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Correlation between Air Quality Index and construction activities: An assessment in urban areas

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Abstract: *This study explores the Air-Quality Index (AQI) co-relation with building and road construction activities occurring in urban areas, analyzing how different scales, distances, and intensities of construction impact air quality. Data from various cities is examined to identify patterns in AQI fluctuations, with a focus on health implications. The study specifically investigates construction activities in Smart city Bhubaneswar and Cuttack, Odisha, over three-month timeframe, deriving correlative equations to establish these relationships. Based on Indian National Air Quality Standards, recommended construction limits are defined, suggesting 30–35 sites for Bhubaneswar and 8–10 for Cuttack within the selected timeframe. The correlative equations help to determine construction site limits to maintain air quality. The study highlights the role of pollution control authorities in mitigating air pollution under the smart city initiative. However, since construction activity is just one of several factors affecting air quality and the dataset is limited, the correlation analysis has certain constraints. Potential improvements and future research are also discussed.*
Keywords: *Air Quality Index (AQI); Regression Analysis; Smart City; Total Suspended Particulates (TSP), Urban Planning.*

I. INTRODUCTION

Air quality is a key environmental and urban development indicator. Current research studies indicate a link between pollutant concentration and infection rates, with dust being a significant contributing factor [1]–[4]. Bhubaneswar and Cuttack, the first smart city in Eastern India under the Smart City Mission, are experiencing extensive construction activity in recent years. The air quality index and pollutant concentration are crucial parameters for urban development, andit is necessary toanalyse thecorrelation of these parameters with construction sites for effective urban planning. As Odisha's capital, the Twin City has a population of 1,820,363 and widespread construction. A well-designed air quality-based model can aid local governance in managing environmental impacts, particularly during critical periods. This paper examines the connection between air quality metrics and the density of construction sites in the Twin City, offering insights for improved urban planning. Research indicates that the consistent daily concentration of over-all suspended-particulates, including Particulate Matter(10 and 2.5), increases substantially around construction sites [3]. Large-diameter particulate matter is a major pollutant from construction activities, significantly contributing to urban dust levels [5]. It is indicated in [1] that, the PM-10 releases from building construction areas contribute 44% of the overall PM-10 emissions linked to that region. Construction regions generate various pollutants on air, but identifying specific influential factors is complex. Emissions arise from machine-driven processes like transporting and processing different materials, drilling activity,milling activity and grading activities[4]. Additionally, construction vehicles on unpaved roads can produce emissions comparable to or even exceeding those from other site activities [3], [4], [6]. The mobile construction vehicles contribute major percentage of pollutants like NOxvehicle-related Particulate Matters[7]. Moreover, machinery exhaust from mechanical and thermal building processes further increases particle and trace gas emissions [8]. Environmental factors also play a role in air quality near construction sites. Wind, humidity, and temperature influence pollutant dispersion, with studies showing a strong correlation between emissions and wind speed or humidity, while temperature exhibits a weaker correlation [9].

