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Multivariate analysis of air pollution and associated potential respiratory health risks in urban areas of the Southeast Asian region and Africa

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ABSTRACT

Introduction: The nature of heavy pollution incidence that plagues the South East Asian (SEAR) Region and the African region demands the understanding of air pollution dynamics within these regions to inform policy formulation to improve environmental health. This study therefore aims to grasp the transformation of air pollutants in the last 10 years in the two regions and their potential to influence respiratory health.

Materials and methods: This study used the 6th edition of the ambient air quality data from the WHO website, which was revised and published on January 22, 2024. 1609 dataset was used for this research, spanning the 16 countries.

Results: The results of the analysis show that in the last 10 years, the mean PM_{10} (64.15 ± 40.38 g/m³), $PM_{2.5}$ (22.98 ± 23.65 g/m³), and NO_2 (8.83 ± 7.99 g/m³) were 64.15 ± 40.38 g/m³, 22.98 ± 23.65 g/m³, and 8.83 ± 7.99 g/m³, respectively. Consequently, the air quality index for PM_{10} and $PM_{2.5}$ stands at 57.73 and 96.59 for the African Region and 55.53 and 74.61 for SEAR, indicating a satisfactory air quality. The principal component analysis showed that NO_2 exposure and monitoring explained 39.91% of the variance in the data, while component 2 (PM_{10} and $PM_{2.5}$) explained 19.43%. The regression model showed that PM_{10} temporal coverage can be used to predict NO_2 concentration. Indicating that better cover for PM_{10} can be used to estimate NO_2 concentration.

Conclusion: This study has highlighted that temporal coverage can be a useful means for air pollutant estimation. Hence, governments should increase monitoring of air pollutants, in this peak era of industrialisation to capture the many unquantified contaminants.

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Introduction

Fundamental to the survival of every human is air. However, growing population, industrialisation, rapid economic growth, and urbanisation are becoming an existential threat that hinders breathing of quality air in major cities across the world [1]. All around the world evidence shows that pollutants in the air; Particulate Matter ($PM_{2.5 \text{ and } 10}$), Nitrous Oxide (NO_2), Ozone (O_3), Sulphur dioxide (SO_2), and Carbon monoxide (CO) are just a few of the contaminants that have significant health implications on humanity [1–4]. Unfortunately, 99% of humans breathe air that exceeds the WHO air quality standard limits, contributing to many premature deaths annually [5]. To appreciate the importance of air quality, one can infer from the emergence of the new virus SARS-CoV-2 (Covid-19). The pandemic, which left many dead and caused acute respiratory diseases, was transmitted through contaminated air. This issue of poor air quality is most pronounced in low- and middle-income countries, with the highest number of premature deaths occurring in the WHO South-East Asia and Western Pacific Regions [2, 3]. Nevertheless, developing countries tend to have less resilient economies and weaker institutions to address the effects of poor air quality hence, their vulnerability increases.

Today, city authorities, governments, and the WHO have heightened the need for monitoring and investigating air pollution in urban areas [1, 6]. Aside from the pandemic, the most reported air pollutant that exists in urban areas and is known to cause death and lots of health effects (lung disease, compromising the immune system, and respiratory infections) is particulate matter. PM is known to exist in two forms, $PM_{2.5}$ and PM_{10}. The mean diameter size of particulate matter less than 2.5 μm and less than 10 μm is PM_{10} and $PM_{2.5}$. These pollutants are primarily emitted from moving vehicles, residential areas, the energy industry, and dust [6]. Empirical evidence shows every human is exposed to some level of PM daily that can cause health problems [7, 8]. Additionally, other air pollutants that contribute to this assertion include NO_2, an important component of urban air pollution and a precursor to ground-level ozone, particulate matter, and acid rain [7], Sulphur dioxide (SO_2), Nitrogen dioxide (NO_2), Ozone (O_3), Carbon monoxide (CO), and Carbon dioxide (CO_2). Once these pollutants are emitted into the atmosphere, they can interact and react with other chemical species present in the atmosphere [9].

Ironically, low- and middle-income countries have the highest number of premature deaths due to poor air quality, yet they are the nations with the least monitoring [10]. This issue is particularly troubling in the African region, where efforts to record and monitor these pollutants are limited. Continuous and systematic observations are not even effective [11, 12], significantly impacting studies conducted in the area. For instance, of the 47 African countries, only 11 have sufficient data on air pollutant measurements available on the WHO website, while just 6 can produce long-term data that encompasses 161 cities. The World Health Organization (WHO) estimates that the annual median concentration of $PM_{2.5}$ has exceeded 26 μg/m³ across more than half of Africa, far exceeding the WHO-established threshold of 10 μg/m³ for outdoor air quality, with values ranging from 40 to 260 μg/m³ in an analysis of eight different pieces of research on outdoor air pollution in African cities [13].

Technically speaking, monitoring of air quality in the Southeast Asian region has been reported by many studies [14–17]. The clear conclusion from multiple authors indicates a deteriorating air quality. As early as the 2000s, two study [15, 18], opined that the majority of cities in India, Nepal, Sri Lanka, and Bangladesh in the South Asian region have been reported to be very polluted with $PM_{10 \text{ and } 2.5}$ reaching as high as 109 μg/m³ in

Delhi, India, and up to 300 μg/m³ in Bangladesh. Particularly, some of these low- middle-income countries have problems with data accuracy and consistency, as there is no reliable and convincing information on the extent of air pollution and its impacts without good observational data [12].

One significant term that is very important in air quality measurement is temporal coverage. According to the Australian Research Data Commons [19], it describes the time frame in which information was gathered or observations were made, or the time frame to which a collection or activity is conceptually or cognitively related. A representative temporal coverage of data with inter-seasonal variability may be computed to represent a particular air pollutant when data are not available from city measurements [10]. Recent studies such as [20, 21] have used temporal coverage data recorded over two decades to show trends and meteorological influence that is not present in short data, while others have used it for exposure assessment and were able to identify intraday and pollution peaks [22-24]. Additionally, it has also been demonstrated that temporal continuous coverage improves predictive accuracy and reduces bias [2, 25]. With the growing studies on air quality pollutants, a plethora of studies have considered the spatial-temporal dynamics of air pollutants in Africa and the Southeast Asian region [26–28]. Reports indicate that some 89% of those premature deaths that occurred in these countries are associated with air quality. The disproportionate burden of health risks underscores the need for urgent and effective monitoring and intervention strategies [10]. Most air quality data consider annual averages; however, temporal coverage can be used to estimate the concentration of pollutants where there is representative inter-seasonal variability. Yet there is limited study that has attempted to look at how temporal coverage can estimate the concentration of these pollutants and how this can support air quality monitoring and data availability [WHO]. Other studies have also conducted trend analysis to predict air quality with measurements of heavy metals that are present in the air [29, 30].

