Journal of Air Pollution and Health (Summer 2023); 8(3): 299-314

Original Article

Available online at http://japh.tums.ac.ir

Disentangling the impact of COVID-19 lockdown and meteorological factors on air quality in Colombo, Sri Lanka: A data clustering approach

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ARTICLE INFORMATION

Article Chronology:
Received 10 May 2023
Revised 30 June 2023
Accepted 20 August 2023
Published 29 September 2023

Keywords:
COVID-19 lockdown; Sri Lanka; Air pollution; De-weathering; Particulate matter

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ABSTRACT

Introduction: Human activities disrupted by COVID-19 have reduced global air pollution. Meteorological day-to-day and year-to-year variability affects pollution levels and complicates estimating reductions. This paper uses data clustering to remove the complexity of non-linear relationships by separating meteorology from complex emission patterns before modelling. The case study is based on $PM_{2.5}$ concentration time series data and meteorological data for 2018 to 2021 in Colombo, Sri Lanka.

Materials and methods: The southwest monsoon brings sea breezes from the Indian Ocean to land from May to October. To separate the effect of the monsoon winds on $PM_{2.5}$ concentrations, analysis of time series data, polar plots, clusters, and Theil-Sen trends were used based on hourly-average air pollution and meteorological data for the whole dataset.

Results: Two clear clusters were identified from scatterplots, representing the monsoon and non-monsoon periods. The study suggests that due to the combined effect of the monsoon winds and a reduction in the levels of traffic as a result of perturbations in human activity, the $PM_{2.5}$ concentrations decreased at an average rate of 10.61 µg/m^3/year (95% CI: 12.86 - 8.11) over the four years. During the non-monsoon season, due to traffic reductions alone, $PM_{2.5}$ concentrations reduced at an average rate of 7.95 µg/m^3/year (95% CI: 10.07 – 5.51).

Conclusion: These results are relevant to policymakers in the post pandemic planning of traffic and industry, with the methodology readily adapted for use in other locations where a separation of effects may be beneficial.

Introduction

Over the last two years, human activity on a large scale has been perturbed from the usual daily routine, starting around March 2020 when the World Health Organization (WHO) declared COVID-19 "a global epidemic" [1]. In order to help prevent the spread of the virus, many countries imposed various levels of travel restrictions and lockdowns. Schools and universities in many places around the world were closed to in-person sessions and switched to an online delivery mode, and for many employed

Please cite this article as: Jayasundara P, Elangasinghe A, Dirks KN. Disentangling the impact of COVID-19 lockdown and meteorological factors on air quality in Colombo, Sri Lanka: A data clustering approach. Journal of Air Pollution and Health. 2023;8(3): 299-314.

across both the private and public sectors, work from home was also expected. Social distancing and travel restrictions resulted in a significant reduction in all forms of transport (land, water, and air), tourism, construction, mining, and quarrying activities.

During this time, as with many countries around the world, Sri Lanka was severely affected by the virus. The first COVID-19 case was identified on January 27, 2020, with the number of cases increasing continuously from then. On March 24, a curfew was imposed across many parts of the island that continued until May 27, when it was then lifted [2]. Subsequently, two more waves resulted in travel restrictions of various levels of severity throughout the rest of 2020 and into 2021.

While for many countries around the world, COVID-19 disrupted activities from the beginning of 2020, in Sri Lanka, other events of national significance also caused major disruption prior to this period. On Easter Sunday, April 21, 2019, three churches in Negombo, Batticaloa and Colombo, as well as three luxury hotels in Colombo, were subjected to a series of planned terrorist group suicide bombings in which 253 people lost their lives, and more than 485 were injured. Immediately following, the armed forces and police launched a special security operation throughout the country, with the government declaring a state of emergency and imposing a curfew for several days following, and further extended it in various parts of the country due to minor riots that sparked in places. Schools and state universities across the country were also closed for a two-week period. Due to the uncertainty of the situation, these institutions remained inactive for about two months following the event. In addition to educational activities, the attacks disrupted many industries, including tourism, transport, and aviation. Tourist arrival numbers fell by about 70 %, and major religious festivals, including "Vesak", "Poson", and Christmas, were not celebrated that year in the usual ways. Also, in the second half of 2019, the country was affected by severe floods caused by adverse weather conditions that prevailed across the country. Thus, in Sri Lanka, major nationwide disruptions extended beyond the timespan of the global pandemic back to April 2019. The timeline and specific dates associated with these events are depicted in Fig. 1.

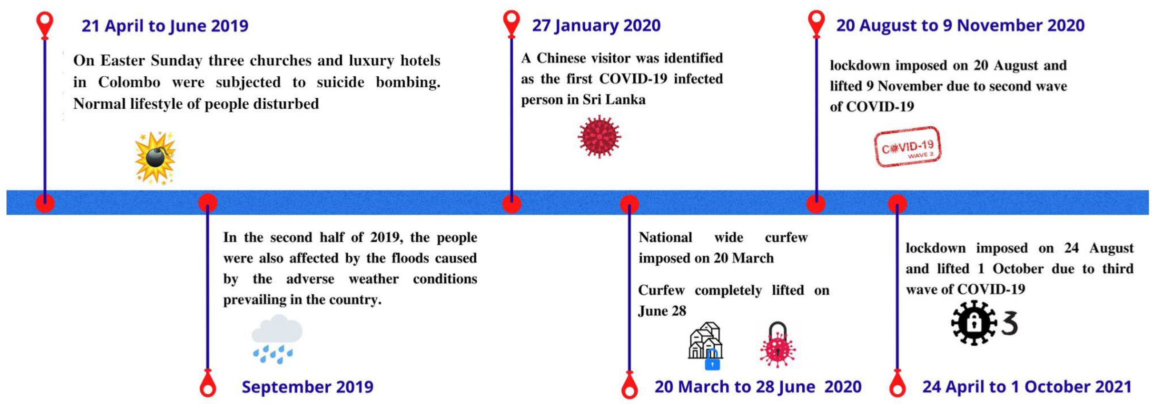


Fig. 1. Interventions that affected ambient concentrations of pollutants from 2019 to 2021

