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ORIGINAL CONTRIBUTION

Assessment of the spatio-temporal dynamics of the atmospheric pollution concentration over the Haldia urban area using AHP based geomatics engineering

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ABSTRACT

Air pollution is one of the major concerns affecting human health and the environmental quality in many advanced and industrial cities across the globe. In this research, an attempt has been made to identify the spatio-temporal change in the concentration of the atmospheric pollutants in the Haldia Development Authority (HDA) area of West Bengal, India from 2016 to 2018 using the Analytical Hierarchy Process (AHP) and geomatics engineering based on the point pollution data collected from the Central Pollution Control Board (CPCB), Govt. of India. The spatial distribution patterns of CO, SO_2, NO, NO_2, and NO_x were identified using the Inverse Distance Weighted (IDW) interpolation technique in the period seasonally and yearly. The results showed that the concentration of these air pollutants is comparatively less during the summer month of April, while it is quite high in the winter month of December. Except for the concentration of SO_2, all the other parameters showed a concentration in the fringing parts of the HDA area. The possible causes behind low concentrations of the summer season in the source industrial areas are the maritime location, wind direction, and prevailing wind speed. The cumulative air pollution concentration maps from 2016 to 2018 showed the alarming increase of the atmospheric pollution concentration in the HDA area with the passage of time.

KEYWORDS: AHP; IDW; Geomatic Engineering; CPCB; Cumulative Pollution Concentration.

1. INTRODUCTION

Atmospheric pollution is of grave concern to the urban planners and policy decision-makers in contemporary urban society. The increasing burden of population and industrial advancement in cities lead to domestic, vehicular, and industrial emissions causing adverse effects not only to the city dwellers but also to the environment and micro-climate. Industrial and vehicular emissions particularly in form of harmful gases and Suspended Particulate Matter (SPM) are responsible for increasing discomfort and deterioration of the cultural and aesthetic patrimony in urban centers[1]. Epidemiological studies showed that outdoor air pollution causes cardiovascular and chronic respiratory diseases that lead to possible and painful death [2-4]. According to the report of the World Health Organization (WHO) air pollution is regarded as one of the ten causes of increased mortality in the world and around 0.8 million people die worldwide due to cardiovascular and respiratory diseases and lung cancer [5]. Out of 0.8 million, 0.15 million people represent from South and South East Asia [4]. Apart from the particulate matter (PM 2.5 and PM 10), harmful gases like CO_2, CO, SO_2, NO, NO_2, and NO_x causing various harmful effects to all living organisms in different ways. Therefore, it is essential to have a system that allows a pollution zonation to alert the inhabitants about the emergence of air

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pollution and facilitate managerial decisions made by urban planners and decision-makers [6, 7]. In this regard, geomatics engineering is considered a powerful and effective tool for designing and creating a spatial database of air pollution parameters from the point pollution values [8]. The system is capable of collecting, storing, analyzing data from different sources and provides clear, modifiable, predictable, and efficient results [9].

In India, the Air Quality Management (AQMS) was developed in 2006. The study examined the role of geoinformatics in air quality monitoring and established its suitability in air quality management [10]. In the United States, GIS is also used in air quality assessment studies [11]. Jha et al. (2011) [12] conducted a study in Port Blair to assess the concentration of SPM, SO_2, and NO_2 using the Inverse Distance Weighted (IDW) and Kriging interpolation methods. Kumar and Goyal (2011) [13] applied the Principal Component Analysis (PCA), Principal Component Regression (PCR), and Time Series Auto Regressive Integrated Moving Average (ARIMA) models to formulate and forecast daily air quality index in Delhi urban area from the Respirable Suspended Particulate Matter (RSPM), SO_2, NO_2, and SPM concentration data. Kumar et al. (2016) [14] conducted a study in Mumbai city to assess the concentration of the above-mentioned three air pollution parameters using geomatics engineering. Grossly, the remote sensing and GIS techniques applied sophisticatedly and efficiently in air pollution management studies [15].

The application of Multi-Criteria Evaluation (MCE) in pollution studies is quite effective. It can be used in a variety of applications for spatial decision analysis and area management [16]. The primary task of MCE is to provide a standardized scale for several criteria to form a simple index of evaluation [17]. In the present research, an attempt has been made to identify the spatio-temporal pollution status of the Haldia urban area using the Analytical Hierarchy Process (AHP) and geomatics engineering. The objectives of the research are firstly to identify the time-series pollution concentration for selected atmospheric pollutants, secondly to assess the change in air pollution concentration, and finally to identify different zones of air pollution based on the AHP based spatial analysis.