Notwithstanding the above, studies highlighting the regression relationship between temporal coverage and the concentration of air pollutants are limited. The novelty of this work lies in the use of 10-year air quality data from the WHO website in the Southeast Asian and African regions to point out the changes in [29] air quality in these regions and how temporal coverage has influenced the pollutant concentration in the last 10 years. To capture the trend, a regression model has been presented in this study, and the air quality index of the two regions has been calculated. Overtly, this study seeks to contribute and advocate for improved air quality monitoring, attempt to fill in the gaps on temporal coverage and pollutant measurements, and contribute to advancing the awareness of the dangerous effects that air pollution has on the respiratory health of people living in urban regions. Additionally, this study is among the seminal studies considering African and Southeast Asian regions together on air quality assessment and thus will seek to (i) offer insights into how air pollution levels have changed over the years in the WHO Africa and South-East Asian regions, (ii) To establish an equation from the regression analysis of particulate matter and temporal coverage in the African and Southeast Asian regions, and (iii) calculate the Air Quality Index and find the health effects associated with them.

Hypotheses

- H1; There is a significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2 and the year of measurement on the concentration of PM_{10} measured in the past 2 decades.
- H2; There is a significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2, and the year of measurement on the concentration of $PM_{2.5}$ measured in the past 2 decades.

• H3: There is a significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2 and the year of measurement on the concentration of NO_2 measured in the past 2 decades.

Limitations of the data and the study

The limitation of the dataset used in this research stems from measurement. Wide range of measurement techniques and procedures per WHO have varying temporal coverage; hence, seasonal fluctuation might cause the measurement to drastically diverge from the annual mean. For this reason, WHO advises that data representing cities cannot be used to classify a city as dirty nor be utilised to make direct comparisons between nations according to the WHO. This is primarily due to the difficulties listed; per [25], it only covers a tiny percentage of cities and is not all-inclusive. In the meantime, the data can be used as input data in models to estimate exposure to air pollution using topographic, population, and satellite data along with chemical transport models, among other data; they can also help advocate for improved global air quality monitoring; they can acknowledge the growing number of monitoring stations worldwide; they can raise awareness of the significance of high-quality, publicly available data; and they can serve as a foundation for calculating the mortality rate.

Materials and methods

Study area

This research is centered on studying the ambient air quality of the Southeast Asia region and the African region. The study countries are listed in Fig. 1.

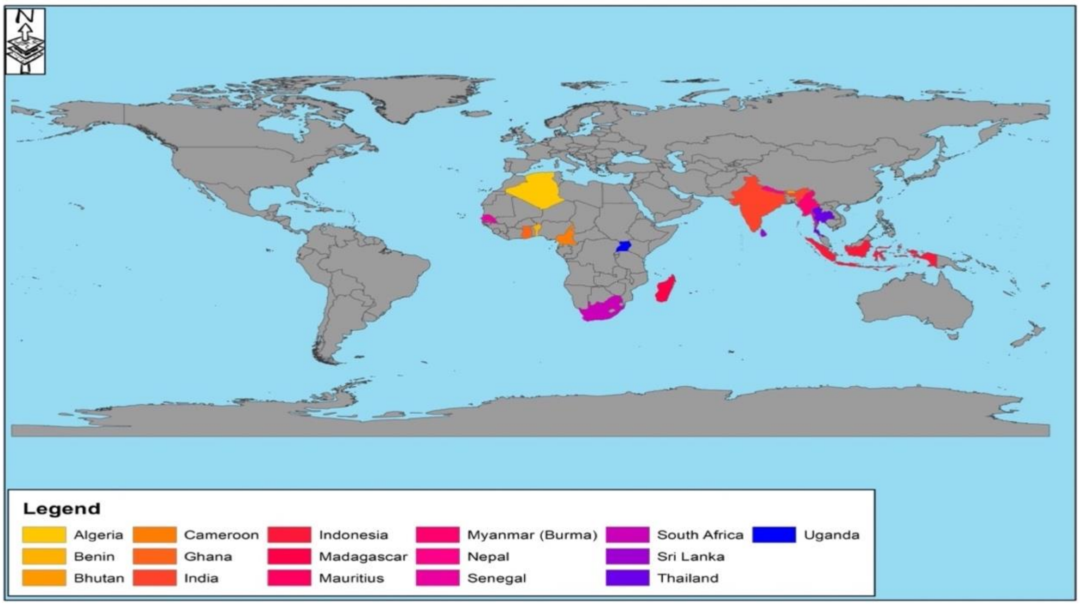

Fig. 1. Map of the countries studied

Data sources

The data utilised in this research are categorised as indicators of air pollution and include the annual mean concentration of Nitrogen dioxide (NO_2) ($\mu g/m^3$) and particulate matter with a diameter of less than 10 µm (PM_{10}) ($\mu g/m^3$) and less than 2.5 µm ($PM_{2.5}$) ($\mu g/m^3$), as well as their temporal coverages in human settlements. This study used the 6th edition (V6.1) of the Ambient Air Quality Data, which was revised and published on January 22, 2024. 1609 data was used for this research, spanning the 16 countries in the SEAR and Africa. The main data sources were official national and subnational reports, official reports from nations submitted to WHO upon request, and national and subnational websites that included PM_{10}, $PM_{2.5}$, and NO_2 readings. Furthermore, some information was gathered straight from official government websites, including the European Environmental Agency, national health and environment ministries, and statistics agencies. Only the most recent data and trustworthy sources were chosen when a city's data was available from multiple sources. The longitudinal data employed was measured between 2010 and 2022. Values from UN agencies, development agencies, regional networks like Clean Air for Asia, the Air Now initiative from US embassies and consulates, and peer-reviewed publications were used in situations where such official statistics were unavailable.

