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A Multi-Country Statistical Analysis Covering Turkey, Slovakia, and Romania in an Educational Framework

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Abstract: This paper uses hierarchical regression analysis, a statistically robust method, to explore the correlations between two meteorological parameters and three particulate matter concentrations. The dataset is provided by six sensors located in three cities from three countries, and the measurements were taken simultaneously for three months at each minute. Analyses and calculations were performed with the Statistical Package for the Social Sciences (SPSS). The results underscore that the complexity of air pollution dynamics is affected by the location even when the same type of sensors is used, and emphasize that a one-size-fits-all approach cannot effectively address air pollution. The findings are helpful from three perspectives: for education, to show how to handle and communicate a solution for local communities' issues about air pollution; for research, to understand how easy a university can generate and analyze open-source data; and for policymakers, to design targeted interventions addressing each country's challenges.

Keywords: particulate matters; meteorological parameters; hierarchical regression; human health; environmental education

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1. Introduction

Everyone's quality of life, no matter age or socio-economic situation, is impacted by the quality of breathed air. Epidemiological studies [1] have revealed an approximately linear rise in health risk with increasing exposure to urban air pollutants such as PM (particulate matter) from road transportation. Also, fossil fuel combustion, biomass burning, construction, and industrial emissions increase health risks. There is no discernible threshold below which no effects are detectable.

PM10 has effects on respiratory health. Long-term exposure to PM10 (fine particles having a diameter of less than 10 μm) is associated with a risk for lung cancer [2], specific circulatory system diseases like cerebrovascular disease, high blood pressure, ischemic heart disease, arrhythmia [3,4], and mutagenic activity and deoxyribonucleic acid (DNA) damage for young people 18–40 years old [5,6]. In recent years, it has been shown that long-term exposure to PM10 during pregnancy is associated with preterm birth and low birth weight [7], infant mortality risk [8,9], and increased risk for multiple congenital heart defects [10,11]. The elderly, people with chronic illnesses, children with allergies, and pregnant women are affected more than others by air pollution [12].

Because fine particles with a diameter of less than 2.5 μm can penetrate deep into the lungs and pass into the bloodstream, PM2.5 is linked with increased rates of chronic obstructive pulmonary disease [13], lung cancer [14], and heart disease and stroke events [15].

Long-term exposure is linked to neurological disorders [16], acute nasopharyngitis [17], progression of diabetes mellitus [18], and children's allergies [19]. Another interesting study [20] shows that using fireplaces and woodstoves in houses for 4 h/day can decrease occupant life expectancy by 1.6 years.

Guo et al. [21] show that in China, the lung cancer incidence rate is higher for male residents in high-temperature or -humidity counties when exposed to PM1 (particulate matter with an aerodynamic diameter of less than one µm). Long-term exposure to PM1 is associated with impaired lung function in children and adolescents [22]. PM1 alert thresholds have not yet been established by the WHO (World Health Organization).

During lockdown, when air pollution was very low, [23] studied the pandemic's influence on air pollution, public health, and economic growth. In this framework of fixed system dynamics analysis, the importance of money was more than evident in the cycle "GDP (Gross Domestic Product) → green investments on declining of air pollution → quality of environment → investment in the fixed assets → GDP". Low-income countries are even more affected by air pollution; the main sources of pollution are represented mainly by fossil fuel and vegetal waste burning in the heating process and industry. Most often, the regulations are not in the interest of the environment because there are no explicit laws dealing with industrial pollution [24]. Sheridan et al. [25] linked air pollution to COVID-19 positivity, hospitalizations, and mortality during the pandemic. Li et al. [26] underline the causal relationship between public attention and air pollution. The results show that public attention could reduce air pollution. The education of the new generations plays an essential role in changing the attitude toward the environment. Li and Ramanathan, in their study from 2018 [27], found a non-linear and negative relationship between command-and-control regulations, market-based regulations (as environmental regulations), and environmental performance. They did not find a significant relationship between informal regulations and environmental performance. Another important detail of this study is related to the time. Command-and-control regulations impact the environmental performance in current and preceding years, market-based regulations produce effects in the current year, and informal regulations in two years.

Refs. [28–30] studied how PM10 reduces atmospheric visibility as an important component of smog, influences meteorological processes and atmospheric chemistry, reduces photosynthesis in plants through deposition on plant leaf surfaces, and alters soil physico-chemical properties [31]. Natural ecosystems and biodiversity are affected by air pollution. For example, some species of lichens disappeared because they took their nutrients straight from the atmosphere. The change in forest vegetation and heathland reductions are other consequences. Ozone-sensitive species of trees (pines) are replaced by others that are not so sensitive (oaks) or even by shrubs, altering the genetic diversity within species [32,33]. Acid rains affect wild vegetation and agriculture [34].

