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POTENTIAL USE OF ARTIFICIAL INTELLIGENCE AND GEOSPATIAL ANALYSIS IN ENVIRONMENTAL MONITORING: Air quality in a large city

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Abstract: *Environmental monitoring of air quality is essential to understanding the impact of pollution on human health and the environment. In urban areas, air quality is a significant concern due to high levels of pollutants emitted by transportation, industry, and energy production. Traditional air quality monitoring methods are often limited in their spatial and temporal resolution and can be expensive to maintain. Recent advances in artificial intelligence (AI) and geospatial analysis provide an opportunity to revolutionize the way we monitor air quality in urban areas. This paper explores the potential use of AI and geospatial analysis in air quality monitoring in the city of Bucharest. We present an overview of a specific supervised AI algorithm and its application in air quality monitoring. We also discuss the use of geospatial data, such as satellite imagery and GIS data, to enhance the accuracy and effectiveness of air quality monitoring. To demonstrate the potential of AI and geospatial analysis in air quality monitoring, this paper presents a case study of air quality monitoring in City of Bucharest. We use machine learning algorithms to analyze data collected from air quality sensors (state-owned and private) and geospatial data, such as traffic density and land use. Our results demonstrate the effectiveness of AI and geospatial analysis in predicting air quality parameters, such as particulate matter and nitrogen oxides, with a high degree of accuracy. Overall, the study highlights the potential of AI and geospatial analysis in air quality monitoring in urban areas. By integrating these technologies into air quality monitoring programs, we can improve our understanding of the sources and impact of pollutants on air quality in cities. This, in turn, can help policymakers and urban planners make better-informed decisions to reduce pollution and protect public health.*

Keywords: *Artificial Intelligence, Geospatial Analysis, Environmental Monitoring, Machine Learning, Air Quality.*

INTRODUCTION

Environmental monitoring of air quality is of great importance in understanding the impact of pollution on human health and the natural ecosystem [1], [2]. Urban areas, in particular, face significant challenges due to the escalating levels of pollutants emitted by various sources, including transportation, industrial activities, and energy production[3]–[5]. Traditional air quality monitoring approaches have proven reliable in providing valuable insights. However, they often suffer from limitations in spatial and temporal resolution, making it challenging to capture real-time variations and localized pollution hotspots. Moreover, maintaining an extensive network of monitoring stations can be economically burdensome[6]–[8].

In recent years, the convergence of AI and geospatial analysis has emerged as a promising solution to revolutionize the field of environmental monitoring, particularly in air quality assessment[9]–[10]. AI offers the potential to process large volumes of data rapidly, recognize complex patterns, and make accurate predictions, while geospatial analysis facilitates the integration of spatial information to contextualize environmental phenomena[11]–[13].

This paper proposes to explore the link of AI and geospatial analysis in the context of air quality monitoring in urban environments, with a specific focus on the city of Bucharest (Bucharest metropolitan area). We explore how these cutting-edge technologies can address the limitations of traditional methods and contribute to a more comprehensive and dynamic understanding of air quality dynamics.

The second part of this paper provides an overview of the methodology used for this research, encompassing the learning techniques for AI, and examines their relevance and potential applications in air quality monitoring. We explore how AI can be harnessed to model and predict air quality parameters, facilitating timely alerts and informed decision-making for pollution mitigation and public health protection. Additionally, we explore the integration of geospatial data, including satellite imagery and Geographic Information System (GIS) data, into air quality monitoring efforts. Geospatial analysis can offer critical contextual information, such as traffic density, land use patterns, and potential pollutant sources, thereby enriching the accuracy and effectiveness of air quality assessments[10], [14].

To highlight the capabilities of AI and geospatial analysis in air quality monitoring, we present a compelling case study centered on the city of Bucharest. Leveraging machine and deep learning algorithms and real-time data collected from air quality sensors, both state-owned and private, we demonstrate how AI-powered models can accurately predict key air quality indicators, such as particulate matter. By fusing geospatial data into the analysis, we gain deeper insights into the spatial distribution of pollutants and identify areas of heightened pollution vulnerability.

The findings of this study demonstrate the great potential of AI and geospatial analysis in transforming air quality monitoring practices in urban areas. Integrating these innovative technologies into existing monitoring frameworks holds the promise of a more proactive and informed approach to combat pollution and safeguard public health. Informed by data-driven assessments, policymakers and urban planners can devise targeted interventions to mitigate pollution sources and foster sustainable urban development. By harnessing the power of these advanced technologies, we can fortify our understanding of air quality dynamics and forge a path towards cleaner, healthier, and more resilient urban environments.