Mode of estimation and measurement of PM_{10}, $PM_{2.5}$, and NO_2

Mode of estimation

The annual means are either an average of the cities' monitoring stations or the values given in the underlying data source. To show air quality that is mostly indicative of human exposure, measurements were taken in urban areas, which were classified as residential, commercial, and mixed regions. Stations classified as only industrial or specific "hot spots" were excluded unless they were part of the stated city means and could not be separated. The selection strategy aligns to obtain representative values for exposure to humans. The location of hot spots, often measured to capture the cities' maximum values, and industrial areas were deemed less likely to be representative of the mean exposure of a significant part of a city's population. 'Hot spots' were either designated as such by the original reports or were qualified as such due to their exceptional nature (e.g., exceptionally busy roads, etc.). Omitting them may have led to an underestimation of the mean air pollution level of a city.

Mode of measurement

The average yearly concentration of NO_2 and fine suspended particles less than 10 or 2.5 µm in diameter is often used as indicators of air pollution. The average city concentration is often calculated using daily measurements or data that can be combined to create annual averages. When annual means were not available, measures from a smaller time frame of the year were utilized in certain cases. Nevertheless, only information whose temporal coverage was thought to be indicative of inter-seasonal variability was included. In general, a 75% temporal coverage criterion was selected, except low- and middle-income nations where there was very little data available.

Data analysis

The secondary data obtained was analyzed using the IBM SPSS version 21. The statistical analysis conducted on the data after coding included principal component analysis, which was aimed at identifying sources contributing to majority of the pollution. Descriptive statistics (Boxplots) and multiple linear regression analysis were conducted to detect linear relationships.

Air quality index (AQI)

The overall AQI is the maximum AQI and the corresponding pollutant is the dominating pollutant. The AQI is divided into six categories: good, satisfactory, moderate, poor, very poor, and severe, depending on whether the AQI falls between 0–50, 51–100, 101–200, 201–300, 301– 400, and 401–500, respectively [6]. The research considered aggregating the countries as one to estimate the region rather than individual countries because of the restrictions associated with the data used, as explained above.

The AQI was computed by using the pollutant concentration data and the linear interpolation equation (Eq. 1):

Where: Ip = the index of pollutant,

Cp = the rounded concentration of pollutant p;

BPH= the breakpoint that is greater than or equal to Cp (upper limit)

BPL= the breakpoint that is less than or equal to Cp (lower limit)

IH= the AQI value corresponding to BPH; and

IL= the AQI value corresponding to BPL.

Results and discussion

The results presented in boxplots (Figs. 2-3) represent an observation of Air quality monitoring data from multiple urban stations collected from 11 African countries (Benin, Kenya, Ghana, Nigeria, Mauritius, Madagascar, Cameroon, Senegal, Algeria, Uganda and South Africa) and 8 South eastern Asia countries (Bangladesh, Bhutan, India, Indonesia, Sri Lanka, Myanmar, Nepal and Thailand). The discussion is segmented into regions studied discussing the various pollutants under study. All the PM_{10} results in this study per country are far greater than the 15 g/m^3 recommended limits suggested by the WHO.

