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Assessment of the causal relationship between air quality of Delhi and neighbouring cities using Granger causality network

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ABSTRACT

Introduction: The present work addresses the temporal characteristics of air pollution in Delhi and the surrounding five cities during the years 2019 and 2020. Further, we have addressed the hypothesis whether air pollution of a particular city is affected by its neighboring cities.

Materials and methods: To test the hyopthesis we have used the Granger causality test to detect the causal relationship (feedback) between the air pollution of Delhi and its neighbouring cities. Initially we have checked whether the Air Quality Index (AQI) time series are stationary and integrated of the same order. This involved employing a unit root test, specifically Augmented Dickey Fuller (ADF) test followed by Granger causality test.

Results: From the descriptive statistical analysis, it is observed that there is a significant reduction in the air pollution across six cities during the year 2020. From causality network, it is observed that bidirectional and unidirectional causal links exists for 2019 and only unidirectional causal links exists for 2020. Air pollution of Delhi is strongly influencing the air pollution of Gurugram city in the year 2019 evident from the higher values of Indegree (0.7) for Gurugram city and high value of outdegree (0.85) for Delhi city. Unidirectional causal links observed from Gurugram city in 2020, whereas unidirectional causal links observed from Delhi, Gurugam and Lucknow cities in 2019. Network in 2020, consists of lesser number of causal links (5), in comparison to the network in 2019, that comprises of more number of causal links (12) that indicates the impact of lockdown on air quality due to COVID-19.

Conclusion: Air pollution of highly polluted cities affects the cities with low air pollution. Present work helps the policymakers to implement the effective mitigation and measures to control the air pollution at regional scale.

Introduction

Worldwide increase in the concentration of surface air pollutants is a major concern for the scientific community. Increasing pattern of surface pollutants spoils the quality of air which creates a serious impact on human health and drags over the economic development of a country [1-3]. According to World Air Quality report in 2019, six out of top ten worlds most populate cities are located in India and India was the fifth most populted country in the world. This ranking is based on the comparison between the concentration of major air pollutants and particulate matter levels at the surface as per

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report by World Health Organisation (WHO) [4]. According to the WHO report, Gurugram is the most polluted city in the world followed by Faridabad, Patna, Lucknow, Delhi, etc. Air quality of Gurugram city is 17 times lower than the prescribed safe limits by WHO. Major factors which spoil the air quality of Gurugram city, are the running of diesel generators for electricity production, vechicular emissions, pollution from construction sites, emissions from thermal power plants and industries. Growing threat of air pollution has an adverse effect on health and its long term exposure increases the risks of various diseases such as asthma, lung cancer and heart attacks etc. Control of such ambient air pollutants associated with the rapid urbanization and industrilizations in developed countries is a major concern [5-7]. From the past years, it is observed that air pollution over Delhi city is rapidly increasing due to the increase in the transport and industrial activities in comparision to the other cities [8]. Vechicular emisions are the significant contributor to the particulate matters $PM_{2.5}$ and PM_{10} concentration in Delhi reported by a study [9]. The concentration of the primary pollutants such as Nitrogen dioxide (NO_2) and particulate matter monitored by air quality monitoring stations claims that the air pollution of Delhi is the worst degraded from the past and is much higher than the permissible limits [10]. According to a study by researchers, vehicular emissions and industrial activities affect the indoor and outdoor air pollution of Delhi city [10]. Other factors such as the burning of crops in neraby cities (Haryana and Punjab), and an increase in the concentration of particulate matter from construction activities and emissions from thermal power plants are degrading the air quality in Delhi. Determining the cause and exposure of pollution levels of a city is important to take some mitigative measure and steps to control air pollution [11]. To determine the air pollution of an area, the concentration of air pollutants is measured over a standard interval of time to provide the level of pollution in that particular area. The level of air pollution in a city, is mainly defined by the Air Quality Index (AQI), and the air quality standard decided by the pollution control board of a particular country. The AQI level of a particular city tells us the pollution level of that particular city. AQI level is determined by the eight criteria pollutants such as Particulate Matter ($PM_{2.5}$ and PM_{10}), Ozone (O_3), Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), Carbon monoxide (CO), Ammonia (NH_3) and Volatile Organic Carbons (VOC's) [12]. The higher the level of AQI, the greater level of air pollution in that particular city and it is a major concern for health.

Air quality index of a particular city is computed based on the minimum three criteria pollutants, in which one of the particulate matter pollutants ($PM_{2.5}$ or PM_{10}) is mandatory.

Table 1 shows the air quality standard levels in India according to the Central Pollution Control Board (CPCB).

Table 1. Air quality standard levels in India according to the CPCB

Air Quality Index (AQI)	Category
0-50	Good
51 - 100	Satisfactory
101 - 200	Moderate
201 - 300	Poor
301 - 400	Very poor
401 - 500	Severe

National Ambient Air Quality Standards (NAAQS) tests the ambient air quality set by CPCB [13]. AQI is mainly determined using the concentration of eight criteria pollutants and then converted into a number or scale to measure the level of air pollution, and this calculated number is termed as sub-index which is AQI [14]. Very few studies have explored the causal relationship between the air pollution of a particular city with the health-related hazards and economic indicators across urban cities [15-20], but none of the studies explore the influence of air pollution of one city on another city in India. Considering this research gap in the present work, we have used the AQI data of Delhi along with its neighbouring and far cities to quantify whether the air quality of Delhi city perturbs the air pollution of neighbouring and far cities using the Granger causality method. The advantage of using the Granger causality method is that the air pollution of a particular city can be explained by the past air quality status of another city which implies that air pollution of one city causes air pollution of another city. We have considered only four months of the summer season (March to June) for both years to compare the behaviour of causality networks and to investigate the impact of lockdown on air quality in urban cities that results from COVID-19. Granger causality method has proven its potential in the climate system such as anthropogenic activity and climate interactions [21, 22]. The main objective of the present analysis is to understand the causal relationships between the air pollution of Delhi and other cities using the Granger causality network and to analyse the behaviour of the causality networks for the year 2019 and 2020.