2. STUDY AREA

The study area chosen for the current research is the Haldia Development Authority (HDA) area, located in the PurbaMedinipur district of West Bengal, India. The city is located approximately 125 Km South West of Kolkata near the mouth of the Hooghly River. The Haldia Township is bordered by the Haldi River, an offshoot of the Hooghly River. It is the hub of several petrochemical industries and being developed as a major trade port of Kolkata. The city is located at 22°03´ N and 88°06´ E at an average elevation of 8 m. The coverage area of the HDA is approximately 100 sq. Km. The atmospheric temperature ranges from 7° C to 22° C in winter and from 24° C to 42° C in summer. The average annual rainfall is 1580 mm [18-20]. The rainfall occurs mainly from May to September. The HDA has got more than 25 large-scale industries with a huge amount of chimney emission. Major industries include IOCL, HPL, MCCI, etc.

3. DATABASE AND METHODOLOGY

The point concentration data of the available parameters, namely, CO_2, CO, SO_2, NO, NO_2, and NO_x were collected from the Central Pollution Control Board (CPCB). The daily database was collected for different stations adjacent to the study area. The analysis was done considering April and December as pre-monsoon and post-monsoon months respectively from 2016 to 2018. Monthly mean values were estimated for these parameters. For interpolation from the point feature class to the raster surface, the Inverse Distance Weighted (IDW) method was used.

The method assumes that each measured value of a point has a neighborhood influence that reduces with the increasing distance. In other words, the higher weights are given to the points located closer to the prediction location (Fig. 1). The weight is proportional to the inverse of the distance raised to the power value p. With the increase of p, the weights for distant points reduce rapidly. The raster surface generated using the IDW depends on the selection of the p-value and the search neighborhood strategy. The output raster is sensitive to clustering and the presence of outliers.