THEORETICAL BACKGROUND

The fusion of artificial intelligence and geospatial analysis has brought about a transformative era in environmental monitoring. This dynamic synergy has not only revolutionized our ability to understand the intricate dynamics of atmospheric conditions but also holds immense promise for its application in urban environments, including Bucharest. In the realm of weather prediction, AI and geospatial analysis have become instrumental tools. AI's data-handling capabilities, combined with geospatial data, enable the processing of vast datasets, such as satellite imagery and meteorological data, with remarkable efficiency. These technologies excel at deciphering complex weather patterns, identifying correlations between atmospheric variables, and providing real-time insights into weather-related phenomena[15]. While initially applied to meteorology[16], this powerful combination of AI and geospatial analysis is now extending its reach to urban environments, where its potential impact is equally profound. In our study, we aim to harness this state-of-the-art technology to enhance our understanding of air quality dynamics and contribute to the development of effective strategies for urban pollution control in Bucharest.

AI, a central player in this evolution, boasts remarkable data-handling capabilities, making it indispensable for managing the extensive datasets generated by air quality sensors, satellite imagery, and geographic data. It has the unique capacity to uncover intricate patterns within air quality data, revealing correlations between pollutants and their spatial and temporal variations. Furthermore, AI enables real-time monitoring and rapid alerts, facilitating swift responses to pollution incidents. In the realm of air quality assessment, geospatial analysis complements AI by offering a crucial spatial dimension. It provides essential context on land use, traffic patterns, and potential pollutant sources, contributing to a comprehensive understanding of pollutant distribution and the identification of pollution hotspots. Geospatial analysis employs interpolation techniques to generate continuous air quality maps, visually representing pollutant concentrations across various regions. Additionally, it enables the exploration of temporal variations in air quality, aiding in the identification of seasonal trends and the development of targeted pollution mitigation strategies.

In the realm of environmental monitoring, recent advancements in both AI and geospatial analysis have opened doors to significant breakthroughs in air quality assessment. Traditionally, AI activities in environmental numerical modeling have concentrated on enhancing model parameterizations, while geospatial analysis has been pivotal in data-driven parameterizations, leveraging observed data to refine subgrid-scale processes. However, a notable avenue yet to be fully explored is the combined use of AI and geospatial technologies in air quality monitoring. AI-driven techniques have excelled in fast emulation of existing model parameterizations, vastly improving computational efficiency, especially for intricate parameterizations such as atmospheric parameters. These techniques, coupled with geospatial analysis, promise to open the gates for a new era of environmental monitoring by aligning numerical models closely with observed data. The integration of AI and geospatial analysis holds the potential to provide a more accurate representation of fine-scale processes and offer improved predictive capabilities, particularly in urban environments. While some studies[2], [3], [14], [17]–[23] have are proposing the complete replacement of dynamical models with ML-based surrogates, the focus here lies in exploring the combined power of AI and geospatial technologies for air quality monitoring, presenting an uncharted territory offering new possibilities for more efficient, data-driven assessments.

Our study aims to harness the capabilities of AI and geospatial analysis to explore air quality monitoring options in urban settings, with a specific focus on Bucharest. The forthcoming sections will detail the research methodology, results, and their implications.