The curfews imposed stemming from all of these events resulted in significant reductions in road traffic flows, leading to similarly large-scale reductions in the quantity of air pollutants released into the air across the country. However, in addition to their emission source strength, local meteorology also plays a significant role in forming patterns of ambient air pollution concentrations in urban areas, whether from vehicle tailpipes or factory stacks. In terms of meteorology, wind in particular, can dilute locally produced air pollution concentrations from pollution sources, and rain readily washes out airborne particles in particular, with strong winds advecting pollutants, especially dust and sea spray, from distant sources. In the case of Sri Lanka specifically, along with many other countries in similar parts of the world, the monsoon impacts the meteorology on a seasonal scale, bringing large-scale shifts in wind patterns and rainfall. Understanding the impacts of such disruptions requires careful consideration of the meteorological conditions and how these might also have changed in recent years as a result of climate change, including, for example, the frequency of extreme events in relation to rainfall, wind and temperature.

Many studies have been carried out worldwide reporting on the effect of lockdown periods on local air quality [3-11]. Some of these studies are based on ground-based routinely collected air quality data, while some are based on satellite data. In some cities, the percentage reduction of NO_2 has been reported to be higher than 70% [5]. Recent research presents the effect of the COVID-19 lockdown on air quality in South Asia based on crude information collected from a range of ground-based and satellite data sources over the years [12]. The results suggest a significant improvement in air quality in India, Afghanistan, Pakistan, Bangladesh, Sri Lanka, and Nepal. Specifically, it was suggested that there was a 27% reduction in air pollution in Sri Lanka during the lockdown period compared with the 2018 period, and a 28% reduction compared with 2019, with results based on information provided by the National Building and Research Organization (NBRO) in Sri Lanka (noting that the original report on which this information was based was not cited anywhere). However, a commentary by an environmental scientist [13], suggests that the reductions in air pollution levels in Colombo, Sri Lanka were not due to the lockdown but due to the southwest monsoon, which began precisely at the same time as the March lockdown; every year around this time of the year, an improvement in air quality is observed as the sea breeze from the Indian Ocean dilutes pollutants in the air. It is expected that the increase in the frequency of extreme weather events that have occurred also had an impact, especially with regard to the resulting concentrations of fine particulate matter. Thus, it is not clear the extent to which the improvement in air quality that was observed was a result of reductions in emission and the extent to which it can be attributed to changes in weather patterns.

In order to address this issue, different meteorological normalization or de-weathering techniques have been adopted by researchers, such as random forest modelling [14, 15], parametric techniques [16] and machine learning-based statistical modelling [17]. These techniques involve training a model to describe the changes in air pollution through several independent variables, including meteorological factors (such as wind speed, temperature, and rainfall) and source strength (emission pattern, time of the day, day of the week). Some models use atmospheric physics to determine relationships, while others are semi-empirical and statistical in nature. Semi-empirical models are trained for a given dataset and can then be used to predict an independent dataset. Previous studies have shown that during the training phase, the data can be expected to exhibit a predictable pattern, resulting in a reasonable degree of accuracy with respect to predictions [18-20]. However, in the case where complex non-linear relationships exist between pollutant concentration and meteorological factors, this pattern-recognition phase requires further pre-processing of the data.

In this study, a cluster analysis is carried out on routinely collected air quality data as an alternative way of understanding the contribution of different factors to the trends in ambient air pollution concentrations so that the source contribution can be separated from that of the meteorology in order to estimate the extent to which the lockdowns of 2020 and 2021 impacted on air pollution concentrations. Such an approach provides a clear view of the source contribution to inform the development of complex models to understand the contribution of changes under a range of different scenarios. We have considered the monsoon and non-monsoon periods, in order to estimate the impact of changes to human activities on air quality, taking into account the impact of changing weather patterns due to the monsoon. Significantly, this study lines up to achieve the following objectives:

- Apply data clustering techniques to separate the effects of meteorology from complex emission patterns to model air quality.
- Analyze time series data, polar plots, clusters, and Theil-Sen trends on hourly average air pollution and meteorological data for Colombo, Sri Lanka, from 2018 to 2021 to understand the effect on air quality due to changes in human behaviour during this period.
- Quantify the average rate of $PM_{2.5}$ concentration reduction during the study period due to the combined effect of the monsoon winds and reduced traffic levels due to disruptions in human activity.
- Assess the individual impact of traffic reductions during the non-monsoon season on $PM_{2.5}$ concentrations.

Though these techniques are well established and applicable in air quality data analysis, they are used for the first time to isolate the trend in air pollution due to the changes in the daily routine experienced in Sri Lanka over the last four years.

Materials and methods

Study site

The study site in Colombo, Sri Lanka, is presented in Fig. 2. Colombo, the capital city of Sri Lanka, is the busiest and most populated district of Sri Lanka's twenty-five administrative districts. Its population density is 13364 persons per km^2, and it is considered the country's commercial centre. The roads in Colombo are congested most of the day. Colombo is a coastal city with its western side bounded by the Indian ocean. The central hills of Sri Lanka act as a significant climatic barrier to the monsoonal winds and contribute significantly to the country's two climate zones: the wet zone and the dry zone. Colombo is located in the wet zone, which is exposed to the southwest monsoon winds. Apart from the monsoon, the first inter-monsoon also produces high rainfall rates in the wet zone [21]. The winds in Colombo are most often from the southwest from May to October [22], then change to the south, east and northeast during the rest of the months of the year (see the wind rose diagram in Fig. 1). Air quality monitoring data, used as an indicator of the pollution levels in the air, are limited to a concentration of particulate matter less than 2.5 μm in size ($PM_{2.5}$) and are collected at the US Embassy of Sri Lanka in Colombo. The site faces Galle Road (located at a latitude of 6.52° N and a longitude of 80.01° E).