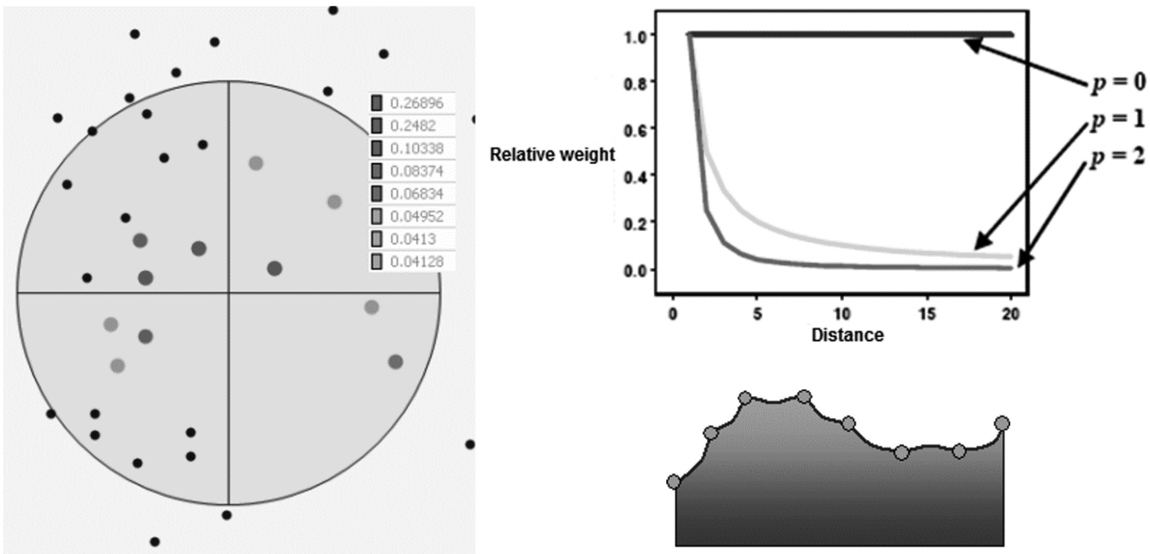

Figure 1: Functioning of the Inverse Distance Weighted (IDW) method

The output value for a cell is limited to the range of values used in the IDW. Since it is a weighted average, the values cannot surpass the highest and lowest input values and causing no ridges and valleys in the distribution. The best results from the IDW are obtained in densely distributed points. The influence of such input points on the interpolated values is isotropic [21]. Various interpolation tools may handle the data condition differently. For example, in some cases, the first coincident point encountered is used for the calculation; in other cases, the last point encountered is used. This may cause some locations in the output raster to have different values than the expected ones. For this purpose, these coincident points need to be removed. The ‘Collect Events’ tool of the ‘Spatial Statistics’ toolbox of ArcGIS software was used to identify the coincident points. The barriers option is used to specify the location of linear features known to interrupt the surface continuity. These features do not have z-coordinates / values. The IDW only uses the x, y-coordinates for linear feature; therefore no z-values are necessary to provide for the left and right sides of the barrier. In the present research, the shoreline or the land-water boundary was considered as the barrier.

Weights of selected atmospheric pollutants were assigned to identify the potential air pollution zones. Based on the prior knowledge, the relative importance of the pollutants in the air pollution zonation was assessed. The Analytical Hierarchy Process (AHP) was used to calculate the normalized weight. The technique proved to be very efficient for Multi-Criteria Evaluation (MCE) [22]. It converts the subjective assessment of relative importance to a set of overall scores or weights. The method is the choice between the alternatives or finding priorities in the spatial distribution of air pollution in an area. The AHP employs an underlying nine-point recording scale to rate the relative preference (Table 1) on a one-to-one basis of each criterion [23].

Table 1: Nine point rating scale of the pair-wise comparison

Intensity of Importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extremely high importance
2, 4, 6, 8	Intermediate values

Factor weights were calculated from the pairwise comparison matrix considering specific values and vector calculation. The particular vector corresponding to the largest specific value of the matrix provides the relative priorities of the factors. In other words, if one factor has a preference, its specific vector component is larger than that of the other [24]. The pairwise comparison matrix contains options of multiple paths by which the relative importance of the factors can be estimated. Thus, to develop judgments, it is possible to calculate the degree of consistency. Consistency Ratio (CR) was calculated subsequently taking the ratio between the Consistency Index (CI) and Random Index (RI). CR indicates the probability that the matrix judgments were randomly generated. RI depended on the matrix order given by Malczewski (1999) [25].

$CR = \frac{CI}{RI}$ ---------------Equation (1)

The Consistency Index (CI) was estimated using the following equation 2.

$CI = \frac{(\lambda_{max} - n)}{(n-1)}$ -----Equation (2)

[Where, λ_{max} = largest specific value of the matrix, n = order of matrix]

The value of CR ranges from 0 to 1. If it is close to 1, then it will indicate that the matrix rating was randomly generated. If it falls to <=0.1 then it offers reasonable consistency [25]. The adopted methodology to conduct the present research is described below (fig. 2).