Materials and methods

In the present work, we have used the air quality data from the Centre for Pollution Control Board (CPCB) for a period of four months March–June for two years 2019 and 2020. Daily values of the air quality index (AQI) for six stations (Delhi, Gurugram, Lucknow, Jaipur, Chandigarh and Amritsar) from Kaggle (online community that allows users to find the dataset, publish datasets, cloud based online platform for data science and AI education) that is publicly made available by CPCB have been utilized to investigate whether the air pollution of one city may influence the air pollution of its neighbouring cities and vice versa. We have used the granger causality test to detect the causal relationship (feedback) between the air pollution of Delhi and its neighbouring cities during the year 2019 and 2020. Our main aim is to investigate the behaviour of air pollution over these cities during both the years by means of a causality network. Here in the present work, we have considered the air quality data at the city level rather at a particular station from CPCB. Before applying Granger causality test, the first step is to investigate whether the time series of AQI is stationary or not. Hence, we have used the Augmented Dickey Fuller (ADF) test to test the stationarity and then we have applied the Granger causality test over the AQI time series for both years to construct the causality network. Fig. 1 shows the illustration for the location of Delhi city and its neighbouring cities considered in the present work to investigate the causal relationship between air pollution of these urban cities. The focus of the study area is Delhi and its neighbouring cities with an aerial distance less than 500 Km. Delhi city is bordered by Haryana on three sides and by Uttar Pradesh in the east. It is located at North Latitude from 28.24–28.53 degrees and East longitude from 76.50–77.20 degrees. Delhi covers an area of 1483 Km^2 of which 1114 Km^2 designated as urban area and 370 Km^2 as rural [23]. According to the data compiled by IQAir Air Visuals 2019 World air quality report [24], six Indian cities are in top ten out of which Delhi is one of the most polluted city with worst level of air pollution. Delhi capital territory of India is one of the major industrial region and contributes to the economic development of the country. Despite of the economic achievement from the last few years Delhi placed one of the highest polluted metropolitan cities in the world [25]. Air quality data from CPCB used in the present work can be downloaded from the following link [26]. Air quality data which is used in the present work compiled from the CPCB website [27], with temporal coverage from 2015–01-02 to 2020–07–28. For AQI calculation, the prepared AQI dataset uses 7 criteria pollutants $PM_{2.5}$, PM_{10}, SO_2, NOx, NH_3, CO and O_3. For $PM_{2.5}$, PM_{10}, SO_2, NOx and NH_3 average value in the last 24 h is used with the condition of having at least 16 values. For CO and O_3 the maximum value in the last 8-h is used. Further each measure undergoes conversion into a Sub-Index according to predefined groups. Final AQI is computed based on considering the maximum Sub-Index while adhering to the condition that at least one of $PM_{2.5}$ and PM_{10} must be available and a minimum of three out of seven criteria pollutants should be present. For more details for the calculation of AQI please refer to the link [26].

Testing examined time series for stationarity

The primary condition for the Granger causality test is to investigate whether all the variables are stationary and integrated of the same order. In the present work, we have tested the AQI data for stationarity using the unit root test method as Augmented Dickey Fuller (ADF) test proposed by Dickey and Fuller [28]. ADF test is applied over the AQI time series for six urban cities during both years for testing the null hypothesis which examined whether the time series has unit roots that indicate the stationarity or non-stationarity.

ADF test comprises three types of assumptions, namely no intercept and no trend refer to Eq. 1 , intercept (Eq. 2) and intercept and trend (Eq. 3) [29].

$$\Delta Y_t = \theta Y_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta Y_{t-1} + \mu_i \quad (1)$$

Here Y_t is the time series at time t, Δ denotes the first difference, μ is the error term with mean 0 and a variance σ^2.

$$\Delta Y_t = \alpha + \theta Y_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta Y_{t-1} + \mu_i \quad (2)$$

Here α denotes the intercept term.

$$\Delta Y_t = \alpha + \beta t + \theta Y_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta Y_{t-1} + \mu_i \quad (3)$$

Here β denotes the time trend: Null hypothesis of ADF test is H_0: $\theta = 0$; and the alternate hypothesis is H_1: $\theta < 0$.

Granger causality network

To investigate the causal relationship between air pollution of six cities we have used the Granger causality test proposed by Granger [30]. The Granger causality method is used to investigate whether one time series can be a cause for another and vice-versa, with an optimized lag with minimum Bayesian Information Criteria score (BIC) [31]. Granger causality method is used to analyse the numerical time series based on a statistical hypothesis test to find out if one variable affects another from its immediate past and the adding lagged values of one variable can enhance the explanation. The Granger causality method is described by following equations [29].

$$Yt = \phi o + \sum_{j=1}^{m} \alpha j Yt - j + \sum_{j=1}^{m} \beta j Xt - j + \varepsilon 1t \quad (4)$$

$$Xt = \lambda o + \sum_{j=1}^{m} \delta j Xt - j + \sum_{j=1}^{m} \omega j Yt - j + \varepsilon 2t \quad (5)$$

Null hypothesis in the first regression equation is that "X" does not granger cause "Y". Similarly, null hypothesis in the second regression equation is that "Y" does not granger cause "X". A tool that helps to judge the granger cause is the F-test. The null joint hypothesis is given as.

$$H0: \beta_1 = \beta_2 = \text{-----} = \beta_m = 0, \omega_1 = \omega_2 = \text{-------} = \omega_m = 0 \quad (6)$$

There is no Granger causality.

On the other hand, the alternative hypothesis is given as

$$H1: \text{At least one } \beta_m \text{ or } \omega_m \neq 0 \quad (7)$$

There is dependence between both direction from X to Y and Y to X.