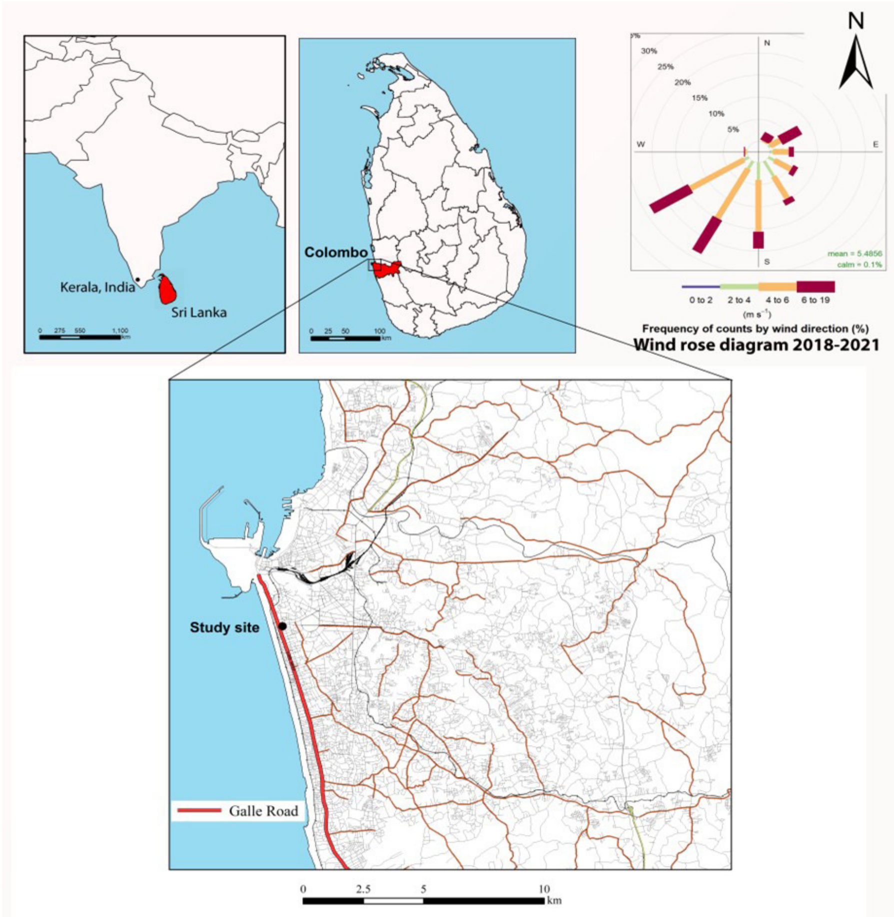


Fig. 2. Site Map showing the location of the study site with wind rose diagram (upper right corner) showing annual wind pattern

Data

$PM_{2.5}$ data collected at the above site were obtained from the "Air Quality Open Data Platform – Worldwide COVID-19 Data Set" [23]. The air quality data at this site is collected using a Beta Attenuation Monitor located at the US Embassy of Sri Lanka. Meteorological data were obtained from visual crossing Weather Data & API [24]. The Visual Crossing Weather platform provides weather data to help analysts better inform decisions using hyper-local and worldwide weather and climate data.

Data analysing tools

This study uses dedicated functions for analyzing air pollution data, available in the openair R 'package' [25]. R is a computer programming language mainly developed to analyse data and produce statistical outputs and graphics. R is available as free software under the terms of the free software foundation's GNU general public license [26]. The dedicated functions introduced in the Openair manual [27] are used in this study.

Time series data analysis

Daily, weekday and monthly variations in air pollutant concentrations were studied to help determine the contributing sources based on the expected patterns. Specifically, road traffic sources typically manifest as diurnal variations, those from firewood burning for home heating show a distinct seasonal pattern, while sources such as sea spray show more irregular patterns. The "TimeVariation" function in Openair was used to study the mean concentrations of the time series.

Theil-Sen trend analysis

In this paper, temporal trends are estimated using the Thiel-Sen approach on de-seasonalized data using the Openair platform. Ordinary linear regression is the most commonly used method for identifying linear trends [27]. However, the autocorrelation effect, the non-linearity and the non-normality of air pollution data can all lead to poor interpretation of trends when linear regression is used. The Thiel-Sen estimator [28, 29] is an effective technique used to overcome the autocorrelation effect and issues of non-linearity and non-normality of air pollution data where the error variance is not constant [27]. The "Thiel-Sen" function in the Openair platform uses a bootstrap resampling technique to estimate the slope from the median of the slope of all pairs of data points in the dataset.

Concentration polar plots and polar cluster analysis

Concentration polar plots and polar clusters were used in this study to identify the possible emission sources and effects of wind speed and direction on $PM_{2.5}$ concentrations graphically. The polar plots illustrate the joint wind speed and direction dependence on the concentration of pollutants and have been used effectively in previous source apportionment studies [20, 30, 31]. In the construction of the polar plots, a smoothing technique was used to obtain a smooth surface of the concentrations in polar coordinates. Polar clusters identified on the concentration polar plots were then used to separate the data set into clusters with similar concentration interactions with wind speed and direction using an unsupervised learning technique described as K-means clustering. The number of groups identified by the letter "k" is predetermined. There is no definitive method for determining the optimum number of clusters in this approach; it is decided by careful observation of the time series analysis of the data in each cluster. In this study k=2, 3, 4, 5, and 6 solutions were considered, and each solution was studied carefully to decide the final number of clusters for meaningful interpretation of possible sources that affect the $PM_{2.5}$ concentrations at the study site.

Results and discussion

Fig. 3 shows the box and whisker plot of the monthly median $PM_{2.5}$ concentrations in 2020 at the Galle Road site in Colombo, Sri Lanka. According to the pattern displayed, $PM_{2.5}$ concentrations are high in the months of November, December, January, February, and March and low in April, May, June, July, and October. Also, it indicates that $PM_{2.5}$ concentrations in Colombo exceed the WHO's guidelines, posing potential health risks to the population. When moving from March to April, there is a significant drop in the concentration of $PM_{2.5}$. This could be a result of seasonal changes in the wind pattern. The major lockdown in Sri Lanka happened precisely from the end of March to June 2020. Hence without analyzing data across years together with meteorology, the improvement in air quality in April 2020 cannot be entirely attributed to limited human movement due to the lockdown. Researchers concluded in a study that, there was a significant improvement in air quality because of the lockdown in April 2020 [32]. However, this analysis was limited to 2020 data alone. Other researchers used satellite data across years and showed graphically that there is a drop in NO_2 and SO_2 in 2020, but not together with meteorological data [12]. The present study overcomes this limitation by analyzing $PM_{2.5}$ and meteorological data across the years.