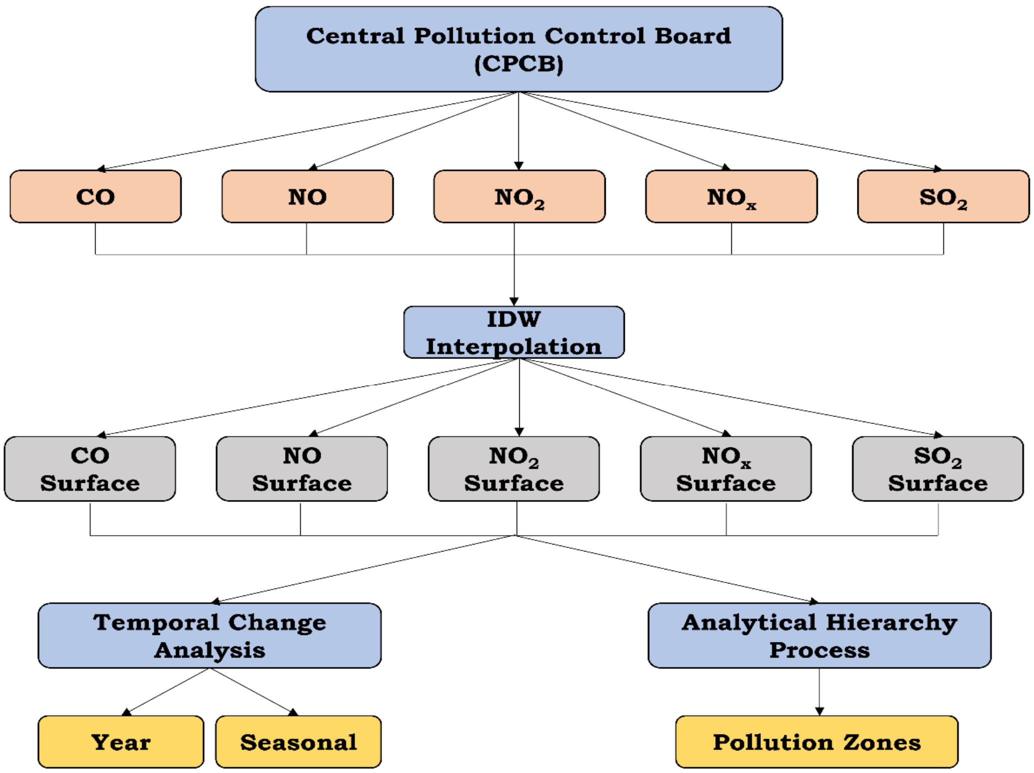

Figure 2: Overview of the adopted methods

4. RESULTS AND DISCUSSION

In order to study the temporal variation of the selected atmospheric pollutants over the HDA area, it was observed that a linear trend persists as the pollution level gradually decreases in the summer season and increases gradually in winter. The possible reason for such decreasing trend of pollution concentration in summer is the maritime location of the study area. The proximity of the Bay of Bengal results in high wind speed during the summer season causing the dispersion of the air pollutants. Conversely, gentle or low winds during the winter season cause the pollutants to stay for more time over the HDA area. The CO concentration varied from 0.7027 µg/m^3 to 0.7057 µg/m^3 in April 2016. It was reduced to in the range of 0.647 µg/m^3 to 0.648 µg/m^3 in April 2017 and decreased farther ranging in between 0.3415 µg/m^3 and 0.3468 µg/m^3 in April 2018. However, in the winter months, the concentration increased a lot. It varied from 2.143 µg/m^3 to 2.169 µg/m^3 in December 2016. Though the concentration was reduced to 1.961 µg/m^3 to 1.993 µg/m^3 in December 2017. A similar trend was also observed in the concentration of NO, NO_2, and NO_x. Striking seasonal variation was observed in the concentration pattern. The wintertime concentration is almost 2-4 times the summertime concentration. Also from 2016, the concentration reduced significantly in 2017. However, in the case of SO_2, the concentration amount increased in course of time. In April 2016, the SO2 concentration was very low ranging from 0.000009 µg/m^3 to 0.26 µg/m^3. However, it was increased in the range of 16.40 µg/m^3 to 16.64 µg/m^3 in April 2018. Wintertime variation is also in the same range varying from 17.16 µg/m^3 to 16.64 µg/m^3 in December 2016 to the range of 19.08 µg/m^3 to 19.68 µg/m^3 in December 2017.

The spatial distribution patterns (fig. 3) for all the air pollution parameters show that the concentration is lowest in the source areas covering the industrial regions of the HDA. The concentration increases outwards. Therefore, the fringing areas are having harmful effects as the concentration levels are quite high there.