Studies indicate that pollutants disperse from construction sites, with concentrations decreasing as distance increases [10]. Hitchins et al. [11] observed PM concentration changes along a roadside, noting that PM-2.5 and fine dust particles reduces about 50 percentfrom peak at 100meter to 150meter. Wind direction influences dispersion and decay rates, with PM2.5 and PM10 levels rising when winds carry pollutants toward monitoring stations [5]. Dust emissions from demolition are notably higher downwind, diminishing logarithmically with distance. Additionally, construction height affects dispersion.When exposure of air-pollutants in a long-term,it may increase infection risk. Specifically, for individually 1 μmeter/m³ rise above the mean value correlates with a 2.7% increase in infection for NO_2 and 3.0% for PM10 [12]. Thus, selecting appropriate air parameters is crucial for an accurate correlation-model. The AQI, which is widely used by different agencies and researchers, represents overall urban air-quality and levels of pollutants[13]. According to WHO guidelines, air quality is assessed based on major pollutants such as particulate matter , ozone , nitrogen dioxide , and sulphur dioxide [14].PM serves as a common air pollution indicator , with PM-10 (≤10 μmeter) and PM-2.5 (≤2.5 μmeter) chosen for this study due to their relevance to construction work and significant health risks, including cardiovascular, respiratory diseases, and cancers [15], [16]. WHO provides strict guidelines for PM concentrations, as construction site dust notably impacts air quality [12],[15]. PM2.5, being smaller, remains airborne longer and has a more prolonged effect than PM10 [15], also showing seasonal variation due to urban agricultural activities [17]. Additionally, O_3, NO_2, and SO_2 significantly impact health, causing respiratory issues, lung inflammation, and strokes [5], [18]–[20]. Their sources are complex, linked partly to construction but mainly to industrial and vehicular fuel combustion [21]. Given construction sites' multifaceted impact on air quality, this study incorporates AQI, PM10, PM2.5, CO and SO_2 to ensure a comprehensive assessment. While construction sites' pollution effects depend on multiple factors, proper site micro-management can aid local governments in mitigating environmental and public health impacts.

II. AIR QUALITY DATA COLLECTION

This study examines the correlation between seven air quality indicators and the construction regionnumbers in Twin City, Odisha. Investigation, conducted at the city level, relies on existing data for comparative assessment. The air-quality information for the chosen city are obtained from the State Pollution Control Board, Odisha. The data is then processed to assess correlations, analyze trends over time, apply a regression model, verify its accuracy, and determine guideline limits for construction sites based on the findings.

Table 1. Twin cityair-quality monitoring sites.

Monitoring Stations at Bhubaneswar	Monitoring Stations at Cuttack
SPCB Office Building, Unit-VIII	Traffic Tower, Badambadi
I.R.C. Village, Nayapalli	RO, SPCB Office building, Surya Vihar
Capital Police Station, Unit-I	PHD Office, Barabati
Patrapada	
Chandrasekharpur	

The chosen air quality indicators align with the National Ambient Air Quality Standards. This study considers air pollutant concentrations and the air quality index (AQI) as key parameters. Data for these indicators were obtained from multiple monitoring stations, with their specific locations detailed in Table 1.

III. CONSTRUCTION ACTIVITY COLLECTION

The Bhubaneswar and Cuttack Development Authority oversees city construction data, and construction projects across different cities in Odisha were analyzed. Over three months, data on construction activities in the Twin City was gathered, with a summarized overview provided in Table 2.

Table2. Number of constructionareasinthe Twincity.

City	Bhubaneswar	Cuttack
Construction number N	30-35	8-10
Area (Km^2)	186	192.5
Density of construction cites	1.161-0.188	0.041-0.052

IV. THE SELECTION OF CONSTRUCTION SITES

The study area was chosen based on the accessibility and reliability of relevant data. Bhubaneswar and Cuttack were selected as representative sites for this research. Figure 1 illustrates the geographic distribution of construction sites within these cities.

Figure1. Some selected construction areas in the Twin city

This research utilizes a dataset comprising 24 air quality samples and corresponding construction site numbers over three months. Data collection is conducted at the city level, maintaining separate records for each city. The Twin City is chosen for correlation analysis. To validate the model, five samples are designated specifically for verification, while eight are allocated for training and validation purposes.

V. METHODOLOGY AND PROCESSING OF DATA

Regression approaches are broadly classified into linear and non-linear types. In the input regression technique, all parameters are included in the correlation model, while the stepwise method identifies and selects only the most impactful parameters. While input regression enhances the R-squared value when mathematical models lack precision, the stepwise method identifies key influencing factors [22]. A combination of multiple techniques ensures a thorough analysis. Among them, non-linear input-regression is chosen as this modeling approach due to its better accuracy.