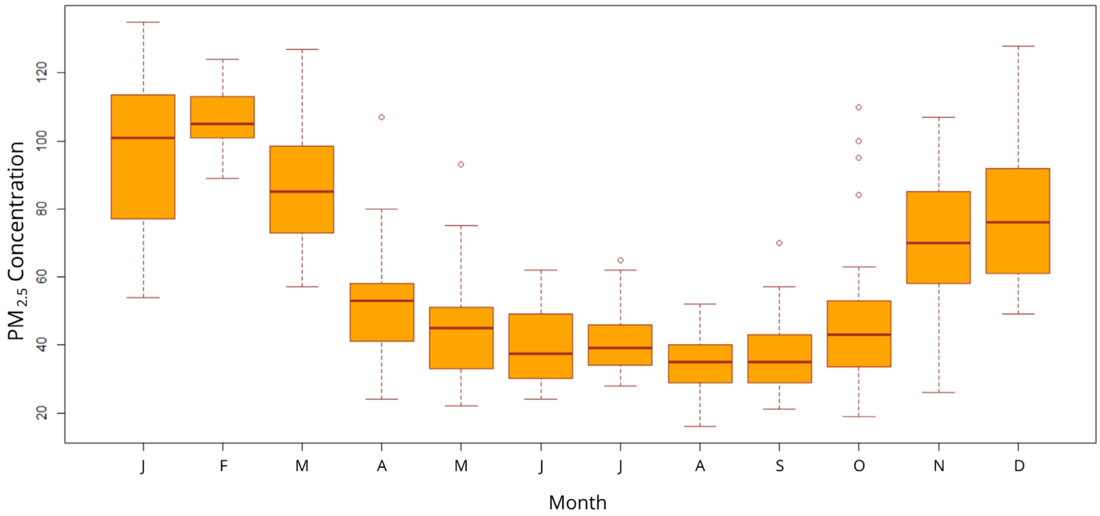


Fig. 3. Box plot showing monthly median $PM_{2.5}$ concentration for the year 2020 with 25/75th quantiles values

Fig. 4a shows the $PM_{2.5}$ data from the Colombo site plotted according to monthly averages from 2018 to 2021. It shows that in all years, the concentrations were high from January to March and also from November to December, while concentrations were low from April to October. Fig. 4a shows a significant drop in concentration when moving from May to December 2019, which was not observed in 2018 (this drop is shown using arrows in Fig. 4a). Fig. 4b shows the yearly variation in $PM_{2.5}$ concentrations measured in Kerala, India, situated in a southernmost point of India (see Fig. 1). The data in Fig. 4b are also plotted separately for the years 2018, 2019, 2020 and 2021. Concentration variations in Kerala and Colombo followed the same pattern in 2018, while this coherence did not persist from 2019 to 2021.

Interestingly, in both regions, the lowest concentrations were reported in 2021. The drop in $PM_{2.5}$ concentrations observed in Colombo, Sri Lanka, from May to December 2019 was not observed in Kerala, India, suggesting that this is not the result of any regional effect. The monthly wind patterns for 2018 to 2021 were investigated to investigate whether this drop in concentration results from changes in wind patterns over the months and years.

Fig. 5 shows the monthly average wind speed and wind direction from 2018 to 2021. According to Fig. 5a, wind speed varies in a similar manner in all years from 2018 to 2021, except with some high winds observed during the months of April and May 2020, exactly when the first lockdown occurred. Dilution effects created by these high wind speeds could have masked the actual effect of the lockdown on the ambient concentrations of pollutants. From Fig. 5b, it can be clearly seen that from May to October in all years, winds are southwesterly (225°). Then, from November, the wind direction changes clockwise and becomes northeasterly (45°) in December and January. From May to October, the southwest monsoon brings air from the Indian Ocean to the island, bringing rain to the study area. The winds from the ocean are strong and thus help to dilute the concentrations of pollutants at the site. When the wind shifts to the opposite direction (moving from south, east, then to northeast) from November to March, the wind is such that the air at the monitoring site originates from the city, bringing a highly polluted air mass to the site. Thus, the seasonal variations in the concentration can be explained by wind shifts brought about by the monsoons (for further detail regarding the wind patterns, see 22).

Fig. 6 shows the monthly average precipitation in millimeters at the study site for the years 2018 to 2021. A very similar precipitation pattern is observed across all years concerned. According to Fig. 6, precipitation is high in April, May, September, October, and November in all of the years concerned, except for a reduction in precipitation in the early months of 2019. It is expected that a reduction in precipitation would lead to an increase in $PM_{2.5}$ concentration during these months. However, the opposite is observed with this data set. However, according to the overall observations from Fig. 5 and Fig. 6, the significant reductions in $PM_{2.5}$ concentration in 2019, 2020, and 2021 compared to 2018 seems to be source-related and not as a result of meteorological changes over the years.

To further understand the possible source contribution of $PM_{2.5}$ at the study site, concentration polar plots for 2018-2021 were created and presented in Fig. 7. Based on Fig. 7, a distinct pattern with respect to the wind direction can be seen. When the winds are mainly from the southwest (225°), that is, from the Indian Ocean, a dilution effect of $PM_{2.5}$ concentration is observed at the study site, with stronger winds leading to lower concentrations. In contrast, when the winds are mainly from the east (90°) and northeast (45°), the air mass at the study site has travelled over the city before reaching the site, bringing in pollutants, with stronger winds associated with higher concentrations. According to Fig. 7, there is a decreasing trend over time in terms of the $PM_{2.5}$ concentrations of pollutants in the air mass travelling across the land from easterly and northeasterly directions from 2018 to 2021, suggesting a reduction in $PM_{2.5}$ emissions over these years.