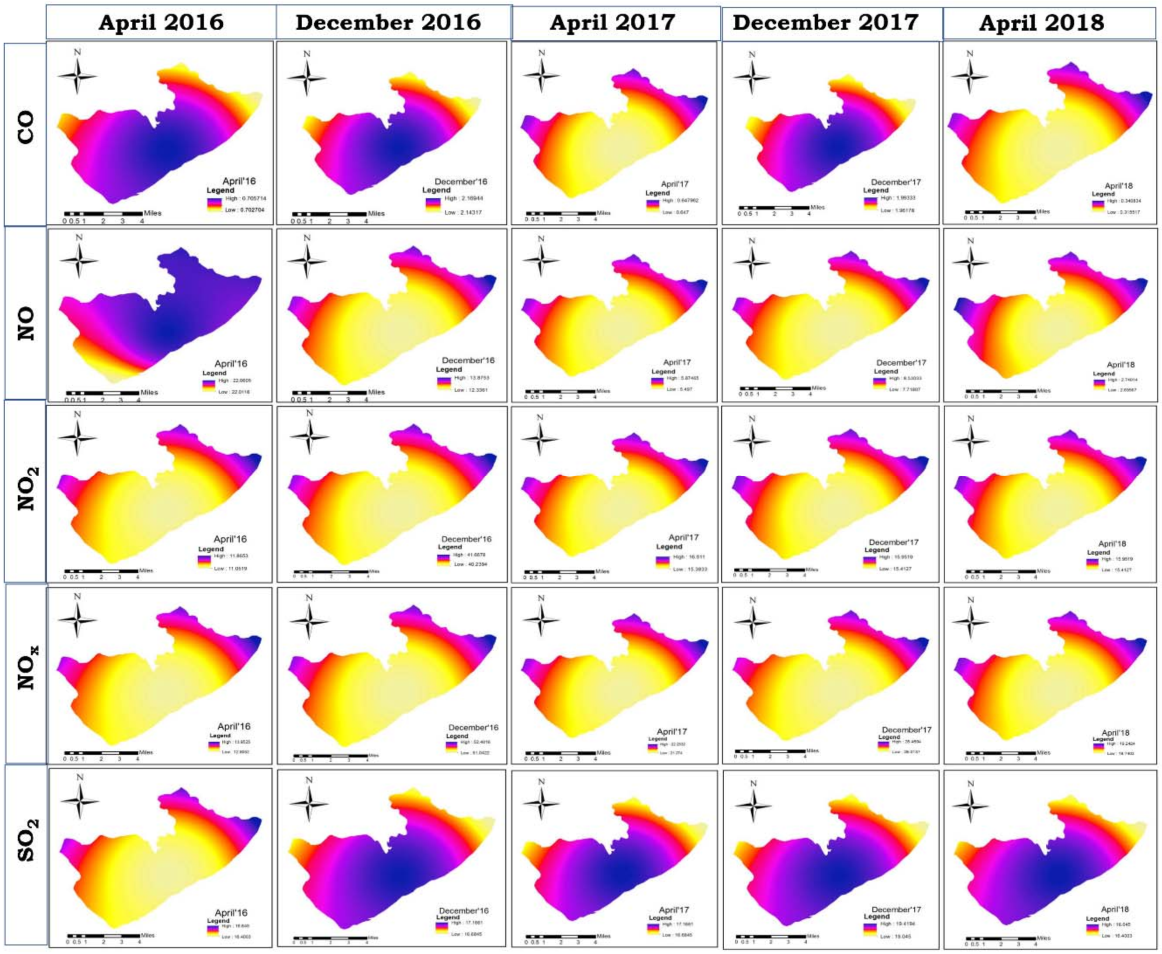

Figure 3: Distribution of selected atmospheric pollution parameters

The AHP shows the CI = (5.033375– 5) / (5 – 1) = 0.01, CR = (0.01 / 1.12) = 0.01. Therefore, the CR < 0.10 indicates a reasonable level of consistency in the pairwise comparison (Table 2). So priority order responsible for pollution is SO_2> NO_2> NO_x = NO > CO, Figure 4 shows the air pollution zones of the HDA from April 2016 to April 2018 based on the cumulative concentration effect of the air pollution parameters selected in this study. The pollution level is quite low at the source areas where most of the large-scale industries are located. The harmful air polluting gases are emitted from the chimneys of these industries. Due to the maritime location of the HDA, the inland wind direction, and wind speed causing the concentration of air pollutants very low at the source areas and these increase rapidly outward towards the human settlements located at the boundary areas of the HDA.

Particulars	CO	NO	NO_2	NO_x	SO_2	GEOMEAN	CORR. GEOMEAN	
CO	**1**	0.333	0.333	0.200	0.140	0.045	0.044	0.229
NO	3.030	**1**	1	0.333	0.200	0.103	0.099	0.514
NO_2	3.030	1	**1**	0.333		0.103	0.099	0.514
NO_x	5.000	3.030	3.030	**1**		0.246	0.237	1.231
SO_2	7.143	5.000	5.000		**1**	0.538	0.519	2.547
Total	19.203	10.360	10.360	4.890	1.870	1.035	1.000	5.033