Many factors influence air pollution dynamics. Zang [3] highlights the most important factors that affect air pollution: relative humidity, temperature, extreme wind speed, sunshine duration, average wind speed, and rainfall. Extreme wind plays the most crucial role in air pollution dynamics, and sunshine duration is essential from a thermal point of view. Air quality is not influenced by average wind speed and rainfall capacity.

This paper aims to investigate the relationships between some variables and test some hypotheses based on the hierarchical regression analysis. According to Chi and Voss [35], there are two advantages of the hierarchical regression analysis standard multivariate regression: the effects of heterogeneous variables can be nested in a hierarchical model, combining both individual and aggregate-level characteristics in a model. Regression techniques have been used for a long time as forecasting tools in air pollution forecasting. STATGRAPHICS software (version 19) was used with good results for forecasting, monitoring, and controlling the air quality conditions in Sofia, Bulgaria [36]. Also, Abdullah et al. [37] used Multiple Linear Regression models for different monsoon seasons with meteorological factors as predictors to forecast air pollution in Kuala Terengganu, Malaysia. Panneerselvam et al. [38] used a support vector machine model to predict air pollution in the study area using historical data from two observation stations, including wind direction and speed. The Gaussian process regression predicts particulate particles with high accuracy. Lee et al. [39] have a different approach, using a threshold quantile regression model. They aimed to capture spatial heterogeneity and heteroscedasticity, adding two threshold variables to define a spatial cluster. Xu et al. [40] conducted a dynamic analysis of air pollution emissions using some nonparametric additive regression models to evaluate sources of PM2.5 in China.

Some authors used hierarchical regression methods based on SPSS to study the correlations between different meteorological parameters, air pollutants, COVID-19 spreading, environmental justice, health effects, health expenses produced by air pollution, and well-being states. The datasets used in this study were provided by field monitoring in different locations using the same type of sensor. Field monitoring can provide vital information for identifying air pollution sources. It might contribute to developing alarm systems for sensitive population categories when the pollution thresholds are exceeded. Moreover, changing behaviors related to air pollution starts locally, mainly based on education.

A. Asadi et al. [41] recognized that field monitoring can accurately measure air pollution, but these measurements have limited spatial coverage. From this point of view, they chose to investigate the potential of the data given by the aerosol optical depth sensors of the Moderate-Resolution Imaging Spectroradiometer to evaluate the air quality parameters. Based on linear regression analysis, they found a relationship among aerosol optical depth, metrological data, and air pollution data.

M. Simoni et al. [42] assessed the effects of indoor air pollution on school children's respiratory health in Norway, Sweden, Denmark, France, and Italy. Using hierarchical regression methods, the authors showed that poor air quality is related to respiratory disturbances and affects nasal patency. Lin et al. [43] used a hierarchical multiple logistical regression model to analyze the associations between kindergarten-level PM2.5 exposure and individual-level outcomes of asthmatic and allergic symptoms in China.

In countries like Spain, Italy, the UK, China, Canada, and the USA, P.D. Huarez et al. [44] found a positive correlation between long-term exposure to high air pollutants and COVID-19 morbidity and mortality. Also, they showed that particulate matter and some meteorological factors represent important carriers of infectious microbes and play a critical role in spreading disease.

Pope et al. [45] detected distributive environmental justice relationships using the hierarchical multiple regression method. In their analysis, they noticed that young people ($\leq$17 years old) are significant predictors for ambient ozone and particulate matter concentrations, and elderly people ($\geq$65 years old) are the only predictors for ambient particulate matter. Children and the elderly represent sensitive categories of air pollution, together with pregnant women and chronic patients. S. Taşkaya [46] used a hierarchical multiple regression model to investigate the relationship between environmental variables such as air pollution and well-being.

The goal of this paper is to perform a hierarchical regression analysis between some meteorological parameters (relative humidity and temperature) and particulate matter concentrations (PM10, 2.5, and 1) in three countries during summer months using SPSS software, version 29. This study is necessary to understand how meteorological parameters influence air pollution and to see if the results are affected by the location when the same type of sensor is used.

