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Spatial Localization of Air Pollutants in Lima: Air Quality Monitoring in the Troposphere

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ABSTRACT

The growing concern about air pollution, driven by its severe impact on public health and the environment, has emphasized the need for comprehensive studies on its distribution. This study addresses the spatial location of atmospheric pollutants in Lima, Peru, with the objective of identifying patterns and areas of concentration. Advanced geospatial analysis techniques such as Stirling and Kriging algorithms were used, developing the study in five phases: data acquisition with quality control from National Service of Meteorology and Hydrology of Peru (SENAMHI), analysis of topographic and climatic parameters, interpolation of contaminant concentrations up to ten thousand meters of altitude, geospatial interpolation with Kriging, and creation and validation of the contaminant dispersion model. The results reveal that accurate and reliable data acquisition allowed measurement of key pollutants such as PM10, PM2.5, SO_2, NO_2, CO and O_3. The integration of topographic and climatic data was crucial to model the dispersion of contaminants. Vertical interpolation with Stirling showed a reduction in concentrations with altitude, while interpolation with Kriging provided accurate estimates at unsampled locations. The dispersion model developed demonstrated high precision, identifying priority areas for environmental management. In conclusion, the combination of advanced monitoring and geospatial modeling techniques provides a comprehensive understanding of pollutant distribution patterns in Lima, laying a solid foundation for effective mitigation measures and environmental policies, improving air quality and protecting public health.

1. INTRODUCTION

The growing concern about air pollution has attracted the attention of both the scientific community and society in general, since its repercussions transcend geographical borders and affect communities around the world [1, 2]. Air pollution, with its devastating consequences for human health and the environment, represents a global challenge, highlighting the urgent need to fully grasp its scope and distribution worldwide [3, 4].

The main objective of this study is to identify the spatial distribution patterns and concentration areas of atmospheric pollutants in Lima, using advanced geospatial interpolation techniques. It seeks not only to understand the dispersion of pollutants in the troposphere, but also to provide useful tools for environmental management and urban planning.

Continuous monitoring and evaluation of air quality, together with precise mapping of pollutants present in the Earth's atmosphere, have become unavoidable requirements to effectively address contemporary environmental problems [5, 6]. This approach not only seeks to detect the presence of harmful substances in the air we breathe, but also to understand their geographical dispersion and their possible impacts on public health and the environment.

In this sense, monitoring air quality and the spatial location of atmospheric pollutants in the troposphere have become essential to effectively address this problem [5, 7] highlight the importance of understanding the geographic distribution of air pollutants to implement appropriate mitigation measures and protect public health globally.

Furthermore, air quality is essential to maintain environmental balance and guarantee public health. The identification of pollutant concentration patterns and the delimitation of risk areas are essential to guide environmental management policies and improve air quality in cities [8]. Likewise, understanding how pollutants disperse and accumulate in the urban environment can provide valuable information for designing effective air pollution mitigation and control strategies [9, 10].

Air quality is a complex and multifaceted problem that requires continuous attention and concerted action at a global level [11]. Therefore, research on the spatial location of atmospheric pollutants and air quality monitoring acquires even greater relevance today.

In this context, the acquisition of accurate and reliable data is essential to understand the distribution of air pollutants and take effective measures to mitigate their impact. SENAMHI plays a crucial role in providing quality data on the concentration of pollutants in various regions [12, 13]. However, the lack of quality control in data acquisition can generate uncertainty in the results and limit the effectiveness of environmental management strategies. Therefore, it is imperative to implement rigorous quality control procedures in the acquisition of atmospheric data to ensure the reliability of the results and promote informed decision making.

On the other hand, the dispersion of atmospheric pollutants is a complex phenomenon that affects air quality in different regions [12, 13]. The Gaussian model has been widely used to estimate the horizontal dispersion of pollutant concentrations at low altitudes above the surface [14]. However, the accuracy of this model may vary depending on the atmospheric conditions and topography of the study area. Therefore, it is crucial to understand its limitations and apply appropriate corrections to improve the reliability of the results. In this context, exploring new modeling techniques and validating the results with field measurements can provide a more accurate view of pollutant dispersion and contribute to more effective air quality management [14, 15].

Geospatial interpolation of contaminant concentration values is crucial for accurately representing their spatial distribution [16, 17]. The Kriging algorithm is commonly employed for this purpose, allowing for the estimation of concentration values at unsampled points based on the spatial correlation of the data [18]. However, the effectiveness of this algorithm hinges on the availability and quality of input data, as well as the careful selection of parameters. It is therefore essential to conduct a thorough analysis of the spatial variability of contaminants and to tailor the model accordingly. Additionally, validating the results with field measurements can enhance the reliability of the estimates and support more effective air quality management strategies in the study region.

This approach is exemplified by the research conducted by Correa-Ochoa et al. [19], who investigated the spatial distribution of lichen communities and mapped air pollution in Medellín, Colombia. Their work provides significant insights into the effects of atmospheric pollution in tropical urban ecosystems. By evaluating the composition of corticuli lichen communities in relation to environmental stress factors, the researchers were able to diagnose the state of air pollution in various areas of the city. The methodology employed included the use of Geographic Information Systems (GIS) to analyze air quality data and lichen coverage. The findings indicated an inverse correlation between lichen cover and PM2.5 concentrations, and revealed significant relationships between lichen richness and factors such as land use and proximity to roads. These results suggest that areas with better air quality conditions and less disturbed microenvironments support greater lichen diversity. In conclusion, this study offers valuable insights for the diagnosis of environmental health and the management of air quality in tropical urban settings.