METHODOLOGY

This study aimed to investigate the potential applications of AI and geospatial analysis in informing policymakers and urban planners about pollution sources, guiding targeted interventions, and mitigating the impact of pollution on public health in Bucharest. The main objective was to develop a predictive model for air quality parameters in specific neighborhoods of Bucharest using AI algorithms and geospatial data while also examining the spatial and temporal variations of air pollution.
The main research question addressed in this study was: How can geospatial data, including meteorological factors, land use, and traffic patterns, be effectively integrated into AI models to enhance the accuracy of air quality predictions?
To achieve the primary objective, air quality data from 23 monitoring stations in Bucharest was collected, encompassing hourly measurements of the PM_{10} pollutant, along with relevant geospatial data, including meteorological factors, land use, and traffic patterns. The data was collected for the years 2021, 2022, and up to July 2023.
Following data collection, thorough preprocessing was conducted to handle missing values, outliers, and inconsistencies. Additionally, the data was scaled and standardized to ensure uniformity in feature ranges, optimizing the performance of the AI model.
Spatial interpolation, a crucial geospatial analysis technique, was employed to interpolate air quality data across the city, generating continuous air quality maps for visualization. These maps provided valuable insights into the spatial distribution of air pollutants across various neighborhoods in Bucharest.
For building the AI predictive model, various methods were considered, and ultimately, Random Forest algorithm was selected for implementation. This choice was based on its suitability for handling complex data, its ability to capture non-linear relationships, and its robust performance in regression tasks. Geospatial data was integrated as additional input features to enhance the model's predictive accuracy. The preprocessed data was divided into training and testing sets, and hyperparameter tuning was performed using techniques like GridSearchCV to optimize the AI model. The model was trained on the training set and evaluated based on key performance metrics, including mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R2), utilizing the test set.

RESULTS

Our study reveals the significant potential of AI and geospatial analysis in air quality monitoring in the city of Bucharest, enabling the identification of certain spatial and temporal patterns. By integrating these advanced techniques, we achieved accurate predictions of key air quality parameters, specifically PM_{10} concentrations, with a good degree of precision.
The Random Forest Regressor is a powerful and versatile algorithm for regression tasks. Its ability to reduce overfitting, handle complex data, and provide robust predictions makes it a popular choice in many real-world applications.The predictive model based on the Random Forest algorithm demonstrated good performance, with an R-squared (R2) value of 0.7. This indicates that approximately 70% of the variability in PM_{10} concentrations could be explained by the model. Moreover, the mean absolute error (MAE) and root mean squared error (RMSE) for PM_{10} were significantly lower than those obtained through traditional monitoring approaches (statistical approach). Figure 1 illustrates the comparison between the observed and predicted values for one station (B1). This highlights the superiority of the AI-powered model in capturing and predicting air quality dynamics.

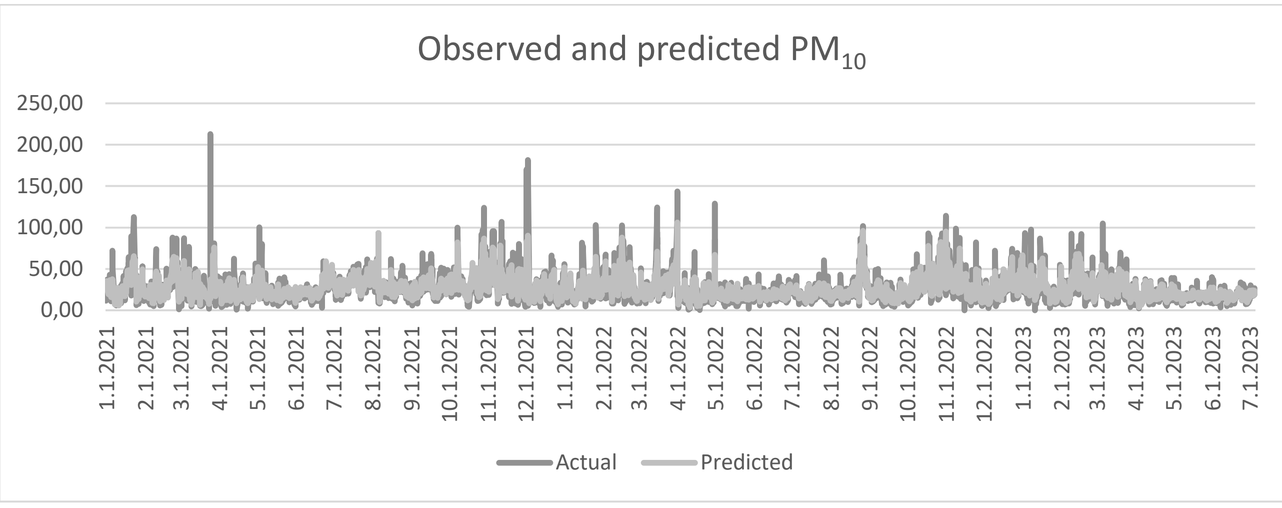

Figure 1: Comparison between observed and predicted PM_{10} values for station B1. Source: authors' work.