Another important detail is that the PM sensors used in this study were made by some international students based on a sensor kit. This activity was organized in the framework of an educational project during summer school [47]. The sensors were installed in students' countries and connected to a more extensive network [48]. All sensors were calibrated by the manufacturer who sold the sensor kit. During summer school, students and researchers discussed air pollution, the values of the alert thresholds given by WHO in 2021 [49], EU environmental regulations [50–52], selective garbage collection, and climate change mitigation and attenuation effects. Students have met entrepreneurs focused on innovation, researchers, mass media, representatives of companies, and national agencies. The steps for solving the air pollution issue that affects citizens' health from Craiova using the power of education were presented by volunteers. They showed how to develop an awareness campaign for different target groups to receive the local community's support. They also showed how people's bad habits (burning tires, plastic, vegetal waste, and using fossil fuels to heat their houses) can be diminished with neighbors' help.

Local decision-makers can monitor and control air pollution in their areas because they cannot ignore the health costs and environmental implications. To address these challenges, funds might be spent on new technology, green spaces, non-polluting heating methods, and infrastructure. They have the authority to oversee industrial facilities and devise strategies [53] to prevent urban air pollution.

The novelty of this study is given by three findings: (1) presents a new multi-country analysis covering Turkey, Slovakia, and Romania in an educational framework; (2) provides a broad perspective on the impact of some meteorological parameters on particulate matter (PM1, PM2.5, and PM10) concentrations; and (3) emphasizes how the sensors' location affects the results. Such comprehensive cross-country studies are limited in the existing literature, making this research a pioneering study in air quality assessment.

There are three significant contributions of this study:

(1) The authors focus on the hierarchical regression analysis from the perspective of finding correlations between meteorological parameters and PM concentrations.
(2) We present two SPPS models considering only one meteorological parameter and two PM parameters.
(3) We conduct a quantitative air quality analysis in three developing countries. By considering the quantitative assessment of air pollution, decision-makers can enhance their decision-making process.

The paper is organized as follows. Theoretical background and review-related work are included in Section 1. Section 2 presents the sensors, their locations, and the dataset, followed by the methodology, results, and discussions in Section 3. Section 4 highlights the conclusions of this study, emphasizing all implications derived from this research.

2. Materials and Methods

2.1. Location and Climate Description

Among Turkey's 81 areas, Adana (1.4 million inhabitants) is the sixth most important and quickly expanding. The city is in the center of the Cilician plain, on the Seyhan River, 37°0′ N, 35°19.28′ E at an altitude of 23 m, in Southern Turkey. Agriculture, industry, and trade are Adana's most important income sources. Adana's most important income sources are agriculture, industry, healthcare, public and private services, and regional trade. Adana's climate is Mediterranean, with long, hot summers and short, moderate winters. Adana is 35 km inland from the Mediterranean Sea and has twenty green parks (Ataturk, Seyhan, ABB-Nation, Ziapașa, and Dilber parks being only a few examples). Temperatures often peak in late July and August, with daily highs topping 35 °C. Winter temperatures typically range from 10 to 15 °C. In Adana, the average monthly relative humidity ranges from 49% in August to 81% in January. Adana has two coal-fired thermal power plants, heavy industry facilities, and construction sites. Adana's infrastructure includes an airport and public transportation (buses).

Craiova (44°20′ N, 23°49′ E, altitude 100 m) is Romania's sixth city from the perspective of the number of inhabitants (243,765 inhabitants). It is a city in development (urban area of 81.41 km^2 city and metropolitan area of 1498.6 km^2) with high traffic, construction sites, and industrial and agriculture businesses. It is in Oltenia Plain, near the east bank of the river Jiu, in the historical Oltenia region (SW part of Romania). The climate is continental with Mediterranean influences, with cold, snowy, and partially foggy winters and hot summers. Craiova has a significant number of companies and firms focused on agriculture (distribution of pesticides and seeds, sales of agriculture equipment) and industry (vehicle construction, automotive providers, electric motors, generators, transformers, construction materials, energy distribution, collection and recovery of ferrous metal waste, transport, and fossil fuel distribution). Also, the city has many housing construction sites and a thermal power plant. The city's infrastructure includes an airport and public transportation (buses and trams). The traffic is busy in Craiova. All of these and the geographical position of Craiova contribute to the city's air pollution. The City has 17 green parks covering 196 ha, with Romanescu, Tineretului, Hanul Doctorului, and Puskin-Crizantemelor parks being the most known.