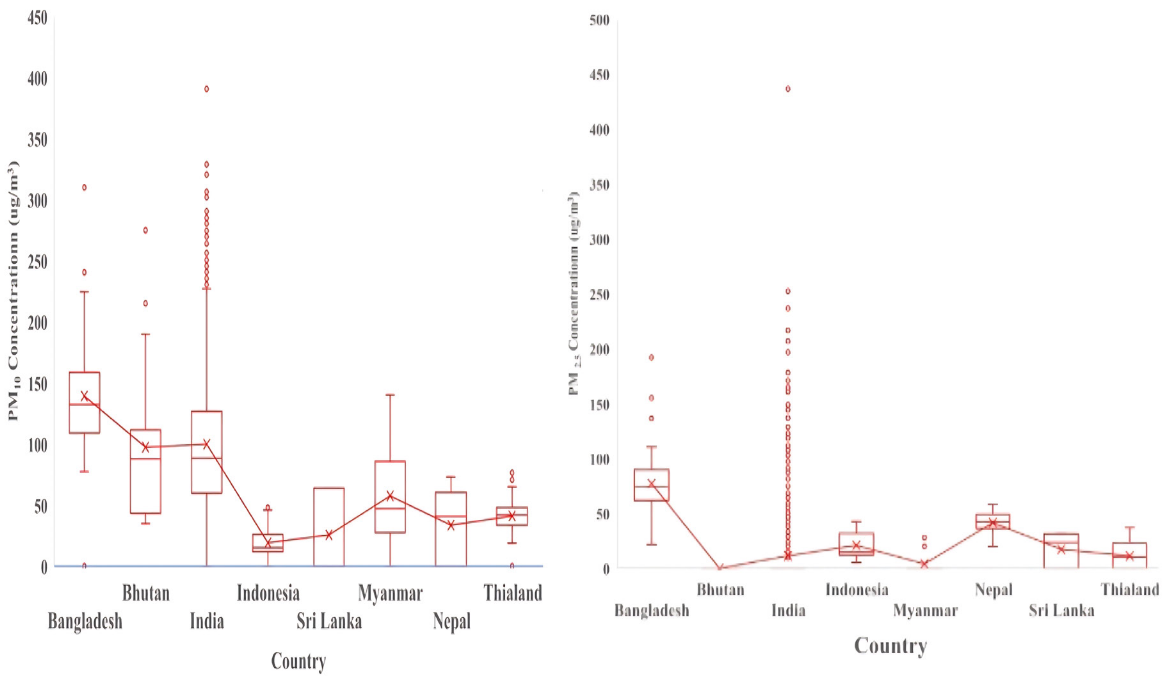

Fig. 2. PM_{10} and $PM_{2.5}$ concentration across selected SEAR

Descriptive analysis of $PM_{10\ and\ 2.5}$ in the Southeast Asian countries

This section discusses the results of PM_{10} concentration in the south east Asian region For Bangladesh, the measured minimum and maximum PM_{10} concentrations included 77.44g/m^3 and 224.76g/m^3 respectively, with the highest outlier at 309.9g/m^3 (Fig. 2). The mean concentration was observed to be 139.28g/m^3 with majority of the data set falling within 109.08g/m^3 to 158.57g/m^3 (Fig. 2). This observation is in line with that of a study [32] which also was reported an average of 302g/m^3. It also resonates with another study [33] who conducted similar longitudinal study and reported as high as 300 g/m^3 to 350 g/m^3 from 2010 to 2023. These observations further reinforce the present findings. In a country like Bhutan, the measured minimum and maximum PM_{10} concentration were 35.00g/m^3 and 224.76g/m^3 respectively, with the highest outlier at 275g/m^3. The mean concentration was observed to be 97.37g/m^3 with majority of the data set falling within 43.5g/m^3 to 111.5g/m^3 (Fig. 2) in the last decade. Similar results have been reported by Humagai et al. [34] in their study, they found PM_{10} concentration of 45.05 which is the range of this study. The majority of data recorded for India were all outliers, ranging from 230.45g/m^3 to 390.6g/m^3. Majority of the data set lies between 59.89g/m^3 to 126.8g/m^3 with a mean concentration of 99.75g/m^3 (Fig. 2). The mean concentration of PM_{10} recorded in Indonesia was 19.14 g/m^3 whereas that of Thailand was 41.00g/m^3 with minimum value of 19 g/m^3. 140 g/m^3 maximum PM_{10} concentration has been reported with a mean of 57.5g/m^3 in Myanmar. These observations are in line with Pandey, [35] and Verma et al. [36] who have reported that the PM_{10} in most SEAR and south Asia are beyond 70g/m^3.

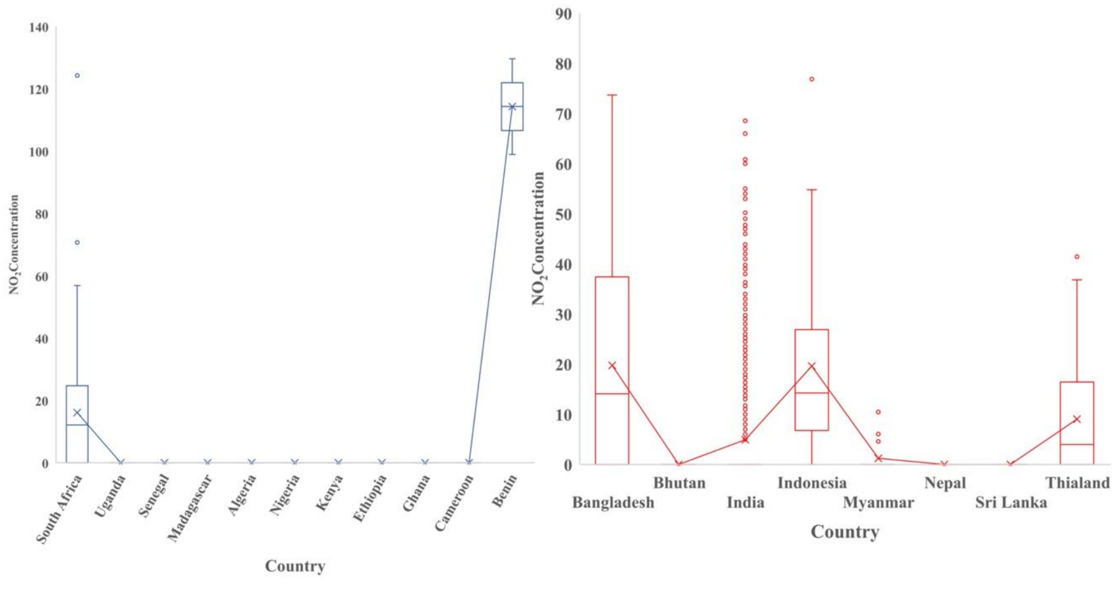

Fig. 3. $PM_{2.5}$ concentration across selected SEAR and African Countries

This section discusses the results of $PM_{2.5}$ concentration in the south east Asian region South Asia is reported to be the most polluted city in the world; This assertion is based on the fact that it hosts 9 of the 10 most polluted cities in the world with its average $PM_{2.5}$ concentration exceeding WHO air quality standards [36]. The findings of this study support this assertion. The results of $PM_{2.5}$ show that majority of the data set for countries like India are outliers with the highest reading set at 436g/m^3 (Fig. 3). The lower limit for Bangladesh was 21.767g/m^3 and the upper limit was 110.524g/m^3 with the majority of the data set lying between 61.8g/m^3 to 89.75 g/m^3 with a mean concentration of 77.2 g/m^3. Apparently, the range for the pollutant measured in Indonesia was from 12.20 to 31.86g/m^3, with an upper limit of 42.69 g/m^3 and lower limit of 5.39 g/m^3 (Fig. 3). The mean concentration was 114.29 g/m^3 (Fig. 3).

Descriptive analysis of NO_2 in Southeast Asian region and Africa countries

Meanwhile, South Africa had two results as outliers, with the highest at 124.28g/m^3. The observed upper limit was found to be 56.9g/m^3 with a mean of 16.11g/m^3. From (Fig. 4), Nepal, Bhutan, Sri Lanka and Myanmar all had concentrations of NO_2 at 0g/m^3 with Myanmar showing mean value of 1.23g/m^3. Similar observations have been reported in 2021 in their study of about 398 cities where they authors reported that an exposure to a minimum of 10g/m^3 NO_2 can cause mortality. Thailand, Indonesia, and Bangladesh had upper and lower limits of 0 to 36g/m^3, 0 to 54.6g/m^3 and 0 to 73.7g/m^3 (Fig. 4). India had majority of its readings as outliers with the highest outlier being 68.55g/m^3. The entire data set for Indonesia lay between 6.77 to 26.9g/m^3, with Thailand having 0 to 16.44g/m^3 and Bangladesh 0 to 37.4g/m^3 (Fig 4). Additionally, research shows that NO_2 may contribute to asthma and epidemiological studies shows a link between NO_2 and mortality [34-37]. Largely, the effects of PM_{10} and NO_2 goes beyond respiratory effects. NO_2 concentration show a non-available or 0g/m^3 concentration of this pollutant in 9 out of the 11 African countries. Only South Africa and Benin showed results for monitoring of NO_2 concentration. The values for the interquartile range for Benin are 106.6 to 114.29g/m^3 with an upper limit of 129.6g/m^3 and a lower limit of 106.6g/m^3. These observations are consistent with Adebayo-Ojo et al. [38]. In their study they affirm that many African countries have higher NO_2 concentration and NO_2 may contribute to asthma and epidemiological studies shows a link between NO_2 and mortality [37]. Hisamuddin et al.[39] and Sopian et al.[40] indicates that it can even increase the formation of micronuclei in children living close to industrial areas. This shows that air pollution is positively associated with increased mortality. Reports indicate that some 89% of those premature deaths occurred in these countries are associated with air quality because $PM_{2.5}$ greatly has negative effect on human health, due to its ability to penetrate into the respiratory system [41].