The code used for creating the model uses sklearn libraries suite (sklear.ensemble, sklearn.metrics and sklearn,model_selection) and pandas, joblib libraries. The steps used to create and train the model include data loading, feature engineering (selecting the relevant features to influence the outcomes and the predicted feature), splitting the data into training and testing sets, creating the random forest regressor (from sklearn.ensemble library), finetuning the model hyperparameters (by applying the GridSearchCV algorithm from sklearn.model_selection library), fitting the model to the training data, making predictions on the test data, evaluating the model (using sklearn.metrics library) and saving the model with joblib library. The Random Forest Regressor, as part of the ensemble learning family, combines the predictive power of multiple decision trees, a technique that we employed in the creation of our predictive model. During the model-building process, we harnessed bootstrapping, a method in which random subsets of the training data were used to train individual decision trees. This bootstrapping technique, combined with feature randomization, added diversity to the ensemble of decision trees, thereby reducing the risk of overfitting and increasing the robustness of our model. In addition to these techniques, we fine-tuned the model's hyperparameters. The Random Forest Regressor offers several hyperparameters, and the ones relevant for our model were the number of estimators, the maximum depth of the algorithm, minimum samples split and minimum samples leaf. By applying the GridSearchCV algorithm from sklearn.model_selection, we systematically optimized these hyperparameters to ensure the model's peak performance, enhancing the accuracy of our air quality predictions.