Banská Bystrica (48°44′07″ N, 19°08′43″, elevation of 361.94 m, area of 103.37 square kilometers) is the sixth city in Slovakia (76,000 inhabitants). The city is in a valley encircled by mountain chains (Low Tatras, Veľká Fatra, Kremnica) in central Slovakia. The climate is humid continental, with no dry season and a warm summer. During summer, average temperatures are between 20 and 26 degrees Celsius. During winter, the temperatures are low (on average between −6 and 6 °C), and moderate snow/rainfall. This city has 19 parks (the most known being Mestský lesopark Urpín, Mestský Park Banská Bystrica, Park s umenim, Park under the SNP Museum). Banská Bystrica is one of Slovakia's most polluted environmental areas due to its adverse geographical location. The city is in the northern part of the Zvolen basin with mountainous surroundings (Staré Hory Hills, Kremnica Hills, and Poľana), which makes this area poorly ventilated. This causes insufficient dispersion of pollutants in the air, especially during inversion situations. The ruggedness and complexity of the landscape of Banská Bystrica and its surroundings cause mainly car traffic to accumulate along the Hron River, which leads to increased air pollution in the central urban areas, where PM particulate matter levels are regularly exceeded. From the industrial point of view, in this area, there is a paper mill and two pharmaceutical companies. Agriculture is mainly concentrated near Banská Bystrica, with maize and cereals grown. The immediate surroundings of the town are relatively wooded and mountainous. Banská Bystrica does not have an airport. Buses are the main type of public transportation.

2.2. Sensors and Datasets

Six identical low-cost sensors were used in this study. They are type uRADMonitor SMOGGIE-PM and are produced by Magnasci SRL, Romania. These sensors are lab-tested for data accuracy and can measure air temperature, relative humidity, and PM1, PM2.5, and PM10 concentrations in the air. The PM concentrations are measured using an integrated laser scattering detector [54]. The meteorological parameters are measured using MEM (Micro Electro Mechanical) systems, and the PM concentrations are measured using a pulse of coherent IR light shining through a cavity with a PIN photodiode located sideways. The sensor has a fan that pushes the air into a chamber. When a particle reaches the laser beam, it scatters the laser light, and a PIN photodiode detects the scattered light. The number of events correlates to the mass concentration based on the proportionality relation between the amplitude of the recorded scattered signal and the particle size. The laser scattering method differs from the gravimetric method that national environmental agencies use. In general, this type of sensor underestimates the PM concentrations. [55,56]. Even though the method used by the SMOGGIE-PM sensor is different than the one used by the National Environmental Agencies, SMOGGIE-PM underestimates the values of PM concentrations.

This study was carried out on data obtained from 6 data loggers: Adana from Turkey, Craiova from Romania, and Banska Bystrica from Slovakia. Two measuring instruments from each country were analyzed, and these measurements were collected during the summer months of 2023. All measurements were taken continuously at each minute. The measurement interval is one minute for all variables. Approximately 650,000 pieces of data were analyzed using SPSS software [57]. All sensors were placed in busy areas of each city: one near a busy traffic intersection and one in the industrial area.

2.3. Methodology

In this study five variables were used: two meteorological parameters (temperature, humidity) and three particulate matter concentrations (PM1, PM2.5, and PM10). The variables were extracted from the uRADMonitor database. Once all the parameters and fields were determined, the probability of the variables was checked. The next step was to examine the results of each stage analysis. The R-square change was recorded. At this point, the contribution of the added variables to the model's power was established. The last step was to analyze the model's validity with SPSS tools. Practically, it tests the reliability and the statistical significance of the included parameters.

Regression analysis was used as an alternative and a quick way to analyze air pollution according to established parameters. In the literature, regression equations are generally obtained by multiple building models. With the support of this analysis, a parametric analysis of dependent parameters was performed. Since there are little input data in such an analysis method, architects can use them to select the most effective alternatives at the initial design stage [58,59]. The regression analysis was performed on a set of independent variables for each dependent variable. The linear coefficients obtained for each parameter represent the impact on the output data [60].

2.4. Statistical Analysis

In this study, first, the Kolmogorov–Smirnov test was used to verify the normality of the distribution of continuous variables. It was evaluated whether there was a significant difference between the countries' data, and the Mann–Whitney U Test was applied [56]. The Pearson correlation coefficient was used for the variables for the correlation analysis. In the present study, we considered PM 2.5 and 10 as dependent variables, whereas independent variables were temperature (T) and relative humidity (RH). Hierarchical regression was used to predict the dependent variable. It is a statistical method of investigating the relationship between a dependent variable and several independent variables and testing hypotheses. Linear regression requires a dependent variable. On the other hand, hierarchical regression is established by the method in which the independent variables are entered into the regression step by step rather than simultaneously. This regression analysis accounts for the dependent variable variation of the independent variables; thus, the relationship between the independent variable x and the dependent variable y (positive and negative) does not always result in the independent variable being the dependent variable. Causality is not necessary for there to be a relationship between two variables. Regression analysis deals with the structure and degree of relationship between variables.

