Pollutants control the process networks of urban environmental-meteorology

Mayank Gupta 1, Tejasvi Chauhan 1, Raghu Murtugudde 2,3 and Subimal Ghosh 1,2,4

1 Centre for Urban Science and Engineering, Indian Institute of Technology Bombay, Mumbai 400076, India
2 Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai 400076, India
3 Earth System Science Interdisciplinary Center (ESSIC)/DOAS, University of Maryland, College Park, MD, United States of America
4 Interdisciplinary Program in Climate Studies, Indian Institute of Technology Bombay, Mumbai 400076, India

E-mail: subimal@civil.iitb.ac.in

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Abstract
The dynamics of interactions between the environmental and the meteorological variables in an urban region is extremely complex due to continuously evolving coupled human–natural processes in an urban setting. We attempt to understand the same with the networks of variables using information theory, known as process network. We monitored local meteorological variables at half-hourly scale using an eddy covariance observation system combined with available concentration of pollutants from other sources. Both the datasets are for Powai, Mumbai, India, from January to April 2020 that includes pre-lockdown and lockdown periods associated with interventions in response to COVID-19. Analysis of the weekly process networks developed with the same data shows that they are more dominated by memory during the lockdown period. We find that a high concentration of pollutants under no-lockdown scenarios, during specific work commute hours, interrupts the memory of the network. A seasonal transition in temperature during the pre-lockdown period failed to make any major changes. Our analysis shows that the dynamics of pollutant concentration drives the interaction between the variables of urban environmental meteorological system.

1. Introduction
Dynamic interactions between atmospheric pollutants and the urban microclimate characterize the urban environmental meteorology, which is a complex nonlinear dynamic system. The variables in such a system form coupling between themselves and provide feedback that not only drives the causal relationship between the variables but also tends to render the whole system self-organizing. Understanding the emergence of such a system is crucial as it dictates cause and effect association, helps in simulating the perturbation of the system to changes in large-scale processes, and improves our predictive capabilities for individual variables in the system.

The study of environmental meteorology in urban areas is important because despite covering a small footprint of the total landmass, cities comprise half of the global population, contribute significantly to environmental changes, and pose risks to human health and well-being due to extreme events and poor air quality. Further, the local urban anthropogenic factors affect regional and large-scale processes such as changes in storm structure (Niyogi et al 2011) and precipitation patterns (Shepherd 2005, Paul et al 2018). This makes it essential to understand the environmental meteorological processes, to monitor and to accurately predict variations in local weather and climate. The urban environmental meteorology is governed by the generation of radiative and convective fluxes through land surface interactions with the atmosphere and through human emissions of heat and pollutants. The urban land surface varies in roughness, density, compactness, and albedo due to varying morphology, land cover, and human activities that influence surface energy and water balance (Oke 1982, Grimmond and Oke 1999a, Mitchell et al 2008, Barlow 2014), and also responsible for modification in the atmospheric boundary layer (Arnfield 2003, Barlow 2014) through variation in the transport...
of heat, water and pollutants (Grimmond et al 2010). The urban microclimate emerges as distinct because of intra-urban variations in geometrical and physical urban forms, land covers along with land use activities (Ward and Grimmond 2017). Human activities modify radiative balance through heat release from buildings, metabolism (Ichinose et al 1999), and release of heat and pollutants from combustion processes, vehicle exhausts, construction practices, and industrial activities. Pollutants are released in the form of aerosols and greenhouse gases, which affect radiative fluxes such as black carbon particles, nitrogen oxides ($\text{NO}_x$), carbon monoxide ($\text{CO}$), ozone ($\text{O}_3$), sulphur dioxide ($\text{SO}_2$), and organic carbon (OC) (Venkataraman et al 2016).