(a)

(b)

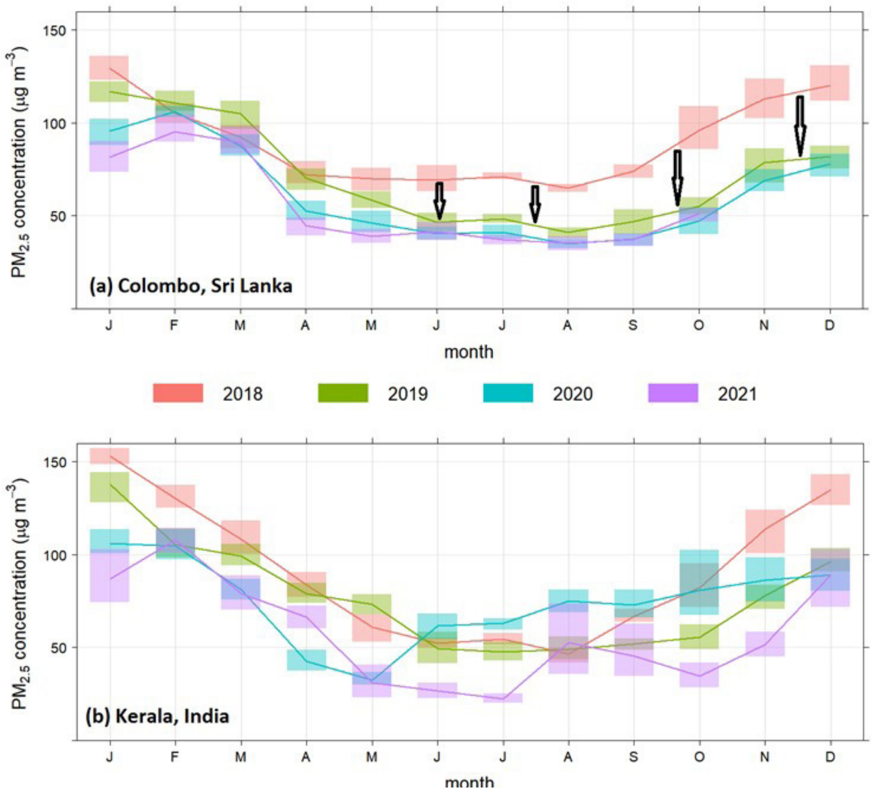
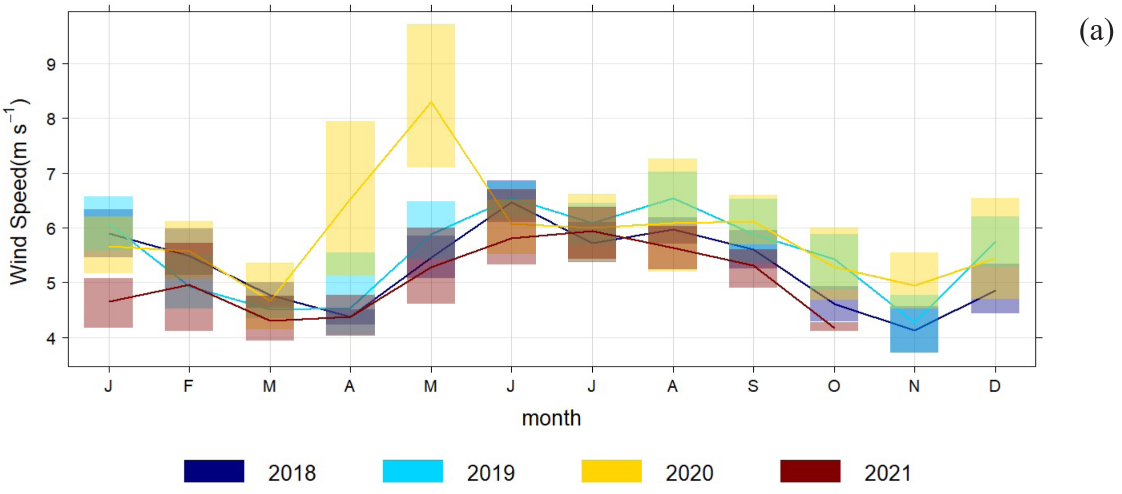


Fig. 4. Monthly average $PM_{2.5}$ concentrations plotted separately by year; (a) In Colombo, Sri Lanka, and (b) In Kerala, India. The black arrows in plot (a) show the distinct drop in the concentration of $PM_{2.5}$ in Colombo after May 2019. The vertical boxes denote the 95% confidence intervals of the monthly mean based on daily averages



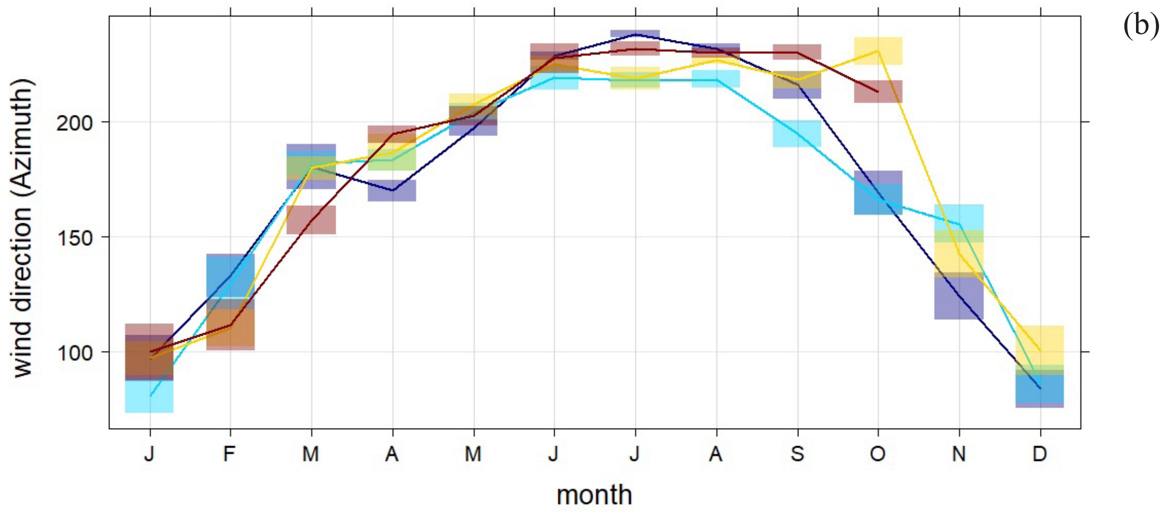


Fig. 5. Monthly average wind speed (a) and wind direction (b) for years 2018 to 2021
North 0°, East 90°, South 180°, West 270°; Northeast 45°, Southwest 225°