There are a few steps to facilitate the estimation of the hierarchical regression model with SPSS software (Figure 1). First, identifying potentially important parameters is crucial for a successful prediction [61]. Once all the parameters and fields are determined, the next step is to check the probability of the variables. By examining the results of each stage analysis, the R-square change is observed, and it is determined how the variables added at each stage contribute to the explanatory power of the model. The model's validity is analyzed by testing the reliability and the statistical significance of the included parameters using SPSS tools.

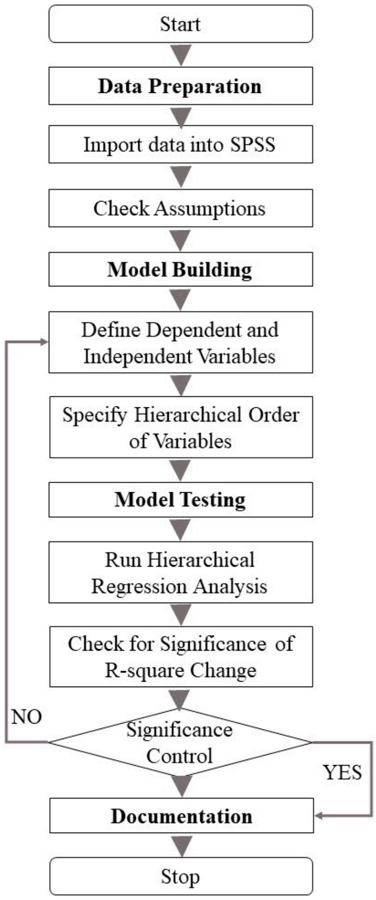

Figure 1. Flowchart of the regression on SPSS.

3. Results and Discussion

Table 1 shows the descriptive analysis of average temperature (°C), relative humidity (%), PM1, PM2.5, and PM10 particulate matter concentrations in June, July, and August in Turkey, Slovakia, and Romania of all the 650,000 pieces of data.

Table 1. Descriptive Analysis of the Data.

		Turkey					**Slovakia**					**Romania**				
Months		**T (°C)**	**RH (%)**	**PM1 (µg/m^3)**	**PM2.5 (µg/m^3)**	**PM10 (µg/m^3)**	**T (°C)**	**RH (%)**	**PM1 (µg/m^3)**	**PM2.5 (µg/m^3)**	**PM10 (µg/m^3)**	**T (°C)**	**RH (%)**	**PM1 (µg/m^3)**	**PM2.5 (µg/m^3)**	**PM10 (µg/m^3)**
June	Mean	26.0	53.1	9.7	15.0	17.0	26.0	58.7	8.7	13.8	15.0	18.0	60.5	5.2	7.7	8.1
	Std. Dev.	3.3	9.4	4.1	6.3	7.6	2.8	9.3	3.9	6.0	7.2	5.9	12.2	7.7	9.1	9.7
July	Mean	30.0	48.8	8.8	13.0	14.4	29.9	52.4	7.3	11.3	12.0	20.1	60.1	5.3	7.6	8.1
	Std. Dev.	4.0	12.9	4.4	6.5	7.8	3.2	13.3	4.6	7.2	8.0	5.5	11.2	3.5	5.0	5.6
August	Mean	30.7	55.7	12.3	17.9	20.4	29.9	67.4	12.0	18.1	20.3	20.4	64.3	6.3	8.9	9.4
	Std. Dev.	3.7	8.6	3.1	5.0	6.5	2.7	8.6	3.2	5.3	6.9	5.9	11.0	18.0	18.4	18.6

According to this dataset, in which approximately 650,000 pieces of data were collected, there is a linear increase in the temperature variable from June to August in the selected countries. Regarding humidity, Turkey, Slovakia, and Romania show a similar pattern in

June, July, and August. While July generally represents a period when the humidity rate is lower, it is seen that the humidity rates increase in August. When PM concentrations are examined, similar trends are observed between Turkey and two other countries. PMs also increase from June to August in all countries.

Table 2 contains the correlation analysis results for three countries, namely, Turkey, Slovakia, and Romania. The table quantifies the strength and direction of the relationships between the relationships between temperature (T), relative humidity (RH), and particulate matter concentrations (PM1, PM2.5, and PM10). Each cell in the table represents the correlation coefficient between the corresponding variables. First, when we examine the relationship between temperature (T) and other variables, a negative correlation is observed between temperature and humidity (H), PM1, PM2.5, and PM10. These negative correlations indicate that moisture and particulate matter concentrations decrease as temperature increases. Additionally, positive and significant correlations exist between humidity (H) and PM1, PM2.5, and PM10. This shows that as humidity increases, particulate matter concentrations also increase.

Table 2. Correlation Results for all data according to countries.