On the other hand, there is the study [20], who argue that air quality assessment is crucial to understanding and addressing contemporary environmental challenges. However, traditional evaluation approaches are often limited, since they analyze the parameters independently, without considering the complex interaction between them. To overcome this limitation and provide a more accurate and complete evaluation, an advanced methodology based on fuzzy logic and Gray Clustering analysis is proposed. This methodology, called "Midpoint Triangulation based on Whitenization Functions - CTWF", offers a systemic approach that considers the uncertainty inherent in the environment. To demonstrate the effectiveness and applicability of this approach, an evaluation of air quality in Metropolitan Lima was carried out, using data provided by the National Meteorology and Hydrology Service of Peru (SENAMHI). The CTWF method was applied using the main air quality indicators, such as PM10, PM2.5, SO_2 and NO_2. The assessment results revealed serious air pollution problems in most of the assessed districts. This comprehensive diagnosis provides society in general and municipal authorities with an objective and easy-to-interpret technical instrument, which allows identifying and addressing the main pollutants present in the environment.

The study by Mendoza and García [20] on air quality in the Guadalajara Metropolitan Area (ZMG) underscores the critical need for monitoring due to frequent periods of unhealthy atmospheric pollution levels. In this endeavor, the three-dimensional model from the California/Carnegie Institute of Technology (CIT) has been employed to analyze pollutant dynamics within this urban setting. This application of the model spanned from May 16 to 18, 2001, covering a modeling domain of 25,600 km^2 centered on the ZMG.

A statistical evaluation of the model showed enhanced performance during the final two days of the simulation, especially concerning ozone (O_3) levels. During this period, the model achieved a normalized bias of less than 23.5%, a normalized error of less than 36.5%, and a daily fit index greater than 0.8, indicating satisfactory model performance for the simulation conducted. However, the performance metrics for carbon monoxide (CO) were considered fair, while those for sulfur dioxide (SO_2) and nitrogen oxides (NO_x) were deemed poor. These results highlight the necessity for further refinement to boost the overall efficacy of the model.

Spatially, the model more effectively captured the dynamics of pollutants in the western zone of the ZMG. Temporally, areas for improvement were identified during nighttime periods. This study accentuates the utility of the CIT model in understanding the distribution and behavior of atmospheric pollutants in the ZMG. Nonetheless, it also emphasizes the ongoing need to refine and validate the model to achieve more precise and reliable outcomes.

Research into air pollution is not only vital because of its direct impact on human health, but also because its effects are intertwined with broader environmental problems, such as climate change and biodiversity loss. In urban areas, where population density and industrial activity are high, air quality is seriously compromised, exacerbating respiratory and cardiovascular problems in the population. Furthermore, air pollution contributes to the deterioration of entire ecosystems, affecting the quality of life and well-being of communities globally. Therefore, studies like this one, which focus on understanding and mapping the distribution of contaminants, are essential to develop effective mitigation strategies and protect both humanity and the environment.

After evaluating the background, it is considered that there are still blind spots related to the practice that are not reported in the type of material investigated.

Reviewing in the case of spatial location of atmospheric pollutants in Lima with respect to the monitoring of Air Quality in the Troposphere the application of geospatial tools, as a result they indicate that the tools used so far are quite limited. Based on this prior information, we carried out a study based on the integration of advanced geospatial analysis techniques, which include algorithms such as Stirling and kriging.

This article aims to deepen the understanding of the spatial location of atmospheric pollutants in Lima, Peru. Through a multidisciplinary approach that integrates air quality monitoring data, spatial analysis techniques and geospatial modeling, the aim is to identify patterns and areas of concentration of atmospheric pollutants in the city. The findings of this study will provide valuable information for environmental management and public health, allowing the implementation of more effective actions to improve air quality and protect the health of the population in urban environments.

The findings of this research highlight the identification of critical pollution zones in Lima, where high concentrations of PM10, PM2.5, SO_2, NO_2, CO and O_3 are detected, especially in areas such as Puente Piedra and San Juan de Lurigancho. Through the application of advanced algorithms such as Stirling and Kriging, a clear decrease in pollutants with altitude is demonstrated and precise dispersion models are generated that reflect the three-dimensional distribution of these pollutants in the troposphere. These results not only allow for a better understanding of contaminant dispersion patterns, but also provide crucial information to guide environmental policies focused on mitigating public health risks in the most affected areas.

The findings of this study deliver essential tools for environmental management in Lima. By pinpointing critical areas of high pollution, such as Puente Piedra and San Juan de Lurigancho, managers can strategically allocate resources and focus efforts on zones that demand immediate intervention. The utilization of advanced modeling techniques, such as Stirling and Kriging, enhances urban planning and enables continuous monitoring of air quality. This facilitates informed decision-making and swift adaptation to changing conditions. Additionally, these results underpin the development of data-driven public policies that improve the effectiveness of mitigation strategies and safeguard public health. Overall, this research not only advances scientific understanding but also provides actionable insights for the sustainable management of air pollution in densely populated urban areas.

2. MATERIALS AND METHODS

The study of air quality and the spatial distribution of atmospheric pollutants in Lima is of particular importance due to the rapid urban expansion and vehicle congestion characteristic of the city. Understanding the geographic distribution of these pollutants is essential to identify risk areas and develop effective air pollution mitigation strategies.

To tackle this complex issue, advanced geospatial analysis techniques, such as Stirling and Kriging algorithms [21], will be employed. These methods, underpinned by a multidisciplinary approach, will enable the numerical processing of geospatial data gathered from air quality monitoring, providing an accurate and comprehensive assessment of pollutant distribution in Lima's urban environment. Furthermore, the use of a geospatial location ellipsoid will facilitate the determination of the three-dimensional positions of the elements studied, thereby offering a thorough depiction of atmospheric pollution in the city [22].