Fig. 6. Monthly average precipitation in millimeters for years 2018-2021

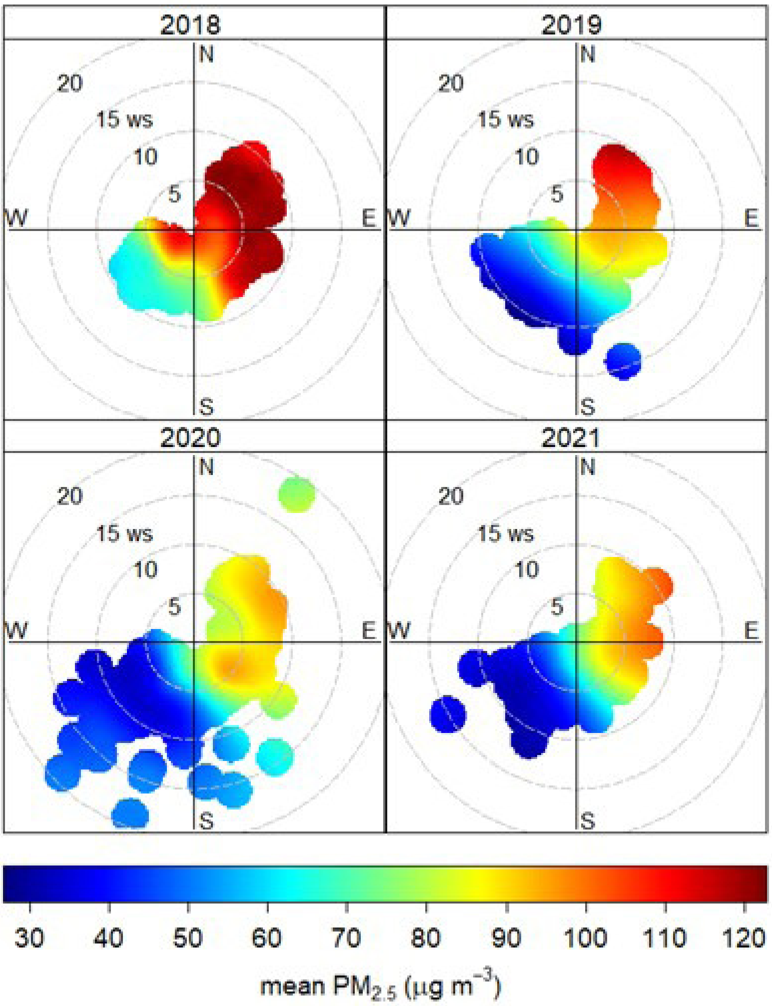


Fig. 7. Concentration polar plot showing wind speed in meters per second and wind direction in polar coordinates while the concentration of $PM_{2.5}$ is given in the colour index in study site Galle Road, Colombo, Sri Lanka. N- north 0°, E-east 90°, S-south 180°, W-west 270°; in text, northeast is 45°, southwest is 225°

To further understand the cause of this reduction, a cluster analysis was carried out on the concentration polar plot drawn for the whole of the dataset from 2018 to 2021. In the cluster analysis, 2, 3, 4, 5, and 6 cluster solutions were carefully studied. Time series and scatterplots drawn for these clusters suggest that the two-cluster solution is capable of separating the data set in the monsoon (winds coming from the Indian Ocean) and non-monsoon (winds coming from land) periods. The two cluster solutions are given in Fig. 8. The total number of data points in Cluster One and Two are 758 and 529, respectively. Fig. 9 shows the whole of the time series of data from 2018 to 2021 according to the colour of the cluster, which confirms that the two-cluster solution separates the air quality data into two main wind sectors. Cluster 1 represents the Colombo southwest monsoon season from May to October, while Cluster 2 represents the non-monsoon season when the winds are predominantly easterly and northeasterly. This time series data analysis confirms the rationale behind the clustering based on the monsoon and non-monsoon seasons. It becomes evident that distinct patterns and effects are associated with these two seasons by examining the trends in $PM_{2.5}$ concentrations.

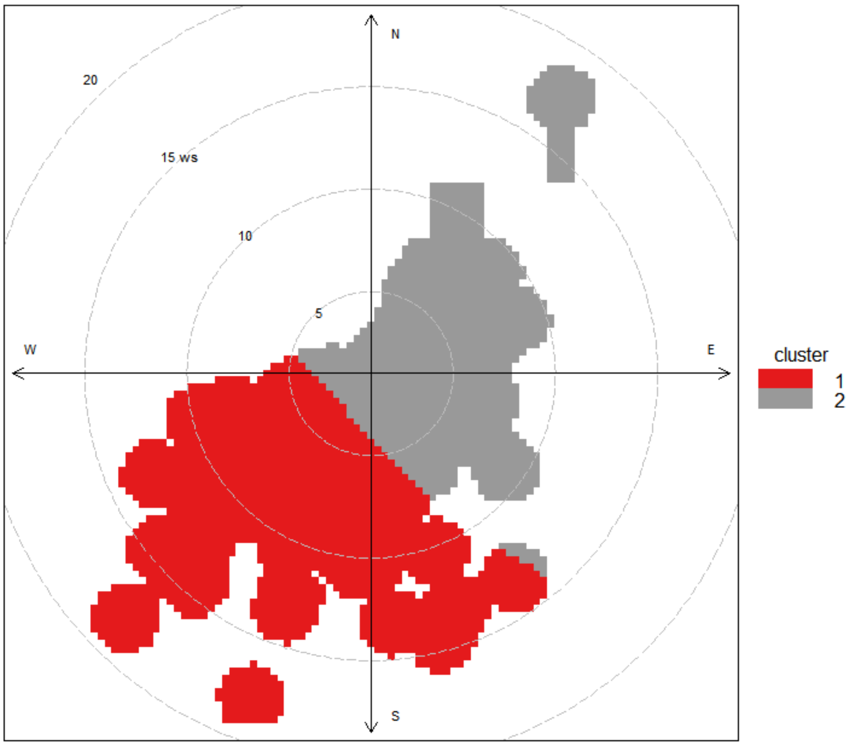


Fig. 8. Two-cluster solution: Cluster 1 represents the southwest monsoon season from April to October while cluster 2 represents the non-monsoon season in Colombo when the winds are northeasterly

