, 313.0)	(310.7, 310.4, 311.1)
Urban nighttime surface temperature (K)	(295.0, 294.8, 295.1)	(294.4, 294.3, 294.6)
Rural nighttime surface temperature (K)	(294.1, 293.9, 294.3)	(293.6, 293.4, 293.7)

Table S2: Summary of data-driven examination of the control of the urban-rural differentials on the change in SUHI using multiple linear and random forest (RF) regressions. For the linear regressions, the combination of variables that lead to the highest adjusted R^2 is listed for increasing subset size. For the RF regression, both the mean and standard deviation of the permutation feature importance scores and r^2 (based on the 50 random training/validation splits) are noted.

Linear Regressions			Random Forest Regressions		
Model	Adjusted R^2	Feature	Importance Scores	r^2	
$\Delta\text{SUHI}=0.14-9.76\Delta\text{NDVI}_{\text{urb-rur}}$	0.15	$\Delta\text{NDVI}_{\text{urb-rur}}$	0.82 ± 0.08		
$\Delta\text{SUHI}=0.13-9.07\Delta\text{NDVI}_{\text{urb-rur}}+23.54\Delta\alpha_{\text{urb-rur}}$	0.18	$\Delta\alpha_{\text{urb-rur}}$	0.46 ± 0.07	0.09	
$\Delta\text{SUHI}=0.12-8.70\Delta\text{NDVI}_{\text{urb-rur}}+24.08\Delta\alpha_{\text{urb-rur}}-1.36\Delta\text{AOD}_{\text{urb-rur}}$	0.19	$\Delta\text{AOD}_{\text{urb-rur}}$	0.27 ± 0.04	$\pm$	
$\Delta\text{SUHI}=0.12-8.67\Delta\text{NDVI}_{\text{urb-rur}}+24.08\Delta\alpha_{\text{urb-rur}}-1.39\Delta\text{AOD}_{\text{urb-rur}}-3.61\Delta\text{CF}_{\text{urb-rur}}$	0.19	$\Delta\text{CF}_{\text{urb-rur}}$	0.21 ± 0.03	0.10	

746 **Table S3:** Regional midday (1:30 pm local time) values (mean $\pm$ standard deviation) of relevant
747 variables for the baseline, the lockdown, and their corresponding changes from both the
748 MERRA-2 reanalysis and the satellite observations.

Variable (unit)	MERRA-2 Reanalysis			Satellite Observations		
	Baseline	Lockdown	Change	Baseline	Lockdown	Change
Aerosol optical depth	0.54 $\pm$ 0.09	0.44 $\pm$ 0.09	-0.1 $\pm$ 0.02	0.54 $\pm$ 0.11	0.49 $\pm$ 0.12	-0.05 $\pm$ 0.07
Cloud fraction	0.18 $\pm$ 0.05	0.23 $\pm$ 0.1	0.05 $\pm$ 0.08	0.1 $\pm$ 0.05	0.14 $\pm$ 0.05	0.04 $\pm$ 0.04
Surface temperature (K)	317.4 $\pm$ 5	313.5 $\pm$ 5.1	-3.9 $\pm$ 1.4	313.2 $\pm$ 4	311.2 $\pm$ 4.2	-2 $\pm$ 1.4
Air temperature (K)	311.2 $\pm$ 3.6	308.1 $\pm$ 3.7	-3.1 $\pm$ 1	NA	NA	NA
Relative humidity (%)	18.1 $\pm$ 8.2	24.8 $\pm$ 7.1	6.7 $\pm$ 3.6	NA	NA	NA
Precipitation (mm day ⁻¹)	0.83 $\pm$ 3.2	1.20 $\pm$ 3	0.37 $\pm$ 0.8	NA	NA	NA
Wind speed (m s ⁻¹)	4.73 $\pm$ 0.7	4.14 $\pm$ 0.6	-0.59 $\pm$ 0.5	NA	NA	NA
All-sky incident shortwave radiation (W m ⁻²)	815.1 $\pm$ 56.8	804.6 $\pm$ 58.4	-10.5 $\pm$ 39.8	NA	NA	NA
Clear-sky incident shortwave radiation (W m ⁻²)	867.4 $\pm$ 41	880.1 $\pm$ 38.9	-12.7 $\pm$ 3.7	NA	NA	NA
Clear, clean-sky Incident shortwave radiation (W m ⁻²)	949.5 $\pm$ 31.4	942.3 $\pm$ 28.5	-7.2 $\pm$ 3.5	NA	NA	NA
Shortwave aerosol radiative forcing (W m ⁻²)	-78.5 $\pm$ 12.6	-58.7 $\pm$ 13.3	19.8 $\pm$ 5.1	NA	NA	NA
All-sky incoming longwave radiation (W m ⁻²)	398.9 $\pm$ 21.2	396.5 $\pm$ 18	-2.4 $\pm$ 4.8	NA	NA	NA
Clear, clean-sky incoming longwave radiation (W m ⁻²)	390.8 $\pm$ 22.5	388.9 $\pm$ 21.1	-1.9 $\pm$ 4	NA	NA	NA
Clear-sky longwave aerosol radiative forcing (W m ⁻²)	4.6 $\pm$ 0.8	2.8 $\pm$ 0.6	-1.8 $\pm$ 0.4	NA	NA	NA
Black-sky albedo	NA	NA	NA	0.164 $\pm$ 0.02	0.158 $\pm$ 0.182	-0.006 $\pm$ 0.008
White-sky albedo	NA	NA	NA	0.181 $\pm$ 0.021	0.176 $\pm$ 0.019	-0.005 $\pm$ 0.009
Surface albedo	0.151 $\pm$ 0.02	0.152 $\pm$ 0.02	-0.001 $\pm$ 0	NA	NA	NA
Normalized difference vegetation index	NA	NA	NA	0.31 $\pm$ 0.13	0.35 $\pm$ 0.12	0.04 $\pm$ 0.04
Sensible heat flux (W m ⁻²)	309.5 $\pm$ 55	246.4 $\pm$ 53.1	-63.1 $\pm$ 38.4	NA	NA	NA
Latent heat flux (W m ⁻²)	107.7 $\pm$ 67.1	198.1 $\pm$ 67.2	90.4 $\pm$ 39.2	NA	NA	NA
Bowen ratio	2.87 $\pm$ 3.02	1.24 $\pm$ 0.76	-1.63 $\pm$ 2.35	NA	NA	NA

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