Preliminary Analysis

Selecting between linear and non-linear regression relies on the Pearson correlation coefficient and the scatter plot pattern. The Pearson correlation coefficient quantifies the strength of a linear association between two variables[23]. It provides an initial assessment of linear correlation by calculating the Pearson correlation -coefficient along with its corresponding significance value. Table 3 illustrates how the Pearson correlation value corresponds to the degree of linear correlation. The significance value indicates the likelihood of an event occurring. Table 4 outlines the level of certainty associated with each significance value.

Table 3. Correlation Coefficient

Corr. Coeff.	0.7≪ CC < 1	0.4≪ CC < 0.7	CC < 0.4
Linear-correlation	Verystrongly	Strongly	Normal

Table 4. Level of certainty with each significance value

value of sig.-P	Sig.P≪0.01	0.01≪sig. P< 0.05	0.05<sig. P
Certainty- level	99 percent	95 percent	No certainty

The graphical plot examines the diverse trends among various parameters, enabling the evaluation of the relationship between construction area density and air-quality factors. As linear models may not effectively capture these complexities, non-linear regression models are required for better accuracy [24].

Regression Analysis

This study employs four regression models: stepwise linear regression, input linear regression, stepwise non-linear regression, and input non-linear regression. Stepwise regression identifies the most significant variables, simplifying the model but potentially reducing accuracy as fewer inputs are used. In contrast, input regression incorporates all available variables, including those with weak correlations. Kernel transformation is utilized to develop non-linear regression models, providing an effective method for analyzing complex non-linear relationships [25]. This approach transforms intricate non-linear data into a higher-dimensional space, enabling the application of linear regression methods[26]. The dataset Np consisting of elements{x1,x2,x3,x4,x5 } undergoes kernel transformation to facilitate improved data representation and analysis[25]:

$N_{p1}=\{x_1,x_2,x_3,x_4,x_5\}$
$N_{p2}=\{x_1^2, x_2^2, x_3^2, x_4^2, x_5^2, x_1x_2, x_1x_3, x_1x_4, x_1x_5, x_2x_3, x_2x_4, x_2x_5, x_3x_4, x_3x_5, x_4x_5, x_1,x_2,x_3,x_4,x_5\}$

The non-linear regression model utilizes the Np2 dataset. The air parameters analyzed in this model are detailed in Table 5.

Table 5. Parameters used in nonlinear regression

2nd order terms	$PM10^2$,CO^2,$PM2.5^2$,SO_2^2,AQI^2, PM10xCO^2, PM10xPM2.5,PM10xSO_2,PM10xAQI,CO x PM2.5,CO x SO_2,COx AQI,PM2.5 x SO_2, PM2.5 x AQI, SO_2 x AQI.
1st order terms	PM10, CO,PM2.5,SO_2, AQI

VI. MODEL VERIFICATION

Forecasting methods inherently involve prediction errors [27]. The mean absolute deviation and mean absolute percentage error are utilized to measure inaccuracies, aiding in assessing the error margin within the least square prediction model[28]. While both methods assess accuracy, they employ distinct calculation approaches, leading to varying results.

Mean Absolute Deviation evaluates prediction accuracy by computing the average of the observed errors.

$$\text{The Mean Absolute Deviation} = \frac{\sum N_x - N_p}{n} \quad (1)$$

In this context, Nx signifies the real count of construction sites within the city, while Np represents the predicted number of construction sites. The variable n indicates the total number of categorized groups.

$$\text{The Mean Absolute Percentage Error} = \frac{\frac{\sum N_x - N_p}{N_x}}{n} \times 100\,\% \quad (2)$$

Here, Nx represents the actual number of construction sites in the target district, Np denotes the predicted number of construction sites in the city, and n refers to the total number of groups.