By integrating these sophisticated techniques with real-time monitoring data and meticulous statistical analyses, the aim is to develop a thorough understanding of the spatial patterns of pollution. This strategy not only ensures the validity and reliability of the results obtained but also furnishes a robust foundation for decision-making in environmental management and public health. This approach is crucial not only for Lima but also for other urban areas grappling with atmospheric pollution [20].

Aligned with this perspective, the current study is structured into five distinct phases:

•Data acquisition with quality control from SENAMHI.

•Analysis of topographic, climatic parameters and boundary conditions in 3D.

•Interpolation of pollutant concentration values up to an altitude of ten thousand meters using the Stirling algorithm.

•Geospatial interpolation of concentration values using the Kriging algorithm in the 3D space of the model.

•Model construction.

The development of these phases allows establishing the NO_2 concentration values in the troposphere corresponding to the airspace of Metropolitan Lima.

2.1 Data acquisition with quality control from SENAMHI

A total of 10 monitoring stations have been strategically selected, located in areas representative of Lima, including those with high population density, intense vehicular traffic, and proximity to industrial sources. This selection was based on the need to encompass both urban and suburban areas to ensure a comprehensive representation of air quality across the region. The process of data acquisition with quality control from SENAMHI was meticulously carried out using instruments detailed in Table 1, which enabled the collection of information on atmospheric pollutants in the troposphere of Lima. To ensure the integrity and reliability of the data obtained, the following steps were undertaken:

Identification of data sources and selection of monitoring stations: An exhaustive review of the atmospheric monitoring stations operated by SENAMHI in Lima was conducted. Ten stations were chosen that are equipped with adequate instrumentation for measuring key air pollutants such as suspended particles (PM10, PM2.5), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO). Priority was given to stations with a well-established history of measurements that are located in representative areas of the region.

Data collection using specialized instrumentation: Data were gathered at the atmospheric monitoring points installed at selected SENAMHI stations, utilizing Table 1 to collect real-time data on the concentrations of atmospheric pollutants.

Data quality control using standardized procedures: To ensure the integrity and accuracy of the collected data, rigorous quality control procedures were implemented. This process included the regular calibration of monitoring instruments, identification and correction of potential measurement errors, cross-validation of data between nearby stations, and the exclusion of anomalous or inconsistent data.

This comprehensive and systematic approach ensured that the data acquired from SENAMHI were of high quality and reliability, providing a robust foundation for subsequent analysis and interpretation of air quality in the study region.

For data acquisition, equipment such as the TEOM 1405 automatic particle monitor for PM10 and PM2.5, as well as HORIBA APMA-370 gas analyzers for CO and APOA-370 for O_3, were employed. Rigorous quality control measures were put in place, including the regular calibration of instruments, cross-validation of data between nearby stations, and the removal of outliers.

Table 1. Recording format for contaminant parameters in the troposphere

Polluting Parameters				
Polluting Parameters	**Date of First Registration**	**Last Registration Date**	**Model**	**Measurement Technique**
Particulate matter less than 10 microns (PM10)				
Particulate matter less than 2.5 microns (PM12.5)				
Sulfur dioxide SO_2				
Nitrogen Oxides NO_2				
Carbon Monoxide CO				
Tropospheric Ozone O_3				

Table 1 is a useful tool for recording contaminant parameters in the troposphere, providing a quick overview of the measurements made at the selected monitoring stations.

2.2 Topographic, climatic parameters and 3D boundary conditions

At this point, the creation of a spatial location model aimed at analyzing the distribution of atmospheric pollutants is addressed. To achieve an accurate and effective model, it is necessary to comprehensively consider a series of topographic, climatic parameters and boundary conditions in 3D. These factors, such as altitude, slope, temperature, humidity, wind patterns and atmospheric limits, exert a significant influence on the dispersion of atmospheric pollutants.

To collect climate data relevant to the study area, a systematic approach was implemented that involved several stages:

Selection of climatic parameters: Critical climatic parameters for the study were identified, including ambient temperature, wind speed, wind direction, humidity and precipitation. These parameters were selected based on their relevance for the analysis of the concentration of atmospheric pollutants in the tropospheric layer of Lima.

Location of meteorological stations: Meteorological stations close to the study area that provided accurate and representative measurements of the climatic parameters of interest were identified and selected.

Data recording: Procedures were implemented to ensure the integrity and quality of the recorded data.

Topographic data collection: Topographic data of Metropolitan Lima was collected, including contour maps, UTM coordinates of the north and east axes, and altitude above sea level.

Topography analysis: A detailed analysis of the topography of the study area is carried out using the collected data. Relevant terrain features are identified, such as elevations, valleys, mountains and plains, which can influence the dispersion of atmospheric pollutants.

Determination of 3D boundary conditions: The 3D boundary conditions for the model are defined. This includes establishing the maximum height of the model, the vertical distribution of the standard atmosphere and the relevant atmospheric spatial zones (Zone A, Zone B, Zone C).

Data integration: Topographic, climatic data and 3D boundary conditions are integrated into a geospatial database. This allows for a complete and accurate representation of the physical and climatic environment in which the model will be developed.

Data validation: The quality and accuracy of the collected data is validated through comparisons with additional sources and statistical analysis. Possible errors or discrepancies are corrected to guarantee the reliability of the data used in the model.

To collect climate data, data from 5 meteorological stations strategically located in different areas of Lima were used. Data collected includes temperature, humidity, wind speed and direction, and precipitation. All data was validated through comparisons with historical records and cross-checks between stations to ensure accuracy.