	Turkey					**Slovakia**					**Romania**				
	T (°C)	**RH (%)**	**PM1 (µg/m³)**	**PM2.5 (µg/m³)**	**PM10 (µg/m³)**	**T (°C)**	**RH (%)**	**PM1 (µg/m³)**	**PM2.5 (µg/m³)**	**PM10 (µg/m³)**	**T (°C)**	**RH (%)**	**PM1 (µg/m³)**	**PM2.5 (µg/m³)**	**PM10 (µg/m³)**
T (°C)	1.00	−0.69	−0.15	−0.22	−0.22	1.00	−0.44	−0.03	−0.10	−0.10	1.00	−0.74	0.02	0.02	0.02
RH (%)		1.00	0.55	0.57	0.55		1.00	0.59	0.60	0.59		1.00	0.08	0.12	0.12
PM1 (µg/m³)			1.00	0.98	0.95			1.00	0.98	0.96			1.00	0.98	0.97
PM2.5 (µg/m³)				1.00	0.99				1.00	0.99				1.00	1.00
PM10 (µg/m³)					1.00					1.00					1.00

Tables 3–5 present the regression results for Turkey, Slovakia, and Romania, focusing on the relationships between temperature (T), relative humidity (RH), and particulate matter concentrations (PM1, PM2.5, and PM10) during the three summer months. In these tables, B represents unstandardized correlation coefficients, Beta (β) represents standardized correlation coefficients, SE represents standard errors, R^2 represents the coefficient of determination, and ΔR^2 indicates the change in R^2 when additional variables are introduced into the model. A regression analysis of 3-month data for Turkey was performed in Table 3. In this analysis, the hierarchical analysis method was used, and firstly, only the effect of temperature was examined (Model 1). Then, the effects of temperature and humidity were examined together for particulate matter (Model 2). According to the results from this analysis, when only temperature was used in Model 1, it explained only 6% of the variation in PM1 concentrations. However, when temperature and humidity are used in Model 2, they explain 23% of the variation in PM1 concentrations. In other words, humidity was a more important factor than temperature on PM1. This shows that using temperature and humidity variables together explains more variance than single PM1 concentrations. For PM2.5, in Model 1, the R^2 value explains 10% of PM2.5 concentrations. When temperature and humidity are used together in Model 2, the R^2 value increases to 23.4%. Again, using temperature and relative humidity variables together explains PM2.5. PM10, when only temperature is used in Model 1, the R^2 value explains 11% of PM10 concentrations. When temperature and humidity are used together in Model 2, the R^2

value increases to 23%. In this case, using temperature and humidity variables together better explains PM10. However, when the analyses were conducted separately for July, it was seen that temperature and humidity explained the most variance of PM2.5 (43.6%), and for August, they explained the most variance of PM2.5 (9%).

Table 3. Regression results for Turkey.

June/Turkey/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.324	−0.245	0.005	0.06	0.06	0.287	0.217	0.007		
RH (%)						0.258	0.622	0.002	0.234	0.233
June/Turkey/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.647	−0.317	0.008	0.101	0.101	0.267	0.131	0.01		
RH (%)						0.385	0.603	0.003	0.234	0.133
June/Turkey/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.795	−0.325	0.009	0.105	0.105	0.287	0.067	0.013		
RH (%)						0.258	0.528	0.004	0.23	0.125
July/Turkey/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.374	−0.315	0.005	0.1	0.099	0.306	0.258	0.006		
RH (%)						0.274	0.804	0.002	0.417	0.318
July/Turkey/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.624	−0.348	0.008	0.121	0.121	−0.402	0.224	0.01		
RH (%)						−0.414	0.801	0.003	0.436	0.315
July/Turkey/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.731	−0.349	0.009	0.122	0.122	0.414	0.198	0.01		
RH (%)						0.462	0.767	0.003	0.411	0.289
August/Turkey/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.124	−0.128	0.004	0.016	0.099	0.034	0.035	0.007		
RH (%)						0.059	0.197	0.002	0.029	0.07
August/Turkey/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.276	−0.173	0.006	0.03	0.121	−0.402	0.075	0.011		
RH (%)						−0.414	0.3	0.003	0.058	0.091
August/Turkey/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.376	−0.18	0.008	0.032	0.032	0.085	0.041	0.014		
RH (%)						0.173	0.267	0.004	0.055	0.023

IV = Independent Variable; DV = Dependent Variable.

Table 4. Regression results for Slovakia.