Descriptive analysis of $PM_{10\ and\ 2.5}$ in African countries

Almost all African countries had measured concentrations for $PM_{2.5}$, except for Ghana and Mauritius (Fig. 4). It was only Uganda and Madagascar that had outliers at 104g/m^3 and 128g/m^3 respectively. The upper and lower limits for countries were; Nigeria (89.55 to 26g/m^3), Cameroon (132 to 49g/m^3) and Senegal (20.5 to 42g/m^3) (Fig. 4). Generally, predictions suggests that heart related mortality increases with 10g/m^3 daily increase in $PM_{2.5}$ concentration [42, 43]. The Findings of this study correlate the report of the WHO, (2021), They indicate that $PM_{2.5}$ has exceeded 26µg/m^3 across more than half of Africa [13] have also reported in a previous study in African countries that $PM_{2.5}$ ranged from 40 to 260 µg/m³ on outdoor air pollution in African cities. $PM_{2.5}$ pollution in Africa exhibits distinctive characteristics, such as the utilisation of biomass fuels for domestic and commercial purposes, reliance on kerosene and diesel generators for illumination, and the practice of burning waste and agricultural materials. According to global satellite data, Africa has the highest frequency of fire incidents, a recognised contributor to PM emissions. It is estimated that the entire population of Africa inhabits areas where annual $PM_{2.5}$ concentrations beyond WHO standards [44, 45].

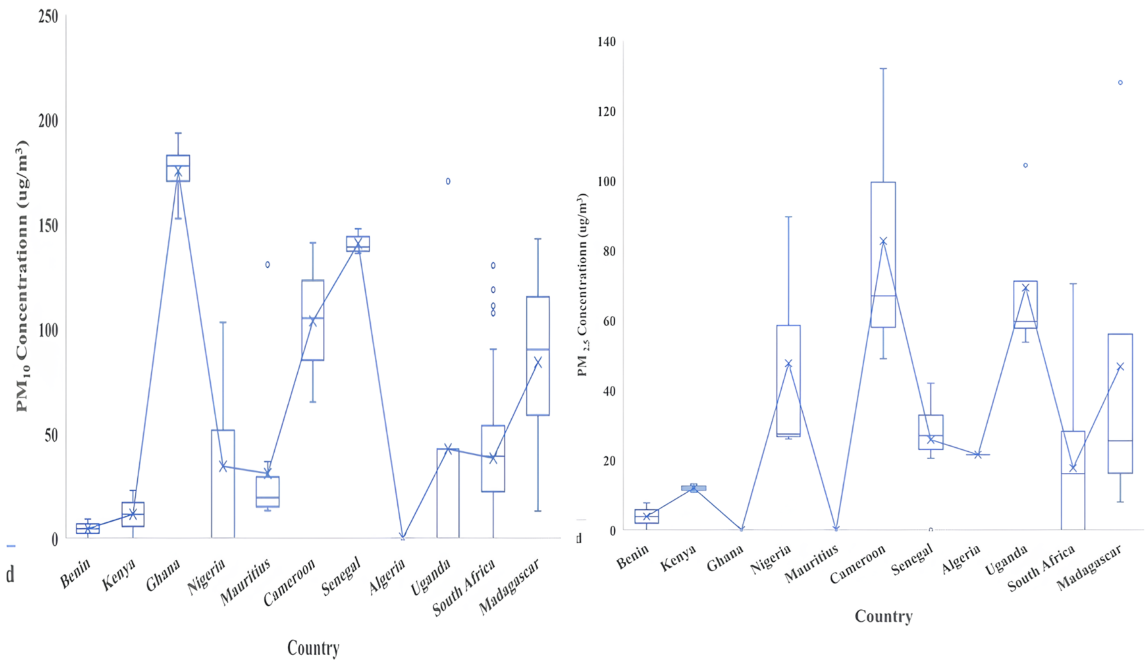

Fig. 4. PM (2.5 and 10) concentration across selected African countries

Table 1. Overall mean decade concentration of air pollutants South East Asian Region (SEAR)

Country	PM_{10} (µg/m³)	$PM_{2.5}$ (µg/m³)	NO_2 (µg/m³)
Bangladesh	139.25	77.25	19.77
Bhutan	97.38	0	0
India	99.75	11.49	4.94
Indonesia	19.14	20.87	19.62
Sri Lanka	25.6	17.33	0
Myanmar	57.52	4.09	1.24
Nepal	33.59	41.47	0
Thailand	41.01	11.33	9.045
Annual Standards (WHO, 2021)	15	5	10
Mean Concentration of SEAR	64.15 ± 40.38	22.98 ± 23.65	8.83 ± 7.99
AQI*	55.53	74.61	

*AQI calculated based on mean concentration of pollutants measured in SEAR from 2010 – 2020. These values aim to show the changes in concentration over the years; they are not to judge the most polluted country.

Aggregated air quality assessment of Southeast Asian region and Africa countries

Results presented in Tables 1 and 2 are cumulative averages of a 10-year air quality monitoring data from the WHO website. The results show that the mean PM_{10}, $PM_{2.5}$, and NO_2 concentration for the entire region were above the annual standard limit of 15g/m^3, 5g/m^3 and 15 g/m^3 respectively set by the WHO. The 10 years mean concentration of the SEAR for PM_{10}, $PM_{2.5}$ and NO_2 were 64.15 ± 40.38g/m^3, 22.98 ± 23.65 g/m^3, and 8.83 ± 7.99 g/m^3 (Table 1). Meanwhile, the data for the African region also presented 60.51 ± 55.29 g/m^3, 29.75 ± 26.89 g/m^3, and 11.86 ± 32.72g/m^3 (Table 1). The AQI obtained as presented in Tables 1 and 2 showthat air pollution is a true challenge. observed in the study regions. Additionally, the results of the air quality index for PM_{10} and $PM_{2.5}$ stands at 57.73 and 96.59 for the African Region and a 55.53 and 74.61 for SEAR. These AQI values indicate an Air quality that is satisfactory. Meanwhile, both regions exceeded the WHO permissible limits for $PM_{2.5}$ & 10 (Tables 1 & 2) while the concentration of NO_2 for SEAR was less than the acceptable annual limit set by WHO (Table 1). PM_{10} is linked to asthma, cardiovascular diseases, and tumor growth [46–48]. Just like being highlighted by [49] this study also re-echoes the debate of economic growth and environmental pollution in realms of the low- and middle-income country.