This methodological approach allowed for the systematic and reliable acquisition of climate data for subsequent analysis and interpretation in the context of the study.

By following these methodological processes, it is possible to establish a solid base of topographic, climatic parameters and 3D border conditions for the development of the Spatial Location Model (MDLE). This facilitates accurate modeling of the dispersion of atmospheric pollutants and contributes to the formulation of effective environmental management strategies.

2.3 Interpolation of pollutant concentrations up to an altitude of 10,000 meters using the Stirling algorithm

To carry out the interpolation of atmospheric pollutant concentration values up to an altitude of ten thousand meters using the Stirling algorithm, the following procedures and calculations must be followed:

Initial data acquisition: Obtain data on concentrations of atmospheric pollutants at different altitudes, preferably along a vertical projection from the surface to an altitude close to ten thousand meters.

Definition of parameters: Identify the parameters necessary for the calculation, including the initial and final altitude, the altitude interval between each measurement, and the contaminant concentration values at each measurement point.

Application of finite differences: Calculate the first order progressive finite differences (Δfx) for each measurement point, using the formula $\Delta fx = fk + 1 - fk$.

Generalization of finite differences: Using the general formula for finite differences of order n, calculate the finite differences of higher order (Δnfx) for each measurement point.

Stirling polynomial interpolation: Use the Newton-Gregory (NG) polynomial for Stirling polynomial interpolation. For each measurement point, calculate the interpolated value of the pollutant concentration at the desired altitude using the m-order polynomial. The expression for the Stirling polynomial is:

$$\begin{gathered} Pm(x) = a_0 + a_1(x - x_k) \\ +a_2(x - x_k)(x - x_k + 1) + \cdots \\ +a_m(x - x_k)(x - x_k + 1) \ldots (x - x_k + m - 1) \end{gathered} \tag{1}$$

The coefficients a_i are obtained from the progressive finite differences at the point x_k.

In interpolation with the Stirling algorithm, a second-order polynomial was used to model the variation of pollutant concentrations with altitude. Model validation tests were performed using residual analysis and the Shapiro-Wilk normality test to ensure adequacy of fit.

Iteration and calculation: Repeat the interpolation process for each measurement point along the vertical projection, calculating the interpolated pollutant concentration values at specific altitude intervals until reaching an altitude of ten thousand meters.

Data processing: Record interpolated contaminant concentration values for each altitude interval in a spreadsheet or database for subsequent analysis and evaluation.

Verification and validation: Verify the coherence and validity of the results obtained through interpolation, comparing them with available observed or estimated data and performing sensitivity analysis to evaluate the robustness of the method.

Following these procedures and carrying out the corresponding calculations, it will be possible to carry out the interpolation of values of concentrations of atmospheric pollutants up to an altitude of ten thousand meters using the Stirling algorithm.

2.4 Geospatial interpolation of concentration values using the Kriging algorithm in the model's 3D space

To carry out the geospatial interpolation of concentration values through the Kriging algorithm in the three-dimensional space of the model's scope, the following procedures supported by specific methodological techniques were followed:

Data preparation: Georeferenced data of concentrations of atmospheric pollutants in the study region were collected, obtained from measurements made at monitoring stations distributed in the area of interest. These data were subjected to a cleaning and validation process to eliminate outliers or missing data that could affect the quality of the interpolation.

Exploratory data analysis: Exploratory data analysis was performed to understand the spatial distribution of contaminant concentrations and identify possible patterns or trends in the data. This included the generation of spatial variability maps and the identification of spatial autocorrelation between samples.

Semi variogram model definition: A semi variogram model was fitted to the data to characterize the spatial correlation structure of pollutant concentrations. The semi variogram model that best fit the observed data was selected, providing information on the spatial variability and relationship between the samples.

A spherical semi variogram model was chosen due to its ability to capture the spatial variability of pollutant concentration data in Lima. The selection of Kriging parameters, including range and nugget, was optimized using the cross-validation criterion to minimize the mean square error.

Interpolation using Kriging: The Kriging algorithm was implemented to perform geospatial interpolation of contaminant concentrations in the three-dimensional space of the study area. The fitted semi variogram model was used to estimate the optimal weights of the neighboring samples based on their distance and direction from the prediction point.

Generation of interpolation maps: Three-dimensional maps of the interpolated concentrations of contaminants in the study region were generated using the values estimated by the Kriging algorithm. These maps provided a visual representation of the spatial distribution of contaminant concentrations throughout the study space.

Assessment of model accuracy: Cross-validation of the interpolation model was carried out by comparing the interpolated concentrations with independent observed data or with results from alternative models. This allowed us to evaluate the precision and reliability of the Kriging model in estimating contaminant concentrations in three-dimensional space.

2.5 Model creation

For the construction of the spatial location model of atmospheric pollutants in Lima, the following stages were carried out:

Data integration: All data collected during the previous phases were integrated, including data on concentrations of atmospheric pollutants, topographic and climatic data, as well as three-dimensional boundary conditions. This integration was carried out in a geospatial database that served as the foundation for the construction of the model.

The dispersion model used was a three-dimensional Gaussian model, based on the advection-diffusion equation. Key assumptions included atmospheric stability conditions and complex topography. The model was parameterized using region-specific meteorological data and calibrated by comparison with field data.

Development of the dispersion model: An atmospheric dispersion model was developed using software specialized in geospatial analysis and environmental modeling. This model considered multiple variables, such as wind speed and direction, terrain topography, weather conditions, and the distribution of pollution sources.