The mesoscale impacts of the land surface on urban climate is well covered in recent literature, though the understanding of processes along with their simulations needs further investigations. Uncertainty exists in the understanding of direct and indirect interactions between the pollutants and local meteorological variables that form the urban microclimate. This specific area is not yet well explored due to the complexity of urban environmental meteorological system and lack of monitoring needed to generate high-resolution datasets. With the perturbations in pollutants, the system tends to move towards stabilizing the boundary layer, with inversions between surface and atmospheric temperatures by balancing of radiative and convective effects (Ackerman 1977, Wang et al 2014, Miao et al 2016). Literature has typically focused on one to one associations between variables (e.g. pollutants and meteorological), but it is rare to consider the coexistence of multi-dimensional nonlinear interactions among all the variables (Deng et al 2016). For example, changes in temperature and wind result in changes in pollutant transport and concentration, which in turn perturbs the local temperature and radiation fluxes (Väkevä et al 2000, Liang and Keener 2015, Miao et al 2016, Kajino et al 2017, Wu et al 2017, Yu et al 2020). Overall, in urban areas, a consensus is found in the decrease of incoming radiation due to a high concentration of pollutants (Liang and Keener 2015, Wu et al 2017, Yu et al 2020), and thus, in the reduction of latent and the sensible heat fluxes. Further, it has been reported that this reduction in latent heat is greater for greater latent heat or greater moisture availability (Steiner et al 2013, Liu et al 2014, Murthy et al 2014, Latha et al 2019).

The coexistence of multi-dimensional interactions between the urban environmental and meteorological variables creates a nonlinear environmental meteorological system whose dynamics are still not very clear with regional specificities. Such a complex system may be best visualized as a network of variables, where the links between them represent the association and causality. However, to the best of our knowledge, such an approach has not been adopted thus far to represent the processes associated with urban environmental—meteorological systems and their dynamics. Here, we apply the network approach to understand the role of pollutant concentration in perturbing the urban microclimate. We installed a low-cost eddy covariance system and developed a dataset of the fluxes and the meteorological variables such as sensible heat flux ($H$), latent heat flux (LE), relative humidity (RH), incoming shortwave (SW) radiation, net radiation ($R_n$), temperature ($T$), vapor pressure deficit, wind direction (WD), and wind speed (WS) at half-hourly timescale for a relatively small region of radius 1.5 km, at the Indian Institute of Technology—Bombay in Powai, Mumbai. The data for January 2020 to April 2020 being employed here includes pre-lockdown and lockdown periods straddling the COVID-19 interventions. We also secured data for pollutants (particulate matter 2.5 $\mu$m ($\text{PM}_{2.5}$), particulate matter 10 $\mu$m ($\text{PM}_{10}$), $\text{NO}_x$, $\text{SO}_2$, $\text{CO}$) for the same period at Powai, Mumbai from the Maharashtra Pollution Control Board (MPCB), India. Consideration of both pre-lockdown and lockdown period offers us a unique opportunity to understand the impacts of pollutants on the urban microclimate with observational evidence, albeit for a relatively short period. The perturbations in complex interactions among variables within the urban micro-environmental meteorological system, due to a considerable decrease in the pollutants during the lockdown, is presented here with a network-based approach that utilizes information theory. Based on the weekly networks developed for pre-lockdown and lockdown periods, we test the hypothesis that the basic characteristics of the urban micro environmental meteorological system is controlled by the concentrations of the pollutants. The following section provides details of the study area for this research. The instrument setup and various sensors used in this study are also described.