Table 2. Overall mean concentration of air pollutants in African countries

Country	PM 10 (μg/m^3)**	PM 2.5 (μg/m^3)**	NO_2 (μg/m^3)**
Benin	4.55	3.85	114.30
Kenya	11.38	11.96	0
Ghana	175.37	0	0
Nigeria	34.33	47.66	0
Mauritius	30.86	0	0
Cameroon	103.67	82.67	0
Senegal	140.68	25.81	0
Algeria	0	21.53	0
Uganda	42.6	69.30	0
South Africa	38.22	17.73	16.11
Madagascar	84	46.75	0
Annual Standards (WHO, 2021)	15	5	10
Mean Concentration of Africa	60.51 ± 55.29	29.75 ± 26.89	11.86 ± 32.72
*AQI	53.73	96.59	

*AQI calculated based on the mean concentration of pollutants measured in Africa from 2010 – 2020. ** These values aim to show the changes in concentration over the years; they are not to judge the most polluted country.

These higher values may partly be associated with climate change. Reports also have it that, climate change may also account for the high levels of particulate matter in developing countries, and already temperature in the region is observed to be high and will rise within this century [50]. The relationship between climate change and air pollution is still been studied. However, Fuzzi et al. [50] has hinted that formation and geographical distribution of air pollutants may be affected by climate change. Again, this indirectly means that populations in the urban areas where these measurements were taken are exposed to relatively high volumes of particulate matter. One major factor that contributes to excessive particulate matter concentration in these regions is the smoke haze that dominates the entire landscape as a result of biomass burning, compromising the air quality [51–53] and contributing to lungs malfunctioning and increased hospitalisation. Othman et al. [28] and Ramakreshnan et al. [54] The findings of this study on particulate matter 2.5 differs from the reported values per [55,43] and agrees with that of [56] who asserts that $PM_{2.5}$ concentrations have increased by 65% in the last decade. Similarly, accounts per the world bank [57] assert that a 3.1–3.8% urban growth is observed in Africa annually, corresponding to excessive air pollution. This observation supports the findings of Fang et al. [58], who indicates in a trend analysis study into 2036 on the state of $PM_{2.5}$ that Southeast Asia and Sub-Saharan Africa are among the regions which are disproportionately affected by high concentrations of $PM_{2.5}$. Additionally, this issue is further exacerbated by the concerns that monitoring of these parameters are less stringent. Again, in Africa, the use of predominantly old fleet of vehicles for commuting is very high and exhaust emissions are not regulated in most African countries. Burning of household waste and biomass as well as lack of urban planning as the number of vehicles keeps increasing on the continent [4,55,59,60] are all possible factors that could have contributed to the observed high readings. It is, however, not surprising that the African countries, even with limited resources and monitoring of air pollutants, still show excessively high pollutant concentrations.

Principal component analysis and correlation

The correlation matrix presented in Table 3. shows the correlation between temporal coverage for PM_{10}, $PM_{2.5}$ and NO_2 and the concentration of these pollutants. There exists a weak positive correlation between PM_{10}, and $PM_{2.5}$ of 0.130 in the overall data of air quality monitoring in the African and Southeast Asian regions. Meanwhile, $PM_{2.5}$ and NO_2 also have a weak positive correlation of 0.214. Similar observations have been reported by [37] and [61]. Partly, these observations may have been as a result of consensus on NO_2, which highlights the pollutant as a major indicator for other pollutants rather than relating to health effects. Again, pooled data from multiple continents found greater mortality with $PM_{2.5}$ than NO_2 [37, 62]. Meanwhile, NO_2 concentration and $PM_{2.5}$ temporal coverage had a weak positive correlation of 0.249 (Table 3). Again, a moderately weak positive correlation of 0.405 is observed between $PM_{2.5}$ temporal coverage and $PM_{2.5}$ concentrations, while a similar correlation is observed between $PM_{2.5}$ temporal coverage and PM_{10} temporal coverage at 0.508. Additionally, PM_{10} temporal coverage and $PM_{2.5}$ temporal coverage had a moderate positive correlation of 0.571 and 0.560, respectively, with NO_2 temporal coverage (Table 3). These findings demonstrate a clear path to monitoring air quality. The moderate correlation of various parameters presented in this study informed a Principal Component Analysis (PCA). The PCA conducted on the decade data showed a KMO test for sampling adequacy of 0.644 and a p-value < 0.005 (Table 4). From the analyses, the PCA have shown that the existing variance in the data set is coming from components 1 and 2. They contribute to 59.3% of the entire variance (Table 5). This observation demonstrates the variability that exits in the data

Table 3. A decade correlation matrix between particulate matter and temporal coverage measured African and South East Asian Region.