Table 2: Pairwise comparison matrix of the selected air pollutants

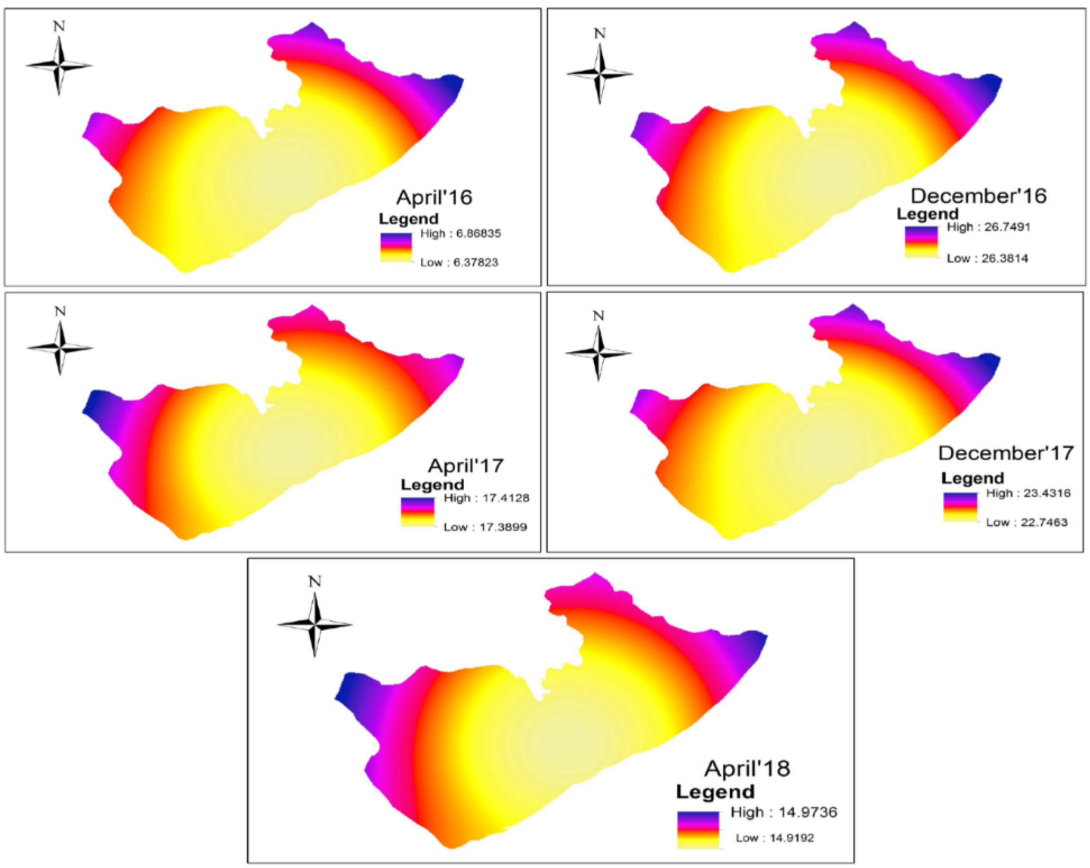

Figure 4: Spatio-temporal distribution of the atmospheric pollution of the HDA from 2016 to 2018

Like the individual air pollution parameters, the cumulative pollution concentration level also shows a higher effect in the wintertime than in summer. It was observed that due to some other reasons, the air pollution concentration was quite low in 2017. Therefore, both the summer and the wintertime concentrations showed low values. However, if we look at the concentration levels in April 2016 and April 2018, the temporal increase is more than double. Therefore, it can be concluded that air pollution is increasing at an alarming rate in the HDA in course of time, and proper management is required for chimney emission specifically in the winter period when the wind speed is less and the dispersion effect is low.

5. CONCLUSION

Urban atmospheric pollution owes its consequences since the industrial revolution that started almost three centuries earlier. The pollution concentration increases day by day keeping with the pace of the urban and industrial development in different parts of the world. In this research, an attempt has been made to identify different sectors of the HDA area that suffer from air pollution problems. In this regard, the AHP based geomatics engineering approach was used to estimate the spatio-temporal change in the concentration of the selected atmospheric pollutants. The AHP proved to be quite efficient in identifying the importance of such parameters in air pollution concentration zonation. Higher concentrations of CO, NO, NO_2, and NO_x were observed at the peripheral zone, but the distribution of SO_2 showed greater concentration in the source industrial areas. It was also observed that the summertime concentration is comparatively less than the wintertime concentration. However, the overall concentration of pollution is increasing in the HDA area from 2016 to 2018. The lack of availability of a regular record of the atmospheric data collected by the CPCB for all the stations posed challenges in the research. The continuity may provide better results and fewer approximations. However, the outcome of the research may be useful for the administrators and policymakers to monitor and control the harmful effects of atmospheric pollution in Haldia.

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