2. Materials and methods

2.1. Site description, Flux observations, and study period

The campus of the Indian Institute of Technology Bombay (IIT Bombay) is situated in Powai area of Sward, Mumbai, India. Mumbai is the economic and financial capital of India and contributes about 6% of India’s GDP. It is the second-most populous city in India, and among the cities with a very high population density with 20 316 persons per square km (Census 2011). Mumbai, a tropical coastal city, is characterized by the tropical hot and humid climate. According to the Köppen–Geiger climate classification, Mumbai is situated under the category of ‘Aw—Tropical Savanna Climate’ (Mehrotra et al 2019). To monitor the meteorological variables and fluxes, we installed an eddy covariance flux tower (figure 1(a)) on the rooftop of the central and tallest building.
in IIT Bombay campus known as the Victor Menzes Convention Centre (VMCC). The location of the tower is 19° 07' 57.10" N, 72° 55' 02.100" E. The measurement height is 37 m above the ground level, which is around 2.46 times of average canopy height ($Z_h = 15$ m) of the region. We assumed the observations to be above the blending height, such that it represents atmospheric fluxes of the overall contribution from the upwind local area. The roughness length ($Z_o$) and displacement height ($Z_d$) were calculated based on the rule of thumb with $Z_o$ as 1.5 m ($=0.1 \times Z_h$) and $Z_d$ as 10.5 m ($=0.7 \times Z_h$) (Grimmond and Oke 1999b). The source area of the fluxes was estimated based on the footprint model of Kljun et al (2015). The footprint area, averaged over the study period, i.e., from January 2020 to April 2020, is presented in figure 1(b). The buffer area of 500 m radius shown in figure 1(c) covers around 70% of the source area of fluxes. The study area comprises of (a) built-up land cover with 33% of buildings and 11% of paved area, (b) green cover with 38% of trees and 4% of grass, and (c) 12% of open areas within a buffer of 500 m radius around the tower site (figures 1(c) and (d)). The surrounding area beyond the buffer constitutes the Sameer hills and the Sanjay Gandhi National Park to the north, Powai Lake to the west, dense urban areas of Powai to the South, and urban areas of S ward to the east. The detailed information on the flux observations using low cost eddy covariance (LC-EC) (Markwitz and Siebicke 2019) is provided in the supplementary text S1 of supporting information (available online at https://stacks.iop.org/ERL/16/014021/mmedia). The details comprise instrumentation, setting of sensors, data collection, and post-processing to estimate fluxes. To the best of our knowledge, such a measuring and monitoring system at an urban location is the first of its kind in India. The observational data of pollutant concentrations was taken from the MPCB station situated in the campus of IIT Bombay at a distance of around 570 m in northwest direction from VMCC. We used pollutants data from the MPCB site and meteorological variables from the flux site to carry out the analysis. Detailed analysis of the consistency between the data from the two sites is provided in the supplementary text S2 of supporting information. The MPCB and flux sites are located within the campus of IIT Bombay, which is homogeneous in terms of microclimate, with a similar land use land cover pattern. The WDs are different values at the sites. The MPCB site is located at the height of 6 m above ground, with WDs affected by surrounding buildings. The flux instruments are located at the height of 37 m, and hence, the WD measured is not as affected by the surrounding buildings. For our entire analysis, we used the measurements for WD from the flux site. We analyze the monitored meteorological data with the pollutant data of the area from 19 January 2020 to 11 April 2020. The study period was divided into 12 weeks. The first 9 weeks belong to the pre-lockdown period and the last 3 weeks belong to the COVID-19 lockdown period. The complete lockdown started in Mumbai on 22 March 2020, in the name of Junta curfew, which was extended for longer duration by the Government of India.

### 2.2. Network based on information theory
To understand the dynamics of the urban environmental meteorological system and the co-existing complex nonlinear interactions among multiple system variables, we followed the concept of process network theory proposed by Ruddell and Kumar (2009). A process network of a multivariate system is characterized based on Shannon’s entropy (1948). The Shannon’s entropy of a variable describes the amount of uncertainties that is associated due to its perturbation in the environment. The links between the variables in the process network are derived based on entropy-based statistics of MI and transfer entropy (TE). MI denotes real-time interactions between two variables with no directions associated with it. Hence, MI does not convey any information related to causality. TE (Schreiber 2000) shows the strength of information coming from the memory of one variable to the present status of another, and this specific information cannot be explained by the memory of latter variable. TE is associated with both the memory and the direction and hence, with causality. A detailed description of the statistics used in the development of the network is provided in supplementary text S3 of the supporting information.

We used the open source package Process Network version 1.4 (Ruddell 2015) to estimate the statistics for the process networks. We considered the default bin size ($m$) 11 to estimate the significant TE and MI. The significance of TEs and MIs is estimated based on the shuffled surrogate method of Ruddell and Kumar (2009), and only statistically significant TEs and MIs are used to develop the process networks.