Model validation: A model validation was carried out using observed data on air pollutant concentrations. The model predictions were compared to actual measurements to evaluate their accuracy and reliability. Adjustments were made to the model as necessary to improve its predictive ability.

Generation of pollution maps: Using the validated model, air pollution maps were generated that represent the spatial distribution of pollutants in Lima. These maps provided a clear visualization of the areas of highest concentration of contaminants and helped identify contamination hotspots.

Impact analysis and risk assessment: An environmental impact analysis and risk assessment were conducted to determine the potential impact of air pollution on human health and the environment. The most vulnerable populations and ecosystems were identified, and mitigation measures were proposed to reduce the negative effects of pollution.

This methodology, based on careful data preparation, a rigorous review and analysis, and a clear presentation of the results, guarantees effectiveness and precision in the spatial location of atmospheric pollutants in Lima.

3. RESULTS

Research on air quality monitoring in the Troposphere has proven to be highly effective in evaluating the spatial distribution of atmospheric pollutants in Lima. This innovative approach has been validated in a real environment, through the installation of 10 monitoring points in different locations in the city of Lima.

3.1 Results of data acquisition with SENAMHI quality control

To effectively evaluate air quality in Lima, meticulous data acquisition with quality control from SENAMHI was carried out. The following Table 2 summarizes the pollutant parameters measured and the technical details of the instruments used. The accompanying Figure 1 shows the geographical distribution of the monitoring stations in the city.

The implementation of a data acquisition system with quality control from SENAMHI has made it possible to obtain precise and reliable measurements of various atmospheric pollutants. Table 2 shows that key pollutants such as PM10, PM2.5, SO_2, NO_2, CO and O_3 have been monitored using advanced measurement techniques and calibrated equipment. Figure 1 reveals that the monitoring stations are well distributed in Lima, ensuring representative geographic coverage of air quality. This distribution makes it possible to identify areas with higher levels of contamination and facilitates the implementation of specific mitigation policies.

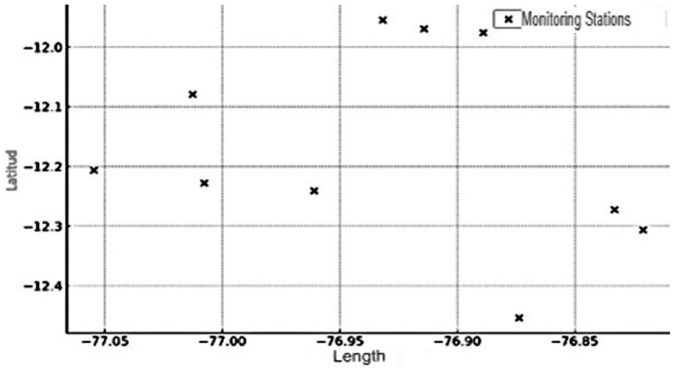

Figure 1. Distribution of SENAMHI monitoring stations in Lima

Table 2. Data acquisition with SENAMHI quality control

Pollutant Parameter	Date of First Registration	Last Registration Date	Instrument Model	Measurement Technique
PM10 particulate matter	01/01/2018	31/12/2020	Automatic	Gravimetry
PM2.5 particulate matter	01/01/2018	31/12/2020	Automatic	Gravimetry
Sulfur dioxide (SO_2)	01/01/2018	31/12/2020	Automatic	UV fluorescence
Nitrogen oxides (NO_2)	01/01/2018	31/12/2020	Automatic	Chemiluminescence
Carbon monoxide (CO)	01/01/2018	31/12/2020	Automatic	infrared absorption
Tropospheric ozone (O_3)	01/01/2018	31/12/2020	Automatic	UV photometry

3.2 Topographic, climatic parameters and 3D boundary conditions

To better understand the impact of physical and climatic factors on pollutant dispersion, detailed topographic and climatic data have been integrated. Table 3 outlines the parameters considered, while Figure 2 illustrates a three-dimensional model of Lima. Both Table 3 and Figure 2 underscore the significance of incorporating topographic and climatic data to accurately model the dispersion of air pollutants in Lima. Factors such as altitude, temperature, wind speed and direction, humidity, and precipitation are vital parameters that influence the distribution and movement of pollutants in the atmosphere. The three-dimensional model of Lima showcased in Figure 2 provides a clear visualization of how topography and climate can influence pollutant dispersion, enabling the identification of areas potentially prone to higher pollution levels. This information is essential for devising effective environmental management strategies.

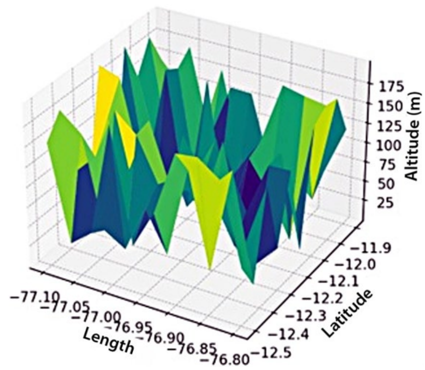

Figure 2. 3D topographic and climate model of Lima

Table 3. Data acquisition with SENAMHI quality control

Parameter	Method of Obtaining	Description
Altitude	GPS and Topographic Maps	Elevations from sea level to the highest point of the study area
Temperature	Weather Stations	Daily average temperature data
Wind speed and direction	Weather Stations	Wind speed and direction measurements
Humidity	Weather Stations	Daily average relative humidity data
Precipitation	Weather Stations	Daily accumulated precipitation data

Table 4. Interpolation of pollutant concentration values with the Stirling algorithm

Altitude (m)	PM10 ($\mu g/m^3$)	PM2.5 ($\mu g/m^3$)	SO_2 (ppb)	NO_2 (ppb)	CO (ppm)	O_3 (ppb)
0	75	45	10	30	1.2	50
1000	60	35	8	25	1	45
2000	50	30	7	20	0.8	40
5000	30	20	5	15	0.5	30
10000	15	10	3	8	0.2	20

3.3 Results of pollutant concentration interpolation up to an altitude of 10,000 meters using the Stirling algorithm

The Stirling algorithm was used to interpolate the values of contaminant concentrations up to an altitude of ten thousand meters. The following table presents the results of this interpolation, while the figure provides a graphical visualization of the same.