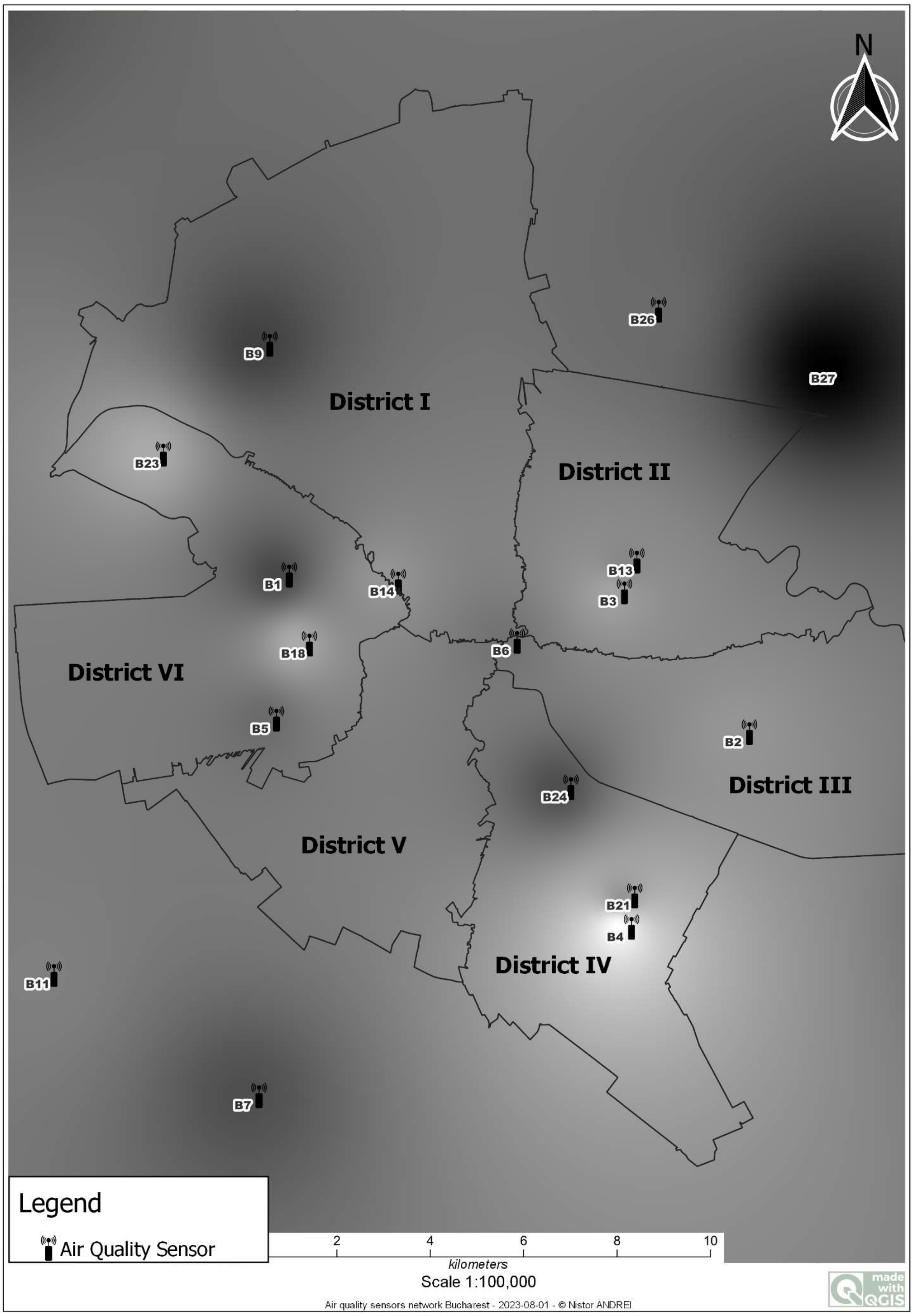

Figure 2: Average high PM_{10} concentrations observed in January, interpolated by IDW. Source: authors' work.

Table 1: Average high for studied air monitoring stations. Source of data: authors' work from Romanian Environment Ministry primary data[24].

Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
B1	76.36	88.54	87.73	53.41	47.45	41.79	47.86	55.51	47.16	76.19	80.53	62.15
B2	64.68	80.83	79.6	49.11	40.34	40.91	46	51.82	48.25	64.77	72.28	51.31
B3	63.47	70.71	70.82	46.7	45.26	46.76	50.62	56.29	51.78	67.49	64.95	56.51
B4	49.8	74.15	87.36	53.11	42.97	47.3	51.57	51.88	51.65	71.75	65.6	50.19
B5	71.25	87.16	93.49	56.1	47.64	60.41	64.77	58.22	57.18	83.62	78.24	60.34
B6	70.45	85.75	81.96	47.74	42.14	43	51.35	53.44	52.9	81.46	73.55	60.2

B7	74.84	89.87	96.94	59.02	48.01	51.44	53.87	54.86	55.53	67.7	71.45	60.08
B8	54.24	76.15	58.77	58.63	42.66	39.84	35.91	45.3	54.56	58.38	52.41	47.2
B9	76.59	97.72	112.11	57.06	50.81	84.53	55.75	75.98	44.37	90.56	118.94	77.39
B11	67.73	78.7	78.56	45.53	52.98	71.17	76.61	61.07	50.22	71	74.85	64.83
B12	67.77	75.89	78.2	53.57	69.2	87.85	51.44	71.33	45.87	78.54	82.77	71.24
B13	66.97	78.55	83.02	49.2	53.35	65.29	58.77	67.42	45.65	89.02	99.87	67.6
B14	65.01	76.01	72.38	44.85	52.9	81.07	55.45	59.95	47.76	88.78	81.65	60.86
B18	62.35	76.93	74.81	44.95	40.42	48.7	47.14	54.25	45.13	70.04	75.68	58.32
B21	64.83	76.82	77.69	47.04	40.57	49.18	47.14	54.25	45.13	72.94	88.59	58.04
B23	62.35	76.93	92.14	65.1	40.57	51.36	47.14	54.25	45.13	70.04	75.68	58.32
B24	74.67	77.2	74.81	44.93	43.29	58.82	50.87	51.25	48.84	72.84	83.07	66.71
B26	71.39	85.39	92.02	49.93	40.86	64.86	65.86	75.94	49.39	91.18	88.15	73.33
B27	85.95	108.45	92.31	49.49	49.7	82.4	65.15	70.82	47.58	129.06	148.26	97.96
B28	74.76	84.28	88.7	54.39	62.25	85.74	89.5	106.33	63.25	122.01	132.27	70.81
B29	60.33	82.07	78.28	47.32	39.77	45.09	56.24	43.86	44.43	73.79	89.87	64.45
B30	76.33	97.59	83.47	49.21	51.41	75.31	52.61	62.2	49.53	78.37	88.17	74.63

Through spatial interpolation techniques, the air quality maps unveiled localized pollution hotspots across the city. Notably, stations B28 and B27 in the eastern part of the region were found to exhibit higher concentrations of PM_{10} and other pollutants. Additionally, specific temporal patterns emerged, with concentrations in January, February, and March being above the average for all stations. Furthermore, October and November registered exceptionally high levels above the average for specific stations, such as B9, B27, and B28, respectively. Table 1 displays the monthly average of daily maximum PM_{10} concentrations recorded at each air monitoring station during the selected data collection period. It is important to note that while this period might not fully capture all pollution patterns, a more optimal timeframe of at least 10 years would be preferable. However, due to limited historical data availability and computational resources, a period of 2.5 years was chosen for this study.