We have analysed the influence of cause-and-effect relationship of air pollution of urban cities using the structure of granger causality network. Here we have defined AQI as nodes and the significant granger causality between the AQI as links (significant at 10% confidence interval as sample size is very small). Granger causality network for the air pollution may be indicated by an adjacency matrix $G_{causality}$ shown in Eq. 8 and Eq. 9.

$$G_{causality} = (N_{causality}, L_{causality}) = \begin{bmatrix} 0 & caus1,2 \ldots & caus1,k \\ caus2,1 & 0 \ldots & caus2,k \\ \vdots & \vdots & \ddots \quad \vdots \\ causk,1 & causk,2 \ldots & 0 \end{bmatrix} \quad (8)$$

Where $N_{causality}$ is the node set and $L_{causality}$ is the links set, $caus_{i,j}$ indicates whether air pollution of i Granger cause air pollution of j.

$$caus_{i,j} = \begin{cases} 1 & \text{air pollution of i Granger cause air pollution of j significantly} \\ 0 & \text{there is no significant Granger causality} \end{cases} \quad (9)$$

Granger causality gives the direction of the perturbation or direction of the coupling between coupled pairs in the network. Thus, Granger causality network is the directed and unweighted graph.

Results and discussion

Descriptive statistics analysis

To investigate the variation in the concentration of air pollution over six cities during the year 2019 and 2020 we have computed the mean AQI and percentage change in the AQI values. Descriptive statistics analysis enables to understand the variation in the air pollution among six cities and allows us to understand the influence of lockdown on noteworthy alterations in urban air quality. But before descriptive statistical analysis, we had simply plotted the time series for daily AQI values across six urban cities during the years 2019 and 2020 to investigate the fluctuating patterns in the AQI time series. Fig. 2 shows the comparison of the time series of daily AQI values for a period of four months March–June during the years 2019 and 2020 across six cities. Here we have used the short abbreviation to describe the city's name DL for Delhi city, GU for Gurugram city, JP for Jaipur city, LK for Lucknow city, AMR for Amritsar city and CH for Chandigarh city which were consistent throughout the study. Due to the limitation of the availability of the ground-based dataset for AQI we have only considered duration of four months for all six urban cities.

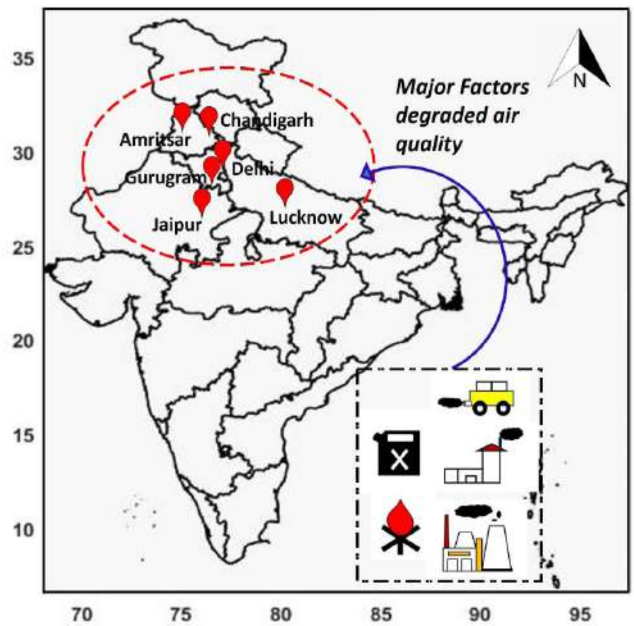

Fig. 1. Illustration shows the location of six cities in India.