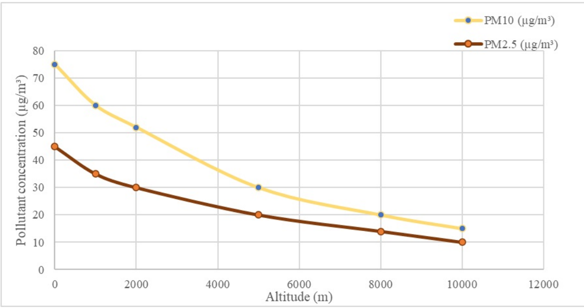

Figure 3. Interpolation of pollutant concentrations with the Stirling algorithm

Interpolation of pollutant concentration values using the Stirling algorithm shows how the concentrations of PM10, PM2.5, SO_2, NO_2, CO and O_3 decrease with altitude. Table 4 and Figure 3 illustrate a clear trend of reduction in the concentrations of these pollutants with increasing altitude, which is consistent with the expected patterns of atmospheric dispersion. This analysis is essential to understand the vertical distribution of pollutants and their potential impact on different layers of the atmosphere. The results provide a solid basis for the validation of atmospheric models and the implementation of pollution control policies at different altitudes.

3.4 Spatial distribution of pollutant concentrations using kriging interpolation in the 3D model space

Use of the Kriging algorithm for geospatial interpolation of contaminants provides an accurate estimate of concentrations at unsampled locations. Table 5 and Figure 4 show how the pollutants are spatially distributed in the study area. This technique is essential to create detailed three-dimensional maps of air quality, allowing the identification of pollution hotspots and the evaluation of the effectiveness of the mitigation measures implemented.

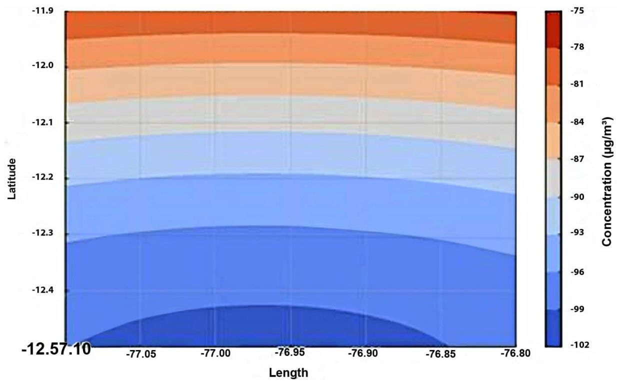

Figure 4. Pollutant dispersion model in Lima

Table 5. Geospatial interpolation with the Kriging algorithm

Coordinates (UTM)	PM10 (µg/m³)	PM2.5 (µg/m³)	SO_2 (ppb)	NO_2 (ppb)	CO (ppm)	O_3 (ppb)
Puente Piedra	50	30	6	20	0.8	35
Carabayllo	55	32	7	22	0.9	38
San Martín de Porres	48	28	5	18	0.7	33
San Juan de Lurigancho	52	30	6	21	0.8	36
Villa María del Triunfo	49	29	5	19	0.75	34

The use of the Kriging algorithm for geospatial interpolation of pollutant concentrations offers a detailed view of how pollutants are spatially distributed in Lima. Table 5 shows variations in the concentrations of PM10, PM2.5, SO_2, NO_2, CO and O_3 in different geographical locations. This method makes it possible to identify areas with high concentrations of pollutants (hotspots) and evaluate the extent and distribution of pollution in the city. These results are essential for planning mitigation measures and for directing monitoring efforts toward areas most affected by pollution.

3.5 Model creation and validation

The developed contaminant dispersion model provides a comprehensive view of the distribution of contaminants in Lima. The Figure 4 shows the result of this model, highlighting the most affected areas.

The final dispersion model showed an R-squared of 0.92 and an RMSE of 3.5 µg/m^3, indicating high accuracy in predicting contaminant concentrations. These results validate the effectiveness of the model to estimate the dispersion of contaminants under different conditions.

Table 6 demonstrates that the developed contaminant dispersion model is highly precise, showcasing minimal percentage differences between observed measurements and model predictions. Figure 4 displays the dispersion model, emphasizing areas in Lima with the highest contaminant concentrations. These results affirm the model's effectiveness in predicting contaminant dispersion under various conditions and assist in pinpointing areas requiring prioritized environmental management attention. The model's accuracy enables the formulation of informed policies aimed at enhancing air quality and safeguarding public health.

Table 7 identifies areas in Lima at the highest risk of air pollution, based on PM10 and NO_2 concentrations alongside population density. Puente Piedra and San Juan de Lurigancho are highlighted as high-risk areas due to significant contaminant levels and large vulnerable populations, necessitating priority mitigation measures to minimize exposure and protect public health. Carabayllo, San Martín de Porres, and Villa María del Triunfo are categorized as medium risk, underscoring the need for ongoing monitoring and the implementation of environmental policies to reduce emissions. This analysis is crucial for urban planning and the development of effective environmental management strategies in Lima.