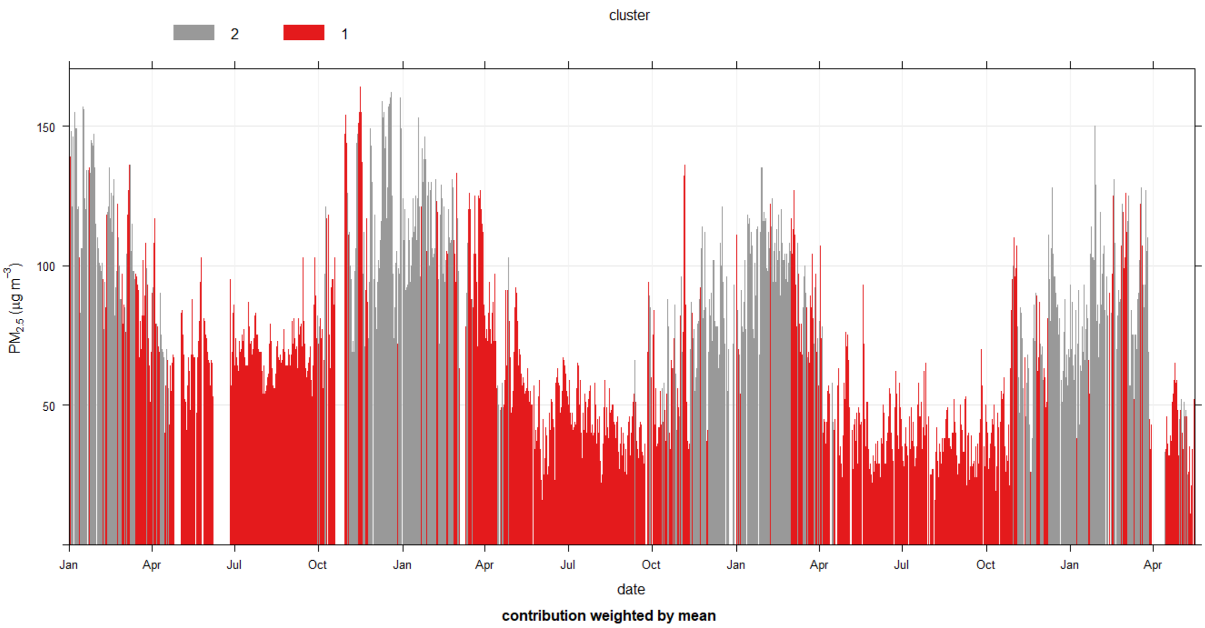


Fig. 9. Time series data of $PM_{2.5}$ according to the two clusters, shown as two different colours