To generate the air quality map presented in Figure 2, an inversed distance weighted (IDW) interpolation technique was employed based on the average high concentrations observed in January. Similar maps were created for all the months and for other values, such as record high, daily mean and average low. This approach helped in extrapolating the air quality data and obtaining comprehensive map series of PM10 concentrations across the study area.

DISCUSSION

The utilization of AI and geospatial analysis in environmental monitoring has opened new horizons for air quality assessment in Bucharest. By harnessing the power of these innovative technologies, real-time and high-resolution information about air quality dynamics can be obtained. This empowers decision-makers to proactively mitigate pollution sources and enhance the overall living conditions for city residents. As we continue to advance in technology, the potential of AI and geospatial analysis in environmental research and policymaking becomes ever more promising, leading towards a cleaner, healthier, and more sustainable urban future.

This study demonstrates that AI and geospatial analysis have the potential to transform air quality monitoring practices in urban environments. By harnessing the power of these technologies, we can obtain real-time, high-resolution information about air quality, enabling proactive decision-making to mitigate pollution sources and improve the living conditions of city residents.

One critical aspect to discuss is the rationale behind choosing a specific algorithm for our research. We opted for the Random Forest algorithm due to its suitability for handling complex data and capturing non-linear relationships. The robust performance of the Random Forest algorithm in regression tasks, as demonstrated by the high R-squared (R2) value and low mean absolute error (MAE) and root mean squared error (RMSE), validates our selection.

While the study focused on the application of the Random Forest algorithm, it's worth noting that there are numerous algorithms available for predictive modeling. Future research could explore the potential of alternative approaches,, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), or a combination of both. LSTM networks are designed to capture temporal dependencies in sequential data. They are particularly useful for time series data where the order and timing of observations matter. In the environmental domain, this is vital for modeling changes in atmospheric variables over time. CNNs are well-suited for processing spatial data, such as images, maps, and grid-based data. In the context of environmental modeling, they can effectively analyze geospatial information, like satellite imagery, climate maps, and terrain data. A combination of both approaches (ConvLSTM model) can simultaneously capture spatial patterns and temporal dependencies within the data. This is especially valuable in environmental modeling, where understanding how weather or air quality conditions evolve over both space and time is crucial. These examples, or other advanced deep learning techniques hold promise for uncovering more intricate patterns and trends in air quality data, presenting an exciting avenue for future investigations.

The information derived from this study, particularly the air quality maps and identified patterns, offers valuable insights for policymakers and urban planners. By recognizing pollution hotspots and understanding temporal variations, targeted interventions can be implemented to improve air quality and protect public health. Furthermore, our research supports the notion that the integration of AI and geospatial analysis can revolutionize air quality monitoring practices in urban environments.

CONCLUSION

In conclusion, the integration of AI and geospatial analysis in air quality monitoring holds the promise of revolutionizing environmental monitoring practices in urban areas. Our study in the city of Bucharest showcases the effectiveness of these technologies in accurately predicting air quality parameters, such as particulate matter concentrations, with a high degree of precision. By leveraging machine learning algorithms and geospatial data, we gain deeper insights into the spatial distribution of pollutants and identify localized pollution hotspots. This information empowers decision-makers to implement targeted interventions that isolate or even eliminate pollution sources and promote sustainable urban development.

Moving forward, it is essential to continue exploring the potential of AI and geospatial analysis in environmental monitoring and air quality assessment. By expanding the scope of data collection to include additional air quality parameters and geospatial features, we can further enhance the predictive accuracy and applicability of these models in diverse urban settings.

The utilization of AI and geospatial analysis in environmental monitoring opens new horizons for air quality assessment in Bucharest and beyond. By harnessing the power of these innovative technologies, real-time and high-resolution information about air quality dynamics can be obtained, leading towards a cleaner, healthier, and more resilient urban future. As technology continues to advance, we have a unique opportunity to leverage these innovations in environmental research and policy-making, working towards a more sustainable and environmentally conscious future. With a collaborative effort from researchers, policymakers, and urban planners, the integration of AI and geospatial analysis can contribute significantly to the improvement of air quality and public health in cities worldwide.

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