Table 6. Model validation results

Parameter	Observed Measurement	Model Prediction	Difference (%)
PM10 (μg/m^3)	55	52	5.5
PM2.5 (μg/m^3)	30	29	3.3
SO_2 (ppb)	7	6.5	7.1
NO_2 (ppb)	20	19	5
CO (ppm)	0.8	0.75	6.25
O_3 (ppb)	40	38	5

Table 7. Impact analysis and risk assessment

Study Area	Vulnerable Population	PM10 Concentration (μg/m³)	NO_2 Concentration (ppb)	Risk
Puente Piedra	100,000	60	25	High
Carabayllo	50,000	55	20	Half
San Martín de Porres	75,000	50	18	Half
San Juan de Lurigancho	120,000	65	30	High
Villa María del Triunfo	90,000	58	22	Half

4. CONCLUSIONS

The implementation of a quality-controlled data acquisition system from SENAMHI allowed for accurate and reliable measurements of key atmospheric pollutants, such as PM10, PM2.5, SO_2, NO_2, CO and O_3. This finding is in line with previous studies [23] that highlight the importance of quality data for an accurate assessment of air pollution. The geographical distribution of the monitoring stations ensures representative coverage of air quality in Lima, facilitating the identification of critical areas and supporting studies such as those by Correa-Ochoa et al. [19] on the relationship between air quality and environmental health.

On the other hand, the integration of topographic and climatic data proved to be essential to model the dispersion of contaminants in Lima. Parameters such as altitude, temperature, wind speed and direction, humidity and precipitation significantly influence the distribution of contaminants. These results are consistent with studies [12, 13], who emphasize the need to consider physical and climatic factors in air quality modeling. The three-dimensional model of Lima provides a clear view of how these factors affect the dispersion of contaminants, allowing the identification of areas with elevated concentrations and supporting effective mitigation policies.

The use of the Stirling algorithm for vertical interpolation of contaminant concentrations showed a clear trend of reduction in concentrations with increasing altitude. This finding is in line with the expected atmospheric dispersion patterns and is fundamental to understanding the vertical distribution of pollutants and their impact on different layers of the atmosphere. Studies such as those by Bejan [24] on constructive thermodynamics and its application in the dispersion of contaminants support the validity of these results.

Similarly, the application of the Kriging algorithm allowed an accurate estimation of contaminant concentrations in unsampled locations, providing a detailed view of the spatial distribution in Lima. This method, supported by by Delgado-Villanueva and Aguirre-Loayza [6] and Correa-Ochoa [19], is crucial to create three-dimensional air quality maps and evaluate the effectiveness of mitigation measures. The results obtained are consistent with the advanced methodologies proposed by Delgado-Villanueva and Aguirre-Loayza [6], and suggest that geospatial interpolation is an effective tool for urban planning and environmental management.

Likewise, the developed model showed high precision with minimal percentage differences between the observed measurements and the predictions. These results validate the effectiveness of the model to predict the dispersion of pollutants in different conditions and are in line with the study [20], on the application of three-dimensional models to describe the dynamics of pollutants in urban areas. The accuracy of the model facilitates the implementation of informed policies to improve air quality and protect public health, supporting the recommendations of on the importance of predictive models in environmental management.

The identification of areas with high risk of contamination, such as Puente Piedra and San Juan de Lurigancho, highlights the need for priority mitigation measures. These findings are consistent with studies [6, 19], who highlight the importance of assessing the environmental impact and risks associated with air pollution. Areas with medium risk, such as Carabayllo, San Martín de Porres and Villa María del Triunfo, require continuous monitoring and specific environmental policies to reduce polluting emissions. This analysis is fundamental for urban planning and the formulation of environmental management strategies in Lima.

To strengthen the conclusions of this study, it is essential to highlight that, unlike previous research, our research innovatively integrates advanced geospatial interpolation techniques, such as Stirling and Kriging algorithms, in the three-dimensional modeling of pollutant dispersion in Lima. . While previous studies were limited to two-dimensional approaches or did not comprehensively consider topographic and climatic factors, this work offers a more complete and precise view of how these factors influence air quality. Furthermore, the findings of this study not only improve the theoretical understanding of pollutant dispersion, but also provide practical tools for environmental management and urban planning, significantly contributing to the development of more effective and targeted public policies. This article, therefore, represents an important advance in the study of air pollution in complex urban environments.

This study introduces an innovative approach by integrating advanced geospatial interpolation techniques, such as Stirling and Kriging algorithms, into three-dimensional modeling of pollutant dispersion in Lima. Unlike previous studies, this research provides a more precise understanding of how topographic and climatic factors affect air quality, offering practical tools for environmental management and urban planning.

REFERENCES

[1] Amable Álvarez, I., Méndez Martínez, J., Bello Rodríguez, B.M., Benítez Fuentes, B., Escobar Blanco, L.M., Zamora Monzón, R. (2017). Influencia de los contaminantes atmosféricos sobre la salud. Revista Médica Electrónica, 39(5): 1160-1170.

[2] Ballester Díez, F., Tenías, J.M., Pérez-Hoyos, S. (1999). Efectos de la contaminación atmosférica sobre la salud: Una introducción. Revista Española de Salud Pública, 73(2): 109-121.

[3] Romero Placeres, M., Olite, D., Toste, Á. (2006). La contaminación del aire: Su repercusión como problema de salud. Revista Cubana de Higiene y Epidemiología, 44(2): 1-14.