VII. CORRELATIONMODELAPPLICATION

Once the correlative model is developed and validated, it will be utilized to estimate optimal construction sites by incorporating recommended air parameter values. Furthermore, its effectiveness will be evaluated at the city level. If the results are satisfactory, The model can help determine the optimal number of construction sites for the city

VIII. ANALYSIS OF RESULT

Correlation-Coefficient and Correlation Analysis

The Pearson correlation coefficient measures the correlation between construction site density and key air quality parameters. The correlation results for the cities are presented in Table 6. Significant correlations are observed at both the 0.001 and 0.005 significance levels.

Table 6. Pearson-correlation coefficient

		PM-10	CO	PM-2.5	SO_2	AQI
Construction Site number	Pearson.	0.66	0.72	0.66	0.63	0.7
	Correlation.					
	Significance	0.003	0.001	0.002	0.005	0.001
	N value	20	20	20	20	20

The finding is summarized in Table 7for selected cities.The finding show the construction project scale in Cuttack andis small. This result is caused by the small number of the construction sites.

Table 7. Level of air-indicators

City	AQI Parameters	Value
Twin city	PM10	15.5 $\mu g/m^3$
	CO	0.74 mg/m^3
	PM2.5	20.20$\mu g/m^3$
	SO_2	5.75 $\mu g/m^3$
	AQI	38.25

Table 8. Regression information of the model

Model number	Value of R	Value of R^2	Adjusted value	Standard error
1	0.48	0.24	0.21	0.32
2	0.44	0.26	0.20	0.31
3	0.85	0.27	0.22	0.29

Predictors Constant[1]-AQI,
Predictors Constant[2]-CO, PM2.5, SO_2, AQI, PM10
Predictors Constant[3]-AQI, CO

IX. REGRESSION ANALYSIS

Table 8 provides a comprehensive summary of the regression model, detailing the model number, correlation coefficient (R), coefficient of determination (R^2), adjusted R^2, and standard error. The findings are obtained through stepwise and multiple linear regression techniques, with the corresponding predictors specified below the table.

Correlative Coefficient

Table 8 displays the estimated regression coefficients for different mathematical models, incorporating both non-standardized coefficients (B) and their corresponding standard errors. The coefficient B signifies each parameter's influence within the correlation equation, enabling the effective formulation of the equation by integrating relevant parameters and coefficients.

Correlative Equation (Non-Linear Regression Analysis).

The optimal simulated model's non-standardized coefficients represent the correlation equation parameters. Thus, the city's correlation equations are given in Equations (3) and (4).

N_1 = -3.509 + 9.975CO + 1.692SO_2- 0.064(SO2)^2-0.001PM10*SO_2-0.007PM2.5*SO_2+0.001SO_2*AQI(3)N_2 = 82.219 + 7.725CO + 0.117PM2.5 + 2.186SO2- 1.279(CO)^2- 0.730(SO_2)^2 +0.013CO*PM2.5(4)

X. PREDICTED COUNT OF URBAN CONSTRUCTION AREAS

By applying recorded air parameter values to AQI guidelines using relevant equations, Table 9 presents the predicted and recommended range of construction sites. The state government can regulate construction within this range to mitigate its impact on air quality and improve environmental management.

Table 9. Predicted Count of City Construction Areasfor better air quality

City	Predicted Count (Np)	Range
Bhubaneswar	20.31	15-25
Cuttack	7.81	7-9

XI. CONCLUSIONS

This work employed both linear and non-linear multiple regression techniques to analyze the relationship between air quality and construction site density. Essential air quality parameters such as PM-10, PM-2.5, CO, SO2, and AQI were assessed to gain a comprehensive understanding of the environmental effects of construction activities.Data on construction activities were collected simultaneously across cities. An increase in construction activity led to higher dust and pollutant emissions. The stepwise regression analysis identified SO_2, CO, and PM-2.5 as the key determinants of air quality. Correlative equations were used for the Twin City, and the optimal number of construction sites was estimated at 15-25 for Bhubaneswar and 7-9 for Cuttack city. The forecasted site numbers were closely linked to actual construction activity. The results emphasize the significant influence of construction work on air quality in the Twin City.

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