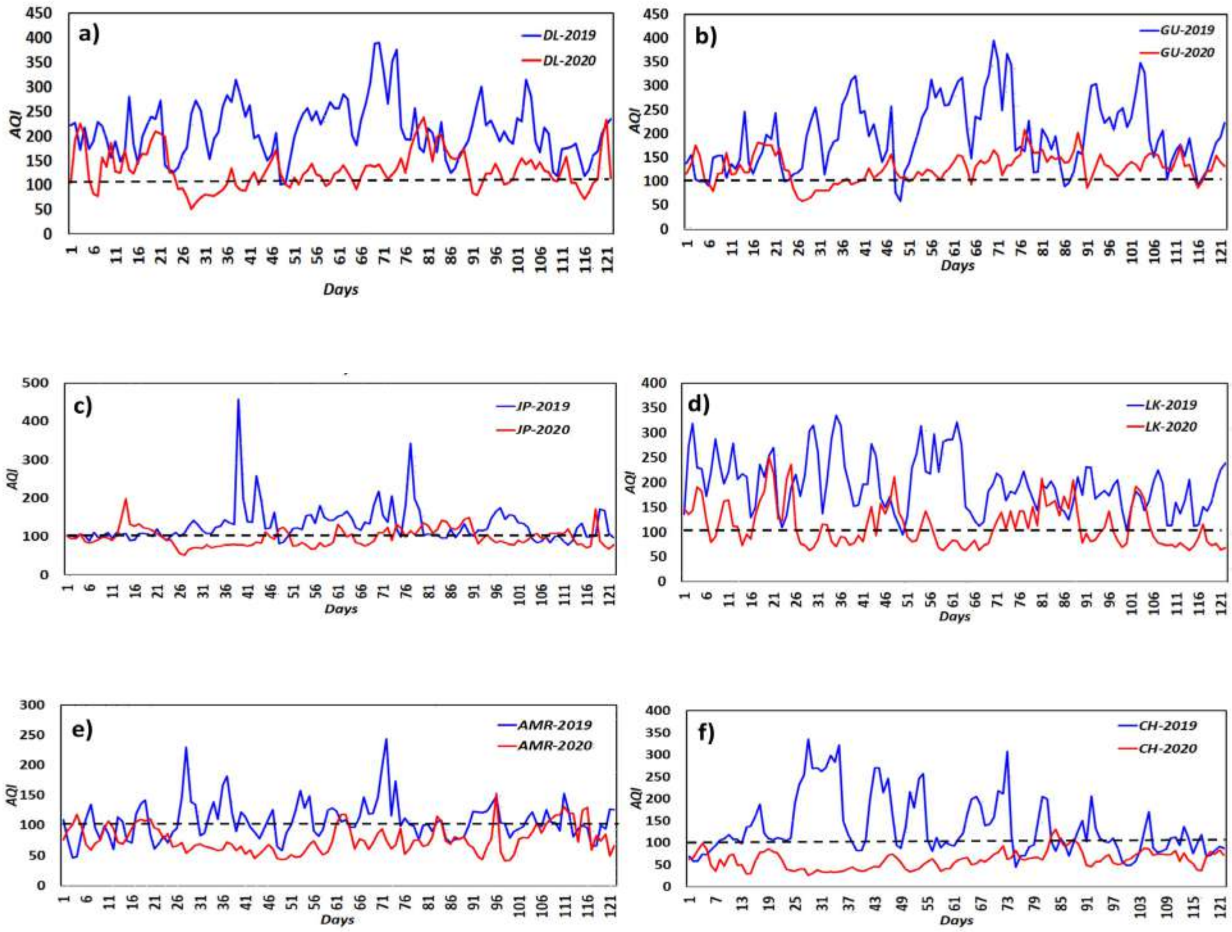

Fig. 2. Time series plot for daily AQI values during the year 2019 and 2020 for a) Delhi city (DL); b) Gurugram city (GU); c) Jaipur city (JP); d) Lucknow city (LK); e) Amritsar city (AMR) and Chandigarh city (CH)

From Fig. 2 it is clearly observed that the daily AQI values across six urban cities during the year 2020 is very low and close to the baseline as per the CPCB Air quality standard which is highlighted with a black dashed straight line over time series plots. AQI indicates how clean or polluted air near our surroundings as per the air quality standards AQI levels below are satisfactory and above 100 is harmful to human health. From the time series plot, it is observed that the impact of the lockdown is clearly noticed across the six urban cities as AQI level during the year 2020 is below or just near 100 indicates the significant difference in the air pollution during the year 2019 and 2020.

Fig. 3a shows the comparison in the mean AQI across six cities for the years 2019 and 2020. From Figure, it has been observed that the mean AQI over Delhi, Gurugram and Lucknow cities is very high indicates the poor quality of air quality standard across these cities during the year 2019. During the year 2020 influence of lockdown across these cities is clearly visible from the low values of mean AQI. Fig. 3b shows the percentage change in the concentration of air pollution across these cities.

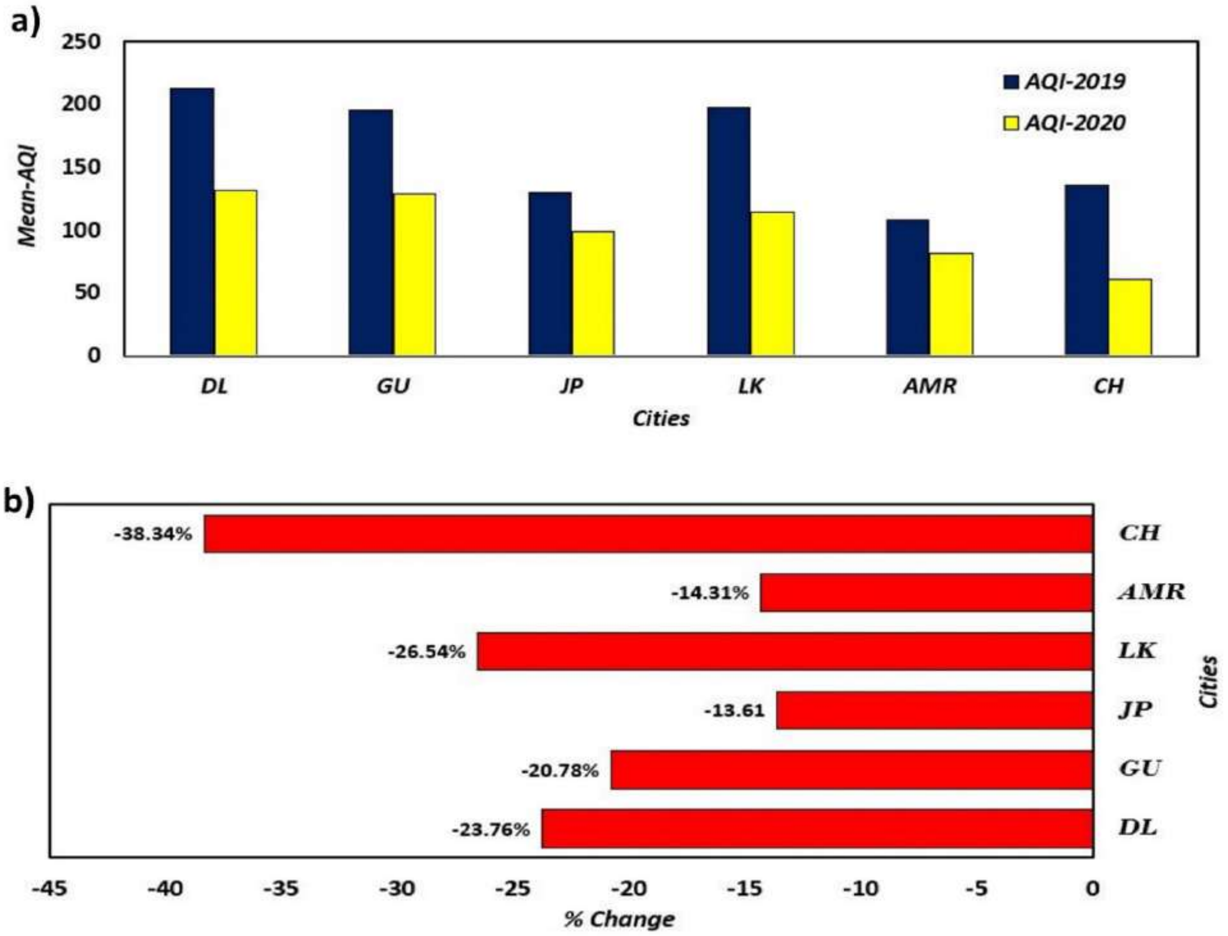

Fig. 3. a) Mean AQI values across six cities during March to June for 2019 and 2020; b) Percentage change in the magnitude of AQI values during the year 2020 across six cities

The Figure illustrates a notable and substantial reduction in the AQI values for the year 2020, with reductions of 38% in Chandigarh, 23% in Delhi, 26% in Lucknow, and 20% in Gurugram. During the year 2020 mean AQI values for Delhi, Gurugram and Lucknow cities shows the moderated level of air Quality standard less than 150. For Chandigarh and Amritsar mean AQI value during the year 2020 is below 100 that indicates the satisfactory level of air quality standard across these cities. A study by [32] reported that on an average of 30-40% reduction in AQI is observed over the northern, western and southern India that indicates the substantial effect of lockdown on the reduction in the deterioration in air quality over India. Several studies from the past [33-36] also found the significant reduction in the AQI over India using satellite and ground based monitoring observations.