Correlation	PM_{10} Conc.	$PM_{2.5}$ Conc.	NO_2Conc	PM_{10} Temporal coverage	$PM_{2.5}$ Temporal coverage
PM_{10} _concentration	1.000	0.130	-0.018	-0.070	-0.126
$PM_{2.5}$ _concentration	0.130	1.000	0.214	0.073	0.405
NO_2_concentration	-0.018	0.214	1.000	0.214	0.249
PM_{10} _temporal coverage	-0.070	0.073	0.214	1.000	0.508
$PM_{2.5}$ _temporal coverage	-0.126	0.405	0.249	0.508	1.000
NO_2_temporal coverage	-0.096	0.103	0.361	0.571	0.560

Table 4. Showing KMO and Bartlett's test for the data

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.644
Bartlett's Test of Sphericity	Approx. Chi-Square	2354.205
	df	15
	Sig.	0.000

The PCA conducted in this study showed how these two (PM_{10} and $PM_{2.5}$) pollutants were related. $PM_{2.5}$ is mostly regarded as a subset of PM_{10}. They weighed strongly on component 2 (Table 6), which can be collectively referred as particulate matter. Largely, this is because they are pollutants originating from similar sources and different per their sizes [17, 56]. The common sources for the emission (Vehicle emissions, burning of biomass, industrial emission). Collectively, they are regarded as air contaminants with related health consequences. Additionally, because $PM_{2.5}$ are formed from both the homogenous and heterogeneous chemical reactions that exist between the precursors of the pollutant (NO_2 and SO_2), they are able to form $PM_{2.5}$ from photochemical reactions and this sometimes depends on seasonal and geographical changes [63–65]. The buildup of these pollutants in the air of these low-and middle-income countries have been hinted to be chiefly caused by anthropogenic activities like fossil fuel combustion, air pollutant emission from traffic, open waste burning [61] and these are the major activities going on in these regions under study. Meanwhile, component 1 had PM_{10} temporal coverage, PM_{10} temporal coverage, NO_2 temporal coverage and NO_2 concentration weighing strongly on the component (Table 6).

Table 5. Total Variance Explained by the data set

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.395	39.915	39.915	2.377	39.622	39.622
2	1.166	19.428	59.343	1.183	19.721	59.343
3	0.875	14.579	73.923			
4	0.824	13.740	87.663			
5	0.418	6.964	94.627			
6	0.322	5.373	100.000			

Table 6. Rotated and transformation component matrix of the data set

	Component	
	1	2
PM_{10}_concentration	-0.222	0.693
$PM_{2.5}$_concentration	0.322	0.761
NO_2_concentration	0.513	0.251
PM_{10}_temporal coverage	0.772	-0.155
$PM_{2.5}$_temporal coverage	0.816	0.159
NO_2_temporal coverage	0.836	-0.101

Testing hypotheses

H1; There is significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2 and the year of measurement on the concentration of PM_{10} measured in the past 2 decades.

To analyze the hypothesis presented in this study on particulate matter 10, the multiple linear regression was employed at 95% confidence level. The analysis showed a significant model summary; F(4,1801) = (30.034,P < 0.005 (P= 0.000), Adjusted r2 = 0.060, r2 = 0.063) (Table 7). The r2 of 0.063 simply means that, only 6.3% of variation in PM_{10} is explained by temporal coverage of $PM_{2.5}$, NO_2 and PM_{10}. Additionally, the regression as a whole is statistically significant based on the p-values and F-statistics presented above, indicating that there is evidence of a regression relationship between PM_{10} (independent variable) and the dependent variables (temperature coverage of $PM_{2.5}$, NO_2, P.M10 and year). The regression analysis showed a constant = 8701.399. In addition, studies employing linear regression to explore relationships among pollutants ($PM_{2.5}$, PM_{10}, NO_2) have demonstrated that correlations and predictive relationships are context-dependent and that multicollinearity and non-linear interactions between variables can further complicate the variance explained by simple linear models [66]. Hence, this pattern of modest explained variance is consistent with other regional air pollution regression analyses indicating that meteorological factors and related covariates explain only part of the observed variability in PM_{10}

A model fit equation that can be used for predicting PM_{10} concentration based on temp coverage is presented below; Yi = 0 +1X1 +2X2+3X3+4X4

PM_{10} = 8701.399 – 0.046 (temp_Cov $PM_{2.5}$) + 0.07 (temp_Cov NO_2) + 0.014 (temp_Cov PM_{10}) – 0.023 (Year) – eqn (1). Invariably, this equation suggests that the baseline value for PM_{10} when all other variables are zero is 8701.399. A unit increase in temporal coverage of $PM_{2.5}$. Simply put, when the percentage of time during the year in which $PM_{2.5}$ data was available, the concentration of the PM_{10} pollutant decreased by 0.046. While for every unit increase in year, PM_{10} concentration decreases by 0.023 (Table 7). These two negative values indicate that; for $PM_{2.5}$, this may suggest that a more complete on temporal coverage of $PM_{2.5}$ helps advance the accuracy hence potentially reducing overestimation of PM_{10} whereas for the year, it shows a slow upward trend in PM_{10}. On the other hand, a 0.007 and 0.014 increase is observed for every temporal coverage of NO_2 and PM_{10} concentration of PM_{10} increases by 0.007 and 0.014. This also suggests that a better coverage for these pollutants mean higher estimates of PM_{10} concentration.

Table 7. Model Summary for PM_{10} concentration prediction via temporal coverage and year

Predictor variables	Standardized β coefficients	t	Sig	Hypothesis
Temperature Cov. of $PM_{2.5}$	-0.046	-1.563	0.118	Not supported
Temperature Cov of NO_2	0.007	0.242	0.809	Supported
Temperature Cov of PM_{10}	0.014	-0.483	0.629	Supported
Year	-0.023	-9.335	0.00	Not supported

Dependent variable; PM_{10} Concentration

H2; There is significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2 and the year of measurement on the concentration of $PM_{2.5}$ measured in the past 2 decades.

Additionally, to test the hypothesis related to particulate matter ($PM_{2.5}$), a multiple linear regression analysis was conducted at the 95% confidence level. The model summary was statistically significant, with $F(4, 1801) = 118.855$, $p < 0.005$ ($p = 0.000$), $R^2 = 0.202$, and adjusted $R^2 = 0.200$ (Table 8). The coefficient of determination ($R^2 = 0.202$) indicates that approximately 20% of the variance in $PM_{2.5}$ concentration is accounted for by the temporal coverage of $PM_{2.5}$, PM_{10}, NO_2, and year. The overall statistical significance of the model, based on the F-statistic and associated p-value, provides evidence of a linear association between $PM_{2.5}$ concentration and the explanatory variables included in the model. The regression analysis produced an intercept (β_0) of −1631.866.