June/Slovakia/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.039	0.035	0.004	0.001	0.001	0.257	0.227	0.005		
RH (%)						0.154	0.291	0.002	0.049	0.048
June/Slovakia/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.051	−0.037	0.005	0.001	0.001	0.384	0.275	0.006		
RH (%)						0.236	0.36	0.003	0.074	0.073
June/Slovakia/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.046	0.031	0.005	0.001	0.001	0.396	0.268	0.006		
RH (%)						248	0.357	0.003	0.073	0.072
July/Slovakia/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.004	0.003	−0.01	0.0001	1×10^{-4}	0.333	0.491	0.004		
RH (%)						0.201	0.622	0.002	0.139	0.139
July/Slovakia/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.019	−0.02	0.005	0.0001	1×10^{-4}	0.481	0.5	0.006		
RH (%)						0.297	0.648	0.003	0.074	0.074
July/Slovakia/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	−0.025	−0.024	0.001	0.099	0.099	0.521	0.492	0.006		
RH (%)						0.325	0.645	0.003	0.15	0.051
August/Slovakia/DV = PM1 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.103	0.033	0.014	0.001	0.001	0.651	0.212	0.023		
RH (%)						0.37	0.224	0.012	0.02	0.019
August/Slovakia/DV = PM2.5 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.142	0.045	0.014	0.002	0.002	0.983	0.311	0.023		
RH (%)						0.568	0.335	0.012	0.043	0.041
August/Slovakia/DV = PM10 (μg/m³)										
IV = Variable	Model 1					Model 2				
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.14	0.044	0.014	0.002	0.002	1.039	0.326	0.023		
RH (%)						0.607	0.355	0.012	0.048	0.046

IV = Independent Variable; DV = Dependent Variable.

Table 5. Regression results for Romania.

June/Romania/DV = PM1 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.11	0.103	4	0.011	0.011	0.258	0.241	0.004		
RH (%)						0.141	0.29	0.002	0.076	0.065
June/Romania/DV = PM2.5 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.142	0.103	0.005	0.011	0.011	0.355	0.258	0.005		
RH (%)						0.203	0.325	0.002	0.092	0.081
June/Romania/DV = PM10 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.156	0.107	0.005	0.011	0.011	0.397	0.273	0.005		
RH (%)						0.23	0.348	0.002	0.105	0.094
July/Romania/DV = PM1 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.084	0.132	0.002	0.017	0.017	0.254	0.398	0.002		
RH (%)						0.183	0.506	0.001	0.20	0.186
July/Romania/DV = PM2.5 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.096	0.102	0.003	0.01	0.01	0.34	0.361	0.003		
RH (%)						0.263	0.491	0.002	0.185	0.175
July/Romania/DV = PM10 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.12	0.109	0.004	0.012	0.012	0.410	0.374	0.004		
RH (%)						0.313	0.504	0.002	0.195	0.183
August/Romania/DV = PM1 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.105	0.049	0.007	0.002	0.002	0.479	0.227	0.01		
RH (%)						0.321	0.25	0.006	0.033	0.031
August/Romania/DV = PM2.5 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.124	0.056	0.008	0.003	0.003	0.689	0.309	0.01		
RH (%)						0.485	0.356	0.006	0.066	0.063
August/Romania/DV = PM10 (μg/m³)										
IV = Variable			Model 1					Model 2		
	B	β	SE	R^2	ΔR^2	B	β	SE	R^2	ΔR^2
T (°C)	0.138	0.06	0.008	0.004	0.004	0.775	0.34	0.011		
RH (%)						0.547	0.393	0.006	0.08	0.076

IV = Independent Variable; DV = Dependent Variable.

Results from Slovakia's measurements show that when only temperature is used in Model 1, it explains only 0.1% of the variation in PM1 concentrations (Table 4). When temperature and humidity are used together in Model 2, this value increases to 4.9% for the analysis of June. For PM2.5, when Model 1 R^2 is 0.1%, Model 2 R^2 is 7.4% However, R^2 values are still low, indicating that temperature and humidity variables cannot explain PM1 concentrations in Slovakia. According to the PM2.5 and PM10 data results, the low R^2 values indicate the limited explanatory capacity of temperature and humidity variables. In July, temperature and humidity explained the most variance of PM10 (15%), and for August, they explained the most variance of PM10 (4.8%)

When the one variable included in Model 1 for Romania is temperature, it explains 1.1% of the variance in PM1 concentrations (Table 5). This figure rises to 7.6% when temperature and humidity are included in Model 2 for June. However, when the analyses were conducted separately for June, it was seen that temperature and humidity explained the most variance of PM10 (10.5%). When July is analyzed, Model 2 reaches the highest R^2 value in PM1, which is 20%. This indicates that using temperature and humidity variables together better explains PM10 concentrations in Romania. For PM1, PM2.5, and PM10, when Model 1 and Model 2 are compared, it is seen that humidity is more effective among the temperature and humidity variables in Romania. However, a higher R^2 value is obtained by using temperature and humidity together.