Variations in the daily values of AQI during the years 2019 and 2020 were analysed using Box and Whisker plot as shown in Figure 4. Box and whisker plot generated based on the mean, median, first quartile, third quartile, the range within 1.5 times the interquartile range for the daily AQI values across six cities. Variability in the AQI values during the years 2019 and 2020 can be observed from the width of the box plot, from figure it has been observed that the variability in the daily AQI values is higher during the year 2019 across Delhi, Gurugram, Lucknow and Chandigarh cities.

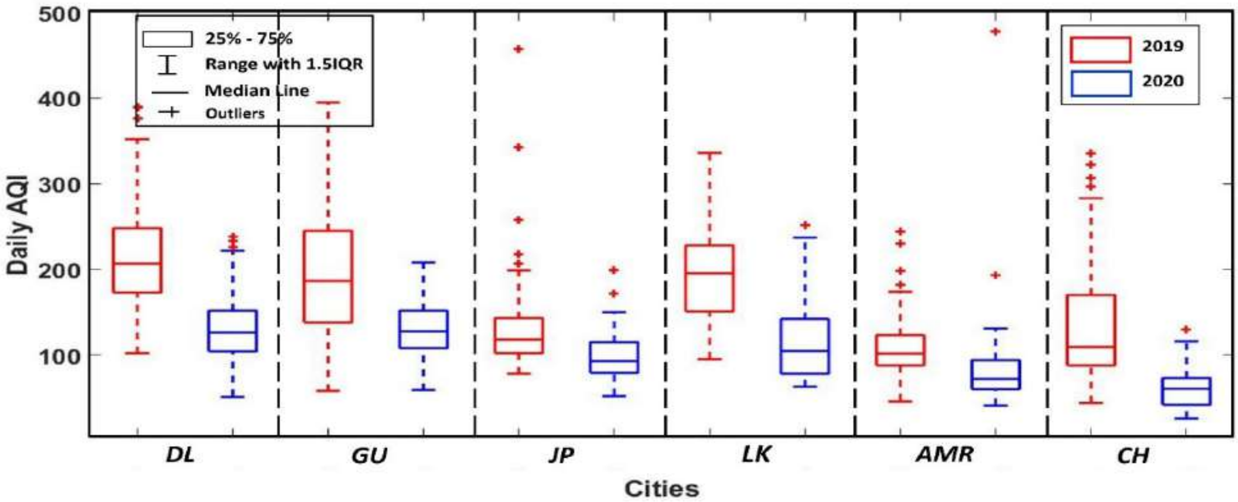

Fig. 4. Box and whisker plot for daily AQI values across six cities for 2019 and 2020

Table 2. Results of Descriptive statistics for AQI across six cities

	Year 2019				Year 2020			
Cities	Mean	STDEV	Max	Min	Mean	STDEV	Max	Min
DL	212.65	57.82	390	102	130.99	38.96	238	51
GU	195.62	73.15	395	58	128.28	29.34	208	59
JP	129.88	47.89	457	78	98.76	24.08	199	52
LK	196.86	56.26	336	95	114.28	43.11	252	63
AMR	107.63	33.96	244	46	80.68	41.70	478	41
CH	134.51	67.84	335	44	60.40	20.20	130	26

Variability in the daily AQI values during both years can be clearly evident from the values of standard deviation for AQI values across six cities listed in Table 2.

Differences in the variability for the daily AQI values during the years 2019 and 2020 across six cities along with the mean AQI value, maximum and minimum AQI values are listed in Table 2 and may be evident from Fig. 4. The magnitude of decrease in daily AQI value is higher for Chandigarh city with a median of 60.5 during the year 2020 and 109.5 during the year 2019. For Delhi and Gurugram cities the magnitude of decrease in AQI is also very high with median values 126, 127.5 during the year 2020 and 206.5, 186.5 during the year 2019. From figure 4 it is clearly observed that air pollution across six cities gets reduced during the year 2020 evident from the decrease in the magnitude of AQI values across these cities. Low values of daily AQI values across six cities indicates the influence of lockdown in India due to amid COVID-19 Pandemic on air quality of these cities indicates the improvement in the air quality. The results showed that the air quality in 2020 relatively improved as compared to the previous year air quality.

Table 3. Results of unit root test for AQI time series

Cities	ADF-2019	ADF-2020	10% Level	P value	Result
DL	-12.71	-6.67	-3.134	<0.1	Stationarity
GU	-5.57	-6.48	-3.134	<0.1	Stationarity
JP	-19.07	-5.27	-3.134	<0.1	Stationarity
LK	-12.88	-6.70	-3.134	<0.1	Stationarity
AMR	-7.93	-9.34	-3.134	<0.1	Stationarity
CH	-5.86	-5.82	-3.134	<0.1	Stationarity

Unit root test results

Results for the ADF test for both years are listed in Table 3. From the unit root test it has been observed that the time series for AQI value for all cities were stationary at a 10 % significance level. The overall result of the unit root test indicates that the AQI times series for all cities are stationary at the first difference, thus we conclude that AQI values for all cities are stationary at I (1) which is first difference. As null hypothesis is strongly rejected the t statistics value across all the cities during both years is less than the critical t value at a 10% significance level.