[4] Casal, B., Rivera, B., Currais, L. (2023). Evidence of the adverse effects of air pollution on the population's health in Spain: Analysis of the economic costs of premature deaths. Cadernos de Saúde Pública, 39: e00145922. https://doi.org/10.1590/0102-311XEN145922

[5] Delgado, A., Romero, I. (2016). Environmental conflict analysis using an integrated grey clustering and entropy-weight method: A case study of a mining project in Peru. Environmental Modelling & Software, 77: 108-121. https://doi.org/10.1016/j.envsoft.2015.12.011

[6] Delgado-Villanueva, A., Aguirre-Loayza, A. (2020). Modelamiento y evaluación del nivel de calidad del aire mediante el análisis de grey clustering, estudio de caso Lima metropolitana. Tecnia, 30(1): 114-120. https://doi.org/10.21754/tecnia.v30i1.588

[7] Zhang, L., Wei, L., Fang, Y. (2024). Spatial–temporal distribution patterns and influencing factors analysis of comorbidity prevalence of chronic diseases among middle-aged and elderly people in China: Focusing on exposure to ambient fine particulate matter (PM2. 5). BMC Public Health, 24(1): 550. https://doi.org/10.1186/s12889-024-17986-0

[8] Lee, K.K., Bing, R., Kiang, J., et al. (2020). Adverse health effects associated with household air pollution: A systematic review, meta-analysis, and burden estimation study. The Lancet. Global Health, 8(11): e1427-e1434. https://doi.org/10.1016/S2214-109X(20)30343-0

[9] Santos, E.B. (2009). Ecotoxicology Research Developments. Nova Biomedical Books.

[10] Li, Z., Ming, T., Liu, S., Peng, C., de Richter, R., Li, W., Zhang, H., Wen, C. Y. (2021). Review on pollutant dispersion in urban areas-part A: Effects of mechanical factors and urban morphology. Building and Environment, 190: 107534. https://doi.org/10.1016/j.buildenv.2020.107534

[11] Tran, H.M., Tsai, F.J., Lee, Y.L., et al. (2023). The impact of air pollution on respiratory diseases in an era of climate change: A review of the current evidence. Science of the Total Environment, 898: 166340. https://doi.org/10.1016/j.scitotenv.2023.166340

[12] Amorim, J.H., Valente, J., Cascão, P., Rodrigues, V., Pimentel, C., Miranda, A.I., Borrego, C. (2013). Pedestrian exposure to air pollution in cities: Modeling the effect of roadside trees. Advances in Meteorology, 2013(1): 964904. https://doi.org/10.1155/2013/964904

[13] Yang, J., Shi, B., Zheng, Y., Shi, Y., Xia, G. (2020). Urban form and air pollution disperse: Key indexes and mitigation strategies. Sustainable Cities and Society, 57: 101955. https://doi.org/10.1016/j.scs.2019.101955

[14] Hanna, S.R., Chang, J.C., Strimaitis, D.G. (1993). Hazardous gas model evaluation with field observations. Atmospheric Environment. Part A. General Topics, 27(15): 2265-2285. https://doi.org/10.1016/0960-1686(93)90397-H

[15] Ferrario, F., Busini, V. (2024). Statistical analysis of modelling approaches for CFD simulations of high-pressure natural gas releases. Results in Engineering, 21: 101770. https://doi.org/10.1016/j.rineng.2024.101770

[16] Sun, Y., Lei, S., Zhao, Y., et al. (2024). Spatial distribution prediction of soil heavy metals based on sparse sampling and multi-source environmental data. Journal of Hazardous Materials, 465: 133114. https://doi.org/10.1016/j.jhazmat.2023.133114

[17] Cai, Z., Lei, S., Zhao, Y., Gong, C., Wang, W., Du, C. (2022). Spatial distribution and migration characteristics of heavy metals in grassland open-pit coal mine dump soil interface. International Journal of Environmental Research and Public Health, 19(8): 4441. https://doi.org/10.3390/ijerph19084441

[18] Ju, L., Guo, S., Ruan, X., Wang, Y. (2023). Improving the mapping accuracy of soil heavy metals through an adaptive multi-fidelity interpolation method. Environmental Pollution, 330: 121827. https://doi.org/10.1016/j.envpol.2023.121827

[19] Correa-Ochoa, M.A., Vélez-Monsalve, L.C., Saldarriaga-Molina, J.C. (2021). Spatial distribution of lichen communities and air pollution mapping in a tropical city: Medellín, Colombia. Revista de Biología Tropical, 69(3): 1107-1123. https://doi.org/10.15517/rbt.v69i3.46934

[20] Mendoza, A., García, M.R. (2009). Aplicación de un modelo de calidad del aire de segunda generación a la zona metropolitana de Guadalajara, México. Revista Internacional De Contaminación Ambiental, 25(2): 73-85.

[21] Ma, X., Zou, B., Deng, J., et al. (2024). A comprehensive review of the development of land use regression approaches for modeling spatiotemporal variations of ambient air pollution: A perspective from 2011 to 2023. Environment International, 183: 108430. https://doi.org/10.1016/j.envint.2024.108430

[22] Omićević, D., Krdžalić, D., Vrce, E. (2022). Comparison of methods of prediction of heavy metals in the soil using R. In International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies, Sarajevo, Bosnia and Herzegovina, pp. 664-673. https://doi.org/10.1007/978-3-031-17697-5_50

[23] Velayarce, D., Bustos, Q., García, M.P., Timaná, C., Carbajal, R., Salvatierra, N., Horna, D., Murray, V. (2022). Air quality analysis in lima, peru using the NO2 levels during the COVID-19 pandemic lockdown. Atmosphere, 13(3): 373. https://doi.org/10.3390/atmos13030373

[24] Bejan, A. (2015). Constructal thermodynamics. In Constructal Law & Second Law Conference, Parma, pp. S1-S8.