Overtly, the model equation presented to predict the concentration of the dependent variable $PM_{2.5}$ indicates that when all other variables are zero, the baseline value for $PM_{2.5}$ is -1631.866. A unit increase in temporal coverage of $PM_{2.5}$, PM_{10}, NO_2 and year will contribute to a decrease in concentration of $PM_{2.5}$ by 0.521, 0.142 0.123 and 0.077. These negative values may suggest that if there is a more complete temporal coverage of $PM_{2.5}$, P.M10, NO_2 this will help advance the accuracy, hence potentially reducing overestimation of $PM_{2.5}$ This observation is supported by Porcheddu et al. [24]. The authors report that when temporal coverage is complete, it improves predictive accuracy and reduces bias, hence enhancing model fit. Zong et al. [25] in their study demonstrated that when temporal coverage is continuous, it produces high-quality models

H3; There is a significant positive impact of temporal coverage of PM_{10}, $PM_{2.5}$, NO_2 and the year of measurement on the concentration of NO_2 measured in the past 2 decades.

In consonance with the preceding analysis, a separate multiple linear regression analysis was conducted to examine the hypothesis related to NO_2 concentration at the 95% confidence level. The model summary was statistically significant, with $F(4, 1801) = 150.058$, $p < 0.005$ ($p = 0.000$), $R^2 = 0.250$, and adjusted $R^2 = 0.248$ (Table 9). The coefficient of determination ($R^2 = 0.250$) indicates that 25% of the variance in NO_2 concentration is explained by the temporal coverage of $PM_{2.5}$, NO_2, PM_{10}, and year. The statistical significance of the F-statistic and associated p-value provides evidence of a linear association between NO_2 concentration and the explanatory variables included in the model. The regression intercept (β_0) was −3209.051. The intercept represents the estimated NO_2 concentration when all explanatory variables are equal to zero. The regression coefficients indicate a negative linear association between NO_2 concentration and temporal coverage of $PM_{2.5}$, and positive linear associations with temporal coverage of NO_2, temporal coverage of PM_{10}, and year, holding other variables constant.

The regression results indicate that temporal variables have pollutant-specific effects on $PM_{2.5}$ concentrations. The temporal coverage related to $PM_{2.5}$ was not statistically significant ($\beta = -0.029$, $p = 0.279$), suggesting that temporal coverage alone does not substantially account for $PM_{2.5}$ variability when considering other temporal and pollutant-related parameters. This finding aligns with recent research indicating weak or non-significant connections between temporal coverage and $PM_{2.5}$ in multivariate frameworks, especially if non-linear and seasonal influences predominate particle behavior [67, 68].

Table 8. Model Summary for $PM_{2.5}$ concentration prediction via temporal coverage and year

Predictor variables	Standardized β coefficients	t	Sig	Hypothesis
Temperature Cov. of $PM_{2.5}$	-0.521	19.192	0.000	Not supported
Temperature Cov of NO_2	-0.142	-5.061	0.000	Not supported
Temperature Cov of PM_{10}	-0.123	-4.595	0.000	Not supported
Year	-0.077	3.413	0.001	Not supported

Dependent variable; $PM_{2.5}$ Concentration

Table 9. Model Summary for NO_2 concentration prediction via temporal coverage and year

Predictor variables	Standardized β coefficients	t	Sig	Hypothesis
Temporal Cov. of $PM_{2.5}$	-0.029	-1.083	0.279	Not supported
Temporal Cov of NO_2	0.251	9.195	0.000	Supported
Temporal Cov of $P.M_{10}$	0.024	-0.932	0.352	supported
Year	0.368	16.742	0.000	Supported

Dependent variable; NO_2 Concentration

The temporal coverage of NO_2 had a notable positive correlation with $PM_{2.5}$ ($\beta = 0.251$, $p < 0.001$), confirming the robust meteorological relationship between the parameter and the temporal dynamics of NO_2. Comparable research indicates that temporal coverage affects NO_2 levels via boundary-layer height, photochemical processes, and seasonal emission patterns, which subsequently exert an indirect impact on $PM_{2.5}$variability [67-69].
This strengthens the assumption that temperature influences $PM_{2.5}$ chiefly through its interaction with gaseous precursors, rather than through direct regulation of particle mass. The temporal coverage influence on PM_{10} was not statistically significant ($\beta = 0.024$, $p = 0.352$), corroborating findings that coarse particulate matter is predominantly influenced by mechanical processes including resuspension and wind-driven transport rather than just by temperature fluctuations [69]. The year variable was identified as the most significant predictor ($\beta = 0.368$, $p < 0.001$), demonstrating a considerable temporal influence on $PM_{2.5}$ concentrations. Prolonged air-quality investigations consistently indicate substantial interannual variations in $PM_{2.5}$, influenced by emission regulations, alterations in energy consumption, and changing meteorological patterns, all of which are statistically represented by the incorporation of calendar year [67, 68].

Conclusion

This study has given insight into the

burgeoning air pollution challenge that exists in the African region and SEAR using a decade of data. The study however, through the use of principal component was able to reduce the size of the data into 2-dimensions and highlighted the potential associated health risks of the pollutants measured. Generally, the mean annual PM_{10} concentration for the SEAR and African countries were 64.15 ± 40.38g/m^3 and 60.51 ± 55.29 g/m^3 where as that of $PM_{2.5}$ was 22.98 ± 23.65g/m^3 and 29.75 ± 26.89g/m^3 respectively and that of NO_2 was 8.83 ± 7.99g/m^3 and 11.86 ± 32.72g/m^3 which are all above acceptable limits, demonstrating the need for urgent measures to bring these values to standard levels. The model developed in this study has also indicated that PM_{10} temporal coverage can be used to explain to some extent the variation in NO_2 concentration. Indicating that there is some form of relationship between better cover for PM_{10} and ability to estimate NO_2.

Recommendations

This study has highlighted the air pollution monitoring in developing countries, per the findings of this research, the data suggest that developing countries are advancing steps in air pollution monitoring, but more efforts still have to be in place to measure these contaminants. Environmental monitoring of air pollutants contributes to the global fight to improve air quality. Governments should invest in the monitoring of these air pollutants and also fund institutions to offer support to developing countries to increase their coverage of measurement. Various research should be conducted on training models to develop a comprehensive assessment of the state of air pollutants in developing countries. The high local industrial activity, like transportation, biomass fuels, and open burning that exist in the region makes people exposed to potential respiratory risk hence consistent and robust measurement regimes for especially $PM_{2.5}$ and NO_2 must be rolled out as a matter of urgency.

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Competing interests

The Authors of this article declare no conflict or competing interest in this research.

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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 authors.

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