Granger causality networks for the year 2019 and 2020

In the present work we have paid more emphasize on the causal relationship between air pollution of six cities using Granger causality method. Before discussing the causal relationship between AQI across six cities we analysed the correlation between AQI values across six cities by calculating Pearson correlation coefficient. Table 4 and Table 5 give the Pearson correlation coefficient between AQI values across six cities during 2019 and 2020. The correlation coefficient provides a measure of how close the AQI time series are. Higher value of correlation coefficient for AQI values between Delhi and Gurugram city during both years indicates that Delhi air quality is closely related to the air quality of Gurugram city. Higher values of the correlation coefficient are also observed between air quality of Delhi city with air quality of other cities without borders with Delhi city (Jaipur and Lucknow) which is significant at a 10% significance level during the year 2019. During the year 2020 significant correlation coefficient values for air quality were also observed between Delhi and other cities without borders (Lucknow, Jaipur and Chandigarh) except with Amritsar city. High positive correlation between Delhi and Gurugram city reveals a similarity in the level of air pollution during both years 2019 and 2020.

Table 4. Correlation coefficient between AQI of six cities for the year 2019

	DL	GU	JP	LK	AMR	CH
DL	1	0.664874	0.355823	0.538434	0.2686705	0.1691007
GU	0.664874	1	0.441163	0.278902	0.484604	0.08615
JP	0.355823	0.441163	1	0.12222	0.100746	0.032772
LK	0.538434	0.278902	0.12222	1	0.175525	0.215339
AMR	0.2686705	0.484604	0.100746	0.175525	1	0.334814
CH	0.1691007	0.08615	0.032772	0.215339	0.334814	1

Table 5. Correlation coefficient between AQI of six cities for the year 2020

	DL	GU	JP	LK	AMR	CH
DL	1	0.796461	0.458833	0.459507	0.156527	0.637176
GU	0.796461	1	0.560607	0.314177	0.224649	0.663991
JP	0.458833	0.560607	1	0.270703	0.13264	0.479601
LK	0.459507	0.314177	0.270703	1	0.076452	0.413771
AMR	0.156527	0.224649	0.13264	0.076452	1	0.286493
CH	0.637176	0.663991	0.479601	0.413771	0.286493	1

VTherefore, the Pearson correlation coefficient does not provide a measure that how the air quality of one city is influence with the air quality of another city and vice versa. Hence to investigate the causal relationship between air qualities among six cities we have used the Granger causality method to construct a causality network for both years 2019 and 2020. Fig. 5a shows the causality network for AQI values across six cities for 2019 and Fig. 5b shows the causality network for the year 2020. As we have already discussed that we have used short abbreviations for the city's name that were highlighted as nodes in the causality network for both years.

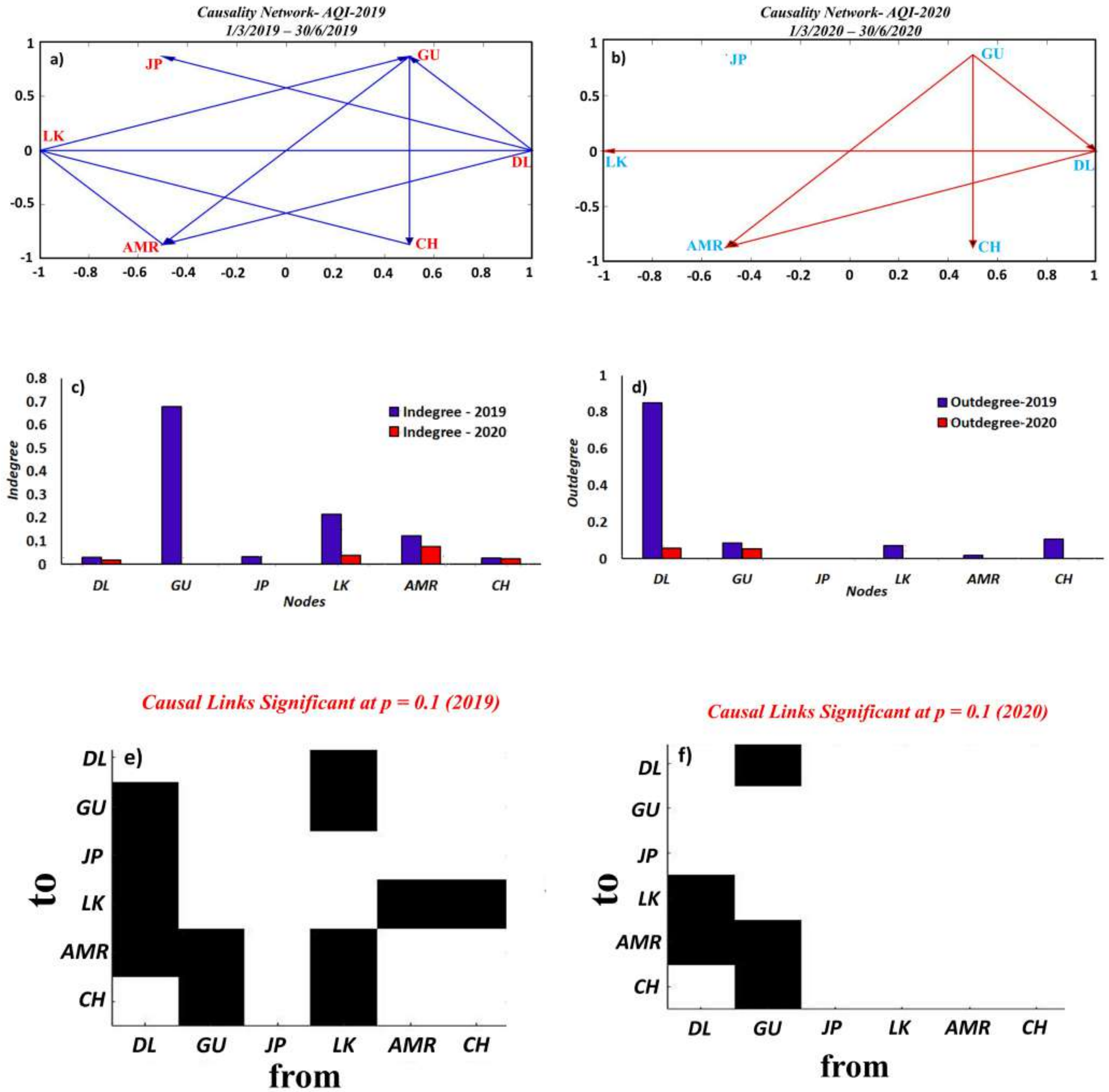

Fig. 5. a) Causality network of AQI for the year 2019, b) Causality network of AQI for the year 2020, c) Indegree analysis for the year 2019 and 2020, d) Outdegree analysis for the year 2019 and 2020, e) Total number of significant causal links in the network for the year 2019 and f) Total number of significant causal links in the network for the year 2020