### 3. Results and discussions

#### 3.1. Changes in meteorological variables and pollutants during the lockdown
Figure 2 shows the weekly averaged diurnal variations along with the interquartile ranges of meteorological variables (figure 2(a)) and pollutants (figure 2(b)) for all 12 weeks. During the pre-lockdown period (first 9 weeks), the pollutants show a peak during morning office commute hours between 1000 and 1200 h (we use local times); however, the evening commute hours do not show a clear second peak but show a spread of pollutant distribution due to variable return travel timings. NO$_x$, which results from direct vehicular emission, indicate high variability during morning hours. As expected, the lockdown period (last...
3 weeks) displays a substantial reduction in pollutant concentration with an average reduction at peak by 91% in NO\textsubscript{x}, 79% in SO\textsubscript{2}, 56% in PM\textsubscript{2.5}, 52% in PM\textsubscript{10}, and 41% in CO. In addition, weeks 8 and 9 also show a lower concentration of pollutants because a major fraction of the population stopped going outside or to workplaces. The study period of Mumbai from mid-January to mid-April is a relatively dry period with clear sky conditions for almost 85% of the days. We observe the maximum (minimum) daily average temperature between 28 °C (21 °C) and 34 °C (26 °C) for all weeks and average of 33 °C (26 °C) during the last 3 weeks of the lockdown period. At our site, we observe an average mean WS of 2.5 m s\textsuperscript{-1}. The mean daily maximum WS, especially between 1200 h and 1800 h, shows a considerable increase to 5.7 m s\textsuperscript{-1} during the lockdown period from 4.5 m s\textsuperscript{-1} before the lockdown period. The radiative input, i.e. incoming SW radiation, depicts a large increase in the daily average peak from 827 W m\textsuperscript{-2} during pre-lockdown to 948 W m\textsuperscript{-2} during the lockdown period. Such an increase started from week 8 onwards. This resulted from the decrease in the concentrations of pollutants.

### 3.2. Surface energy balance

The available energy due to Rn dissipates through sensible and latent heat flux, which are dependent on surface morphology and land cover characteristics, and provide feedback from the land-surface to the atmosphere. With significant proportions of green cover and built-up land uses, the study area shows mixed characteristics of two local climate zones (LCZs), ‘open-mid-rise’ and ‘open high-rise area’ (Stewart and Oke 2012). The Rn follows a similar increasing pattern as SW, with daily peak value averaged over weeks of 407 W m\textsuperscript{-2} during pre-lockdown to 563 W m\textsuperscript{-2} during the lockdown period. The daily sensible heat (H) is found to be 36% of the net radiation, on average. The absolute value of sensible heat flux increases; however, the ratio H/Rn shows negligible change from pre-lockdown to the lockdown period. The magnitude of LE is observed to be very low before lockdown, but the magnitude increases during the lockdown by two-fold with the peak value of 46 W m\textsuperscript{-2}. This increasing pattern in LE during the lockdown may be attributed to the reduction in pollutant concentration and subsequent increase in net radiation along with the increase in WS (figure 2(c)).

We find that the seasonal transition from winter to summer started taking place in Mumbai, during the 5th and 6th weeks, as visible from the temperature plot. However, the changes were not reflected in LE during the same weeks. The changes in the concentration of pollutants starting from week 8 are prominently reflected in the changes of Rn and LE. This also highlights the higher role of pollutants, compared to the seasonal temperature changes in controlling the local environmental meteorological system in the case-study area. To understand these perturbations of the systems further, we used a network-based approach. We have not specifically used the outgoing longwave radiation in our analysis; however, we used
both incoming radiation and net radiation, the latter including the outgoing radiation component.

3.3. Environmental meteorological networks
To understand the dynamics of the urban environmental meteorological system and the co-existing complex nonlinear interactions among multiple system variables, we use the concept of process network theory with the links between variables derived using Shannon’s Entropy. We developed process networks for all the 12 weeks based on both MI and TE. The networks based on TE show the importance of memory of individual causal variables on a specific variable. On the other hand, the network based on MI shows the real-time connections between variables and do not express causality.