When the same type of sensor is used, the location affects the results. The study emphasizes that a one-size-fits-all approach cannot effectively address air pollution. For example, the observed fluctuations in R^2 values point to the complex relationships between meteorological conditions and air quality, indicating a complicated relationship between temperature and relative humidity, and particulate matter concentrations. For instance, compared to PM1, the higher R^2 values for PM2.5 and PM10 in Turkey suggest that temperature and humidity have a more noticeable impact on these particulate matter fractions. However, Slovakia's lower R^2 values imply that other factors—possibly connected to regional characteristics, air circulations, or industrial activity—may impact PM concentrations more. These findings suggest more research into the relationships between local industrial practices, climate, and air quality dynamics. Comprehensive knowledge is necessary to create focused air pollution mitigation plans unique to each location.

Other meteorological factors should be considered to understand the air pollution dynamics better locally. Solar radiation, dewpoint temperature, precipitation, cloud pattern, and ambient temperature affect the spatial distribution pattern of PM, whereas wind speed influences PM's long-range horizontal transport, dispersion, and re-suspension [62,63].

Even a part of the solution to the air pollution problem is represented by the sun and wind energy, with all three cities having good solar and wind potential, whereby it is in the power of decision-makers to install solar panels on the roofs of the buildings, to replace old public transportation with one based on electric energy or biogas, to make rules for construction sites, and to build city bypass belts. Other national or international educational initiatives might aim as project activities to build more complex sensors that can measure other parameters regarding wind velocity and sunshine duration. Some collaborations between the universities with the National Agencies of Meteorology or the National Environmental Agencies might help to improve future datasets. The educational initiatives aim to train new generations to respect the environment and understand the consequences of air pollution on human health and biodiversity.

4. Conclusions

This study investigates the variations in particulate matter (PM1, PM2.5, and PM10), temperature, and relative humidity across Turkey, Slovakia, and Romania during June, July, and August 2023. The findings show significant variations between the results in these three countries. The observed fluctuations in R^2 values point to the complex relationships between meteorological conditions and air quality, indicating a complicated relationship between meteorological parameters and PM concentrations. For instance, compared to PM1, the higher R^2 values for PM2.5 and PM10 in Turkey suggest that temperature and humidity have a more noticeable impact on these particulate matter fractions. However, Slovakia's lower R^2 values imply that other factors—possibly connected to regional characteristics, air circulations, or industrial activity—may impact PM concentrations more. These findings suggest more research into the relationships between local industrial practices, climate, and air quality dynamics. Duration of sunshine, dewpoint temperature, precipitation, cloud pattern, temperature, and wind remain essential factors for air quality prediction. Comprehensive knowledge is necessary to create focused air pollution mitigation plans unique to each location. More effective air quality management can help reduce PM concentrations. Understanding the factors affecting air quality is essential for formulating targeted and effective air pollution abatement strategies.

There are four limitations of this study: 1. a dataset for only three months; 2. the PM sensors can measure only two meteorological parameters and three PM concentrations; 3. the method used by the SMOGGIE-PM sensor to measure PM concentration (laser scattering) is different from the one used by the national environmental agencies (gravimetric); and 4. Adana, Craiova, and Banska Bystrica have different geographical features and sources of air pollution. Each limitation has its consequences.

When examining the differences between PM concentrations, temperature, and relative humidity variables in Turkey, Slovakia, and Romania in more detail, several factors should be considered:

(1) Climatic Conditions: The fact that Turkey, Romania, and Slovakia have different climate zones may affect air pollution differently. For example, Turkey is known for hot and dry summers, while Romania and Slovakia may experience a more temperate and humid climate. This can affect PM concentrations because temperature and humidity majorly impact particulate matter formation, transport, and distribution.
(2) Industrial Activities: Industrial activity levels between countries may vary. Intensive industrial activities can increase PM levels, adding to the sources of air pollution. Polluting sources such as coal, oil, and industrial waste significantly impact PM pollution.
(3) Air Circulation: Air pollution levels also depend on the speed and direction of air circulation. Different local air masses and wind patterns can affect how PM particles are transported. This may explain the differences between countries.
(4) Geographic Factors: Geographical characteristics of countries can affect PM pollution levels. Geographic factors such as mountains, valleys, rivers, and seas can affect air pollution transport and deposition.
(5) Public Behavior: Daily behavior of the public, such as heating, transportation, and industrial activities, can also affect PM concentrations.
(6) Air Quality Management: Each country has different policies for monitoring and managing air quality. These policies may