From Figs. 5a and b, it is observed that the causality network during the year 2019 is denser in comparison to the causality network for the year 2020 which indicates present more number of causal links are present for the 2019 network as compared to the network for 2020. A possible reason for the lesser number of causal links for 2020 network may result from the influence of the lockdown on air quality due to COVID-19 Pandemic during March to June 2020. From Fig. 5a, it has been observed that a unidirectional link exists between DL node and GU node, which is significant at a 10% significance level indicates that DL node is the most active variable (source driver) and GU node as a most active sink that is evident from the Indegree and Outdegree values for both the nodes in Fig.5c and d. Strong significant causal link between DL and GU nodes in the 2019 network indicates that air pollution level of Gurugram city is badly influenced by the air pollution of Delhi city. Such strong influence may be evident from the higher value of correlation for the air pollution between Delhi and Gurugram city and both the cities are very close to each other and shares common border. There also exists a unidirectional causal links between DL node and other nodes in the network such as JP node and AMR node which indicates air pollution of Delhi city is also influencing the air pollution of Jaipur and Amritsar city. From the Indegree and Outdegree analysis, it is observed that the influence of air pollution of Delhi city is not much intense or severe to the other cities without borders (Jaipur and Amritsar) as these cities are very far from the Delhi city and the correlation is also not very high. Bidirectional link exists between DL node and LK node, AMR node and LK node, CH node and LK node in the causal network for the year 2019 evident from Fig. 5e. From Figs. 5 e and f, it is observed that apart from the unidirectional causal links bidirectional causal links also exists in the network for the year 2019 and for the network of the year 2020 only unidirectional causal links exists between each and every node in the network. Study by researchers investigated the spatiotemporal characteristics of air pollution and causal relationships between Beijing and its neighboring cities using Granger Causality test. From results it is observed that air quality of Beijing is perturbed by the air pollution of Baoding which is much polluted city than Beijing [29]. Granger causality test shows that there exists only unidirectional relationship from Baoding to Beijing that indicates the air quality of highly polluted city Baoding influences the air quality of less polluted city Beijing.

From Fig. 5b, it is observed that causal network for the year 2020 is not much dense as compared to the network for the year 2019. In this case there exists only unidirectional causal links in the network. Unidirectional causal links exists between GU node which acts as a source node and other nodes in the network which acts as sink nodes such as DL, AMR and CH nodes. Thus, this indicates that the air pollution of Gurugram city influences the air pollution of Delhi, Chandigarh and Amritsar city. But from the Indegree and outdegree analysis it has been observed that the causal relationship between GU node with other nodes DL, AMR, LK and CH nodes are not very strong evident from very low values of Indegree and Outdegree may be observed from Figs. 5c & d. From the comparison of Figs. 5c & d, it has been observed that for the year 2020 outdegree exists from only DL and GU nodes whereas in degree exists for DL, LK, AMR and CH nodes. Here “out degree refers to the number of edges leaving a particular node in a directed graph and in degree refers to the number of incoming links to a particular node in a directed graph” [37]. A study by [38] used the Granger causality network perspective to investigate the effects of haze pollution in Cheng-Yu urban agglomeration in China. From the Granger causality spatial association network it is observed that haze pollution of each city is directly or indirectly affected by other cities in Cheng-Yu urban agglomeration.

Table 6 provides the statistical results of the indicators for the causality network for the year 2019 and 2020. From the results it is observed that there exists 12 causal links between the coupled pairs in the causality network for the year 2019 and for 2020 only 5 causal links exists between the coupled pairs. Density of the causality network for 2019 is high 0.34 in comparison to the density (0.17) of causality network for 2020. From the density comparison it is observed that the causality network for the year 2020 is sparser in comparison to the network for 2019.

Table 6. Statistical indicators of Granger causality network for 2019 and 2020

	Year 2019		Year 2020	
	Indicators	Values	Indicators	Values
1	Number of edges (links)	12	Number of edges (links)	5
2	Number of vertices (nodes)	6	Number of vertices (nodes)	6
3	Density of network	0.34	Density of network	0.17

Indegree and outdegree analysis helps us to understand the role of air pollution of each city based on the causality network. Nodes with high indegree indicates that the variable is impacted with multiple other variables whereas high outdegree indicates that the variable has an ability to change many other variables in the system [39]. The Indegree and Outdegree of any node i in the network is defined by Eq. 10 and Eq. 11.

$$\mathrm{INdegree}_i = \sum_{j \in N_i} \mathrm{caus}_{i \leftarrow j} \tag{10}$$

$$\mathrm{OUTdegree}_i = \sum_{j \in N_i} \mathrm{caus}_{i \rightarrow j} \tag{11}$$

Granger causality network is a directed complex network which tells the cause of one variable to another variable. From the Indegree and outdegree analysis it has been observed that Indegree of the GU node is very high for the year 2019 followed by LK and AMR, whereas the Outdegree of DL node is very high for the year 2019. Thus, the high value of Outdegree of Delhi and high value of Indegree of GU indicates that the air pollution of Gurugram city is strongly perturbed by air pollution of Delhi city as compared to other cities. Thus, influence of air pollution is noticeable observed between Delhi and its border city Gurugram for the year 2019. From the causality network, it is observed that the air pollution of Gurugram city is mostly influenced by air pollution of Delhi and Lucknow city. Gurugram is the most polluted city in the world with very high AQI value and Delhi is the most polluted capital city in the world. Causality network for the year 2020 clearly indicates the influence of the lockdown on air quality of these city's due to the pandemic situation from COVID-19 that is evident from the presence of lesser number of available causal links in the causality network. From the unidirectional causal links between GU node with DL, CH and AMR indicate that the air pollution of Gurugram city is perturbing the air pollution of Delhi, Amritsar and Chandigarh but the influence is very small which is mainly attributed from the lesser degree distribution for these cities during 2020 evident from Fig. 6.