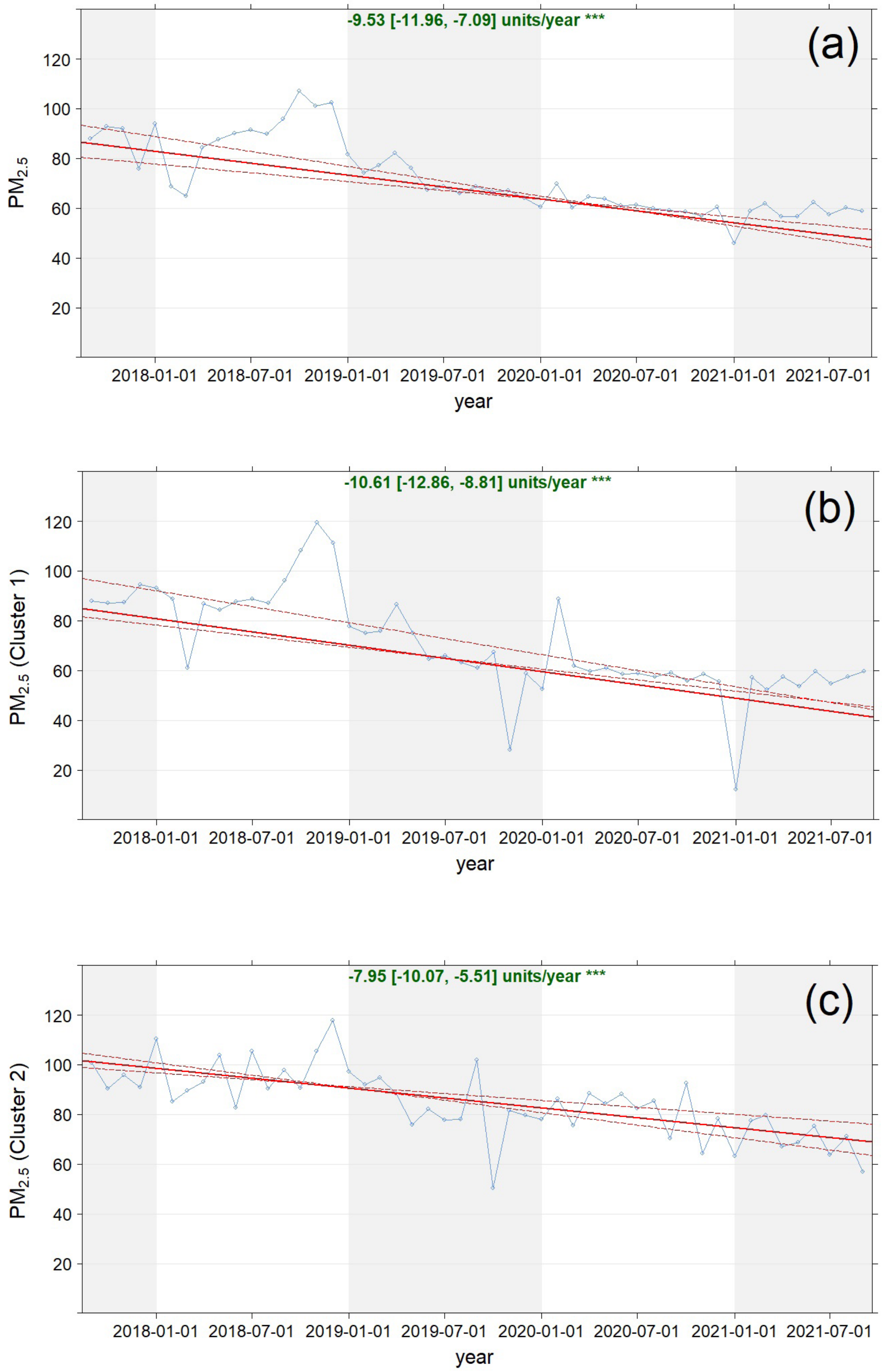


Fig. 10. Thiel- Sen trend analysis of $PM_{2.5}$ Concentration from 2018 to 2021; (a) Whole data set, (b) Cluster 1 (c) Cluster 2

Lastly, long-term trends in concentrations were investigated using Thiel-Sen trends on the deseasonalized dataset as a whole and for the two datasets separated by clusters. These are shown in Fig. 10. Fig. 10a shows the trend for the whole of the dataset from October 2017 to October 2021, indicating a reduction in the concentration of 9.53 $\mu g/m^3$ per year (with a 95% confidence interval of 11.96 – 7.09 $\mu g/m^3$) on average over the four years. Fig. 10b shows the trend for the monsoon season only. This illustrates the combined effect of both a reduction in emissions and a dilution effect due to monsoon winds and precipitation. For this data series, a $PM_{2.5}$ concentration reduction of 10.61 $\mu g/m^3$ per year (with a 95% confidence interval of 12.86–8.11 $\mu g/m^3$) is observed. Fig. 10c shows the equivalent for the non-monsoon season. In this case, the reduction in human activities alone explains a reduction in $PM_{2.5}$ concentration of 7.95 $\mu g/m^3$ per year (with a 95% confidence interval of 10.07-5.51 $\mu g/m^3$). The results of this study suggest that there has been an apparent reduction in emissions from 2018 to 2021 due to the different human-related interventions. Since previous studies [12, 32] considered only the 2020 pre-lockdown and post-lockdown period, this study is the first that has considered long-term trends in $PM_{2.5}$ in Colombo, Sri Lanka, treating the monsoon and non-monsoon periods separately.

Units- $\mu g/m^3$, *** trend p-value<0.005, and 95% confidence interval is given in square brackets

These long-term trend analyses provide valuable insights into the overall trajectory of $PM_{2.5}$ concentrations, indicating a continual decline in emissions over the four years from 2017 to 2021, with other fluctuations witnessed during the monsoonal and non-monsoonal phases. The results gained from this study highlight the significance of considering both short-term and long-term trends to understand air pollution dynamics in the region comprehensively. The dataset used for this research provides desirable details but represents only a specific monitoring location, and it cannot capture the city's total spatial variability of air pollution. Moreover, it is unable to fully understand the sources and their individual impacts due to the lack of detailed information on specific emission sources contributing to $PM_{2.5}$ concentrations, such as nearby factories and constructions.

Conclusion

In this study, simple statistical techniques were used to separate changes in atmospheric pollutant concentrations due to emission strength as a result of changes in human activity from those resulting from changes in meteorology brought about in part by the monsoon. Many previous studies are limited in that the reduction in the level of air pollution was assessed based only on a few months of data on either side of a change in COVID-related lockdown measures. This study highlights the importance of considering the impact of meteorology over a number of years to aid in separating causes.

Several significant events have occurred in Sri Lanka since April 2019, causing major disruptions to everyday life and ultimately to the patterns of emissions of air pollution. The closure of businesses, the implementation of a state emergency and curfew, reductions in the use of public transport, reductions in human movement due to lockdown measures, the closure of schools, the halting of mass gatherings for national festivals, limitations in activities associated with religious festivals and the closure and limitation in the number of people able to visit temples/mosques are all examples of changes that have contributed to the drastic reduction in anthropogenic emissions and air pollution levels that have been observed. As activities move back to some sense of 'business as usual', it can be expected that air pollution levels return to levels commensurate with these conditions.

It is also worth mentioning that a vehicle emission testing programme was initiated in Sri Lanka in 2008 that ascertains whether the vehicular emissions of a particular vehicle are within the allowable limit before it is allowed on the road. This might also have contributed to the improvement in air quality observed over the years. Though temporary changes in human behaviour would have caused the observed negative trend in $PM_{2.5}$ in Colombo from 2018 to 2021, this provides a platform for authorities to consider industrial and traffic emission control and traffic planning. Specifically, we would like to highlight the importance of the development of an emission inventory, receptor modelling and comprehensive traffic monitoring to allow for further investigation into different scenarios, allowing a data-informed emission control plan to be implemented.

As a future study, it would be worth investigating whether there has been a reduction in respiratory-related health problems in Colombo (other than COVID-19-related infections), such as a reduction in hospital admissions to the National Hospitals in Colombo for asthma-related issues related to this negative trend in $PM_{2.5}$ concentration in Colombo from 2018 to 2021. The results of such a study could be used to improve public health policy in Sri Lanka. Future studies could also explore multi-pollutants, including Nitrogen dioxide (NO_2), Ozone (O_3), and Volatile Organic Compounds (VOCs), analyses to provide a more comprehensive understanding of the air quality dynamics in the region.

Financial supports

The present research did not receive any financial support.

Competing interests

The authors declare that there are no competing interests.

Acknowledgements

The authors would like to thank the editor in handling this paper, and also acknowledge the anonymous reviewers for their great comments and edits which helped us to improve the quality of this paper significantly.

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 authors.

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