The Shannon entropy of a variable is a measure of its uncertainty. Supplementary figure S3 shows the variation of entropies across the weeks of the study period for all the collected/monitored variables of the environmental meteorological system. The pollutants show a decrease in entropy during the lockdown period (supplementary figure S3b) as expected because of low anthropogenic emissions and their variability. However, the meteorological variables do not show similar decreases in the entropy (supplementary figure S3(a)). The decrease in entropy affects the entropy of the urban environmental meteorological system, and the total entropy of the system shows a decrease during the lockdown period over the last 3 weeks (supplementary figure S3(c)).

Figure 3 presents the process network of the environmental meteorological system made of TE, where the links represent the role of memories of different variables in the network. A weekly network of TE constitutes the nodes that represent variables and the links that provide information of TE between the nodes. A link represents the maximum TE among all the lags from the source node to the sink node in a clockwise direction. Greater intensity of the color in a link indicates greater TE, and greater width indicates the maximum lag with greater memory dominant information. For example, in week 9 (figure 3), the clockwise link from WD to LE (WD → LE) depicts WD as the source and LE as the sink. Thus, we infer that, during week 9, WD is playing a significant role in the variations of LE. A visual comparison between the weekly process networks clearly shows a higher number of links during the lockdown period. This depicts a higher dominance of memory during the same period. We find that there is a decrease in the amount of TE associated with each link during lockdown and this may attribute to the decreased values of entropies of individual variables. However, despite the decrease in total entropy of the system, there has been an increase in maximum lags associated with each of the links of the weekly networks during the lockdown period. Figure 4 presents the lag of the...
Figure 3. Process networks with links presenting TE from one variable to another. The nodes are the variables edges depict the TE information flow, the color scheme shows TE values, and weights of the edges show the maximum lag from which the TE link is originating. Weeks 1–9 belong to pre-lockdown period and weeks 10–12 belong to lockdown period. PM\textsubscript{2.5}, PM\textsubscript{10}, SO\textsubscript{2} and NO\textsubscript{x} in the figure are used as the notation for PM\textsubscript{2.5}, PM\textsubscript{10}, SO\textsubscript{2} and NO\textsubscript{x}, respectively.

The lag of maximum TE for meteorological variables that contribute to the network did not change from pre-lockdown to lockdown periods. The lag of maximum TE for pollutants (as sources) that contribute to the network is quite low during the pre-lockdown period. This may attribute to high hourly variations in the pollutant concentrations with high shocks during the office hours that probably breaks the memories of the network. In the lockdown period, the lags contributing maximum TE from the pollutant source nodes are seen to increase and overshoot the same for meteorological variables. Consistently, the lag originating maximum TE for all the variables of overall environmental-meteorological systems increases. There is a significant variation in temperature because the study period has the transition from winter to the pre-monsoon summer season. We find that the change in temperature occurred during the 5th and 6th weeks, but we do not find any significant changes in the lag contributions of variables to the network. The maximum visible changes occurred during the start of the lockdown period, which was not coincident with the transition period of temperature from winter to summer. We further find from the process networks of previous years (supplementary figures S5 and S8(a) for Bandra site observations...
of 2019) that there was no such transition to the memory dominated characteristics of the network, as evident in 2020, during the lockdown. This shows that changes in the pollutant concentrations have the potential to perturb the process network that remains stable under the seasonal change in temperatures.