Figure 6 shows the degree distribution of each node in the causality network for the years 2019 and 2020. To identify the important nodes in the network degree of the vertices plays a major role. Here the degree of one node is considered as the number of edges with the adjacent other nodes. From figure it is observed that the degree distribution of DL and GU nodes is very high during the year 2019 that indicates the air pollution of DL and GU nodes plays a vital role in the causality network for the year 2019. Degree distribution for GU node and DL node is also very high as compared to the degree of nodes during the year 2020.

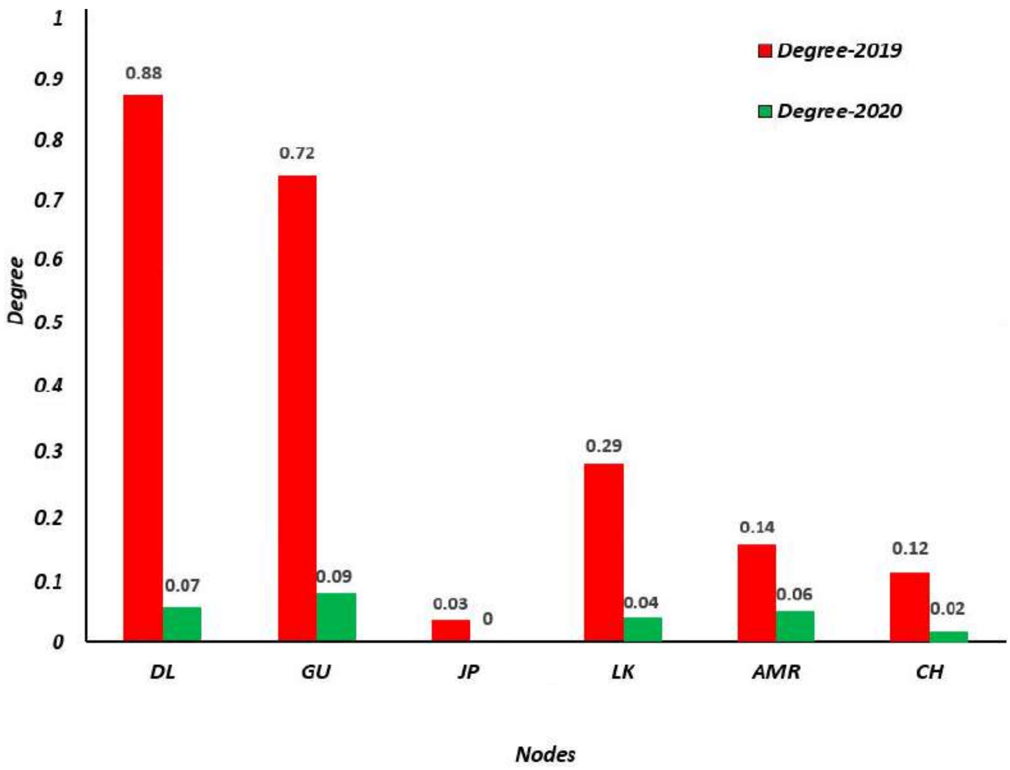

Fig. 6. Comparison of Total degree value from the causality network for the year 2019 and 2020

One of the limitations of the present work is the unavailability of the dataset for the other neighbouring cities of Delhi apart from Gurugram city which we have considered for the present analysis. Another limitation is associated with the limited sample size of 122 days for both years. A more robust method can be generated in the future by enlarging the large sample size of data and the availability of the dataset for more neighbouring cities of Delhi. In the present analysis, causal relationships between air pollution and meteorological variables of urban cities using Granger causality network method have not been addressed. In future further expansion of the present work can be designed to explore the cause and effect relationship between air pollution and meteorological data in these urban cities. Study concludes that using highly polluted cities are affecting the one with low pollution that is evident from the unidirectional causal links between the AQI of highly polluted cities and AQI of low polluted cities. .

Conclusion

In the present work, we have used the Granger causality network method to accesses the causal relationships between air pollution of Delhi and its neighbouring cities. The descriptive statistical analysis reveals that the mean AQI level for the year 2020 in Delhi and nearby cities is notably lower compared to the year 2019. In 2020 consistent AQI levels at or slightly below 100 indicate satisfactory to moderate air quality, likely due to nationwide COVID-19 Lockdown. Considerable and significant amount of reduction in the daily AQI values observed with Chandigarh experiencing a 38% decrease, Delhi showing 23% decrease, Lucknow with 26% and Gurugram with 20%

decrease during the year 2020. From the Pearson correlation coefficient, it is found that the correlation between AQI of Delhi and Gurugram cities is very high greater than 0.6 during both the years. High value of correlation coefficient indicates that the air quality of Delhi city is closely related with the air quality of Gurugram City. Granger causality analysis shows denser network for the year 2019 with more causal links than in 2020. Delhi air pollution significantly influences Gurugram more than other cities in 2019 as indicated by Indegree and Outdegree analysis.

Bidirectional causal links exist between the nodes LK and DL, LK and AMR, as well as LK and CH, which indicates that air pollution of Lucknow city is influencing and being influenced by the air pollution of Delhi, Amritsar, and Chandigarh city during the year 2019. From the causality network for the year 2020 it has been observed that there exists a unidirectional causal link between GU node with DL, AMR and CH nodes in the network. In the causality network for the year 2019, high Indegree for GU and high Outdegree for DL suggest that Gurugram city air pollution is mainly influenced by its neighboring city, Delhi. Present work investigates the causal relationships between the air pollution of urban cities and provides a measure to quantify how the air pollution of one city perturbs the air pollution of another city. The current study also highlights the impact of highly polluted cities on those with lower air pollution levels. This suggests that air pollution in highly polluted cities influences the air quality in cities with lower pollution levels.

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Competing interests

Author declares no competing interest.

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Ethical considerations

Ethical issues (Including plagiarism, Informed Consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc) have been completely observed by the author.

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