Supplementary figure S4 presents the process network made of the links based on MI. Since MI is symmetrical between variables, a link presenting the MI in the network is non-directional and indicates real-time interactions. The changes in networks from pre-lockdown to lockdown are exactly opposite to that observed for TE networks. During the pre-lockdown, the networks are driven more by real-time interactions, and this becomes weaker in the lock-down period. This is associated with a strong dominance of memory in the network during the lockdown. To understand if such a perturbation of environmental meteorological network is case study specific for Powai, we searched for the available datasets at other regions of Mumbai. The results from process networks of 2020 are also required to be compared with other years to rule out the possibility that changes of networks are driven by seasonal temperature change. We searched for available pollutant datasets along with a few microclimate datasets, but unfortunately, there is no site for which the data is available for both the years 2019 and 2020. We found that along with the pollutants, the data for RH, WS, temperature, and incoming SW radiation are available at the Bandra site for 2019 and at Sion and Worli for 2020. The data is collected from MPCB, and the three sites are shown in supplementary figures S5–S7. We developed process networks based on TE for these three cases. We find that no major changes occur in the number of links for the Bandra site in 2019 from January to April, and at the same time (supplementary figure S5), the number of lags contributing highest TE to the network remained stable for all weeks (supplementary figure S8(a)). In 2020, for both the sites, Sion and Worli (supplementary figures S6 and S7), the number of memory-based TE links increase considerably during the lockdown period. The increases in the lags that contribute maximum entropy to the network for both Sion and Worli in 2020 (supplementary figures S8(a) and (c)) are quite similar to that observed for Powai. However, the network for Powai is more rigorous, as it considers a greater number of meteorological variables we gathered with the EC system. Overall, these results collectively show that during the lockdown, the reductions of pollutants make the urban environmental meteorological networks more memory-driven, and seasonal meteorological changes alone are unable to make such overall changes in the process network characteristics. It would have been interesting to see the impacts of monsoon rainfall on the environmental-meteorological process network. The monsoon starts in Mumbai around the beginning of June, but because of the inaccessibility of the site due to the COVID related restrictions, we could not extend the study period.

4. Summary and conclusion

Here we present the observational datasets for an urban environmental meteorological system representing the urban microclimate in Mumbai, India. We have identified the changes in the characteristics of the system due to a decrease in the pollutants during the lockdown period associated with COVID-19 restrictions on human activities. We have used a network-based approach based on information theory to characterize the system and the linkages between the variables of the system. We arrive at the following conclusions:

(a) There was a considerable decrease in the pollutant concentration during the lockdown period in this case study. We found that the average

![Figure 4. Maximum TE time lags, i.e. time lag at which the TE is maximum for all variables in the network, meteorological variables and pollutants.](image-url)
reduction in the peak concentration of pollutants by 91% in $\text{NO}_2$, 79% in $\text{SO}_2$, 56% in $\text{PM}_{2.5}$, 52% in $\text{PM}_{10}$, and 41% in CO. This shows that the maximum decrease in the pollution occurs due to the decrease in vehicular emissions followed by the outdoor human activities.

(b) The decrease in pollutants results in an increase in incoming radiations and net radiation. The increased radiation and increased WS resulted in a considerable increase in the LHF over the area of study, which was not present during the high temperature weeks of pre-lockdown period

(c) During the no-lockdown period, high variations and shocks of pollutant concentration changes disturb the memory and allow the real-time interactions to dominate the network.

(d) The strong influences of pollutant concentration on the environmental meteorological system underscore the need for sufficient sustained monitoring and measurement stations in urban regions for simulations, understanding, and predictions of urban micro-climate.

Data Availability Statement

All data monitored/collected/produced in this article are available at https://doi.org/10.5281/zenodo.4108530 (Ghosh and Gupta 2020).

All data that support the findings of this study are included within the article (and any supplementary information files).

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Author contributions

SG designed the problem, experiments, and the solution approach. MG set up the local eddy flux tower and did the monitoring of meteorological variables. MG and SG performed all the analyses. TC helped MG in developing the process networks. SG, MG, RM, and TC discussed the results. MG and SG wrote the manuscripts. RM and TC reviewed the manuscript.

ORCID iDs

Mayank Gupta https://orcid.org/0000-0002-9377-7403
Tejasvi Chauhan https://orcid.org/0000-0001-6901-0176
Raghu Murtugudde https://orcid.org/0000-0002-3307-7114
Subimal Ghosh https://orcid.org/0000-0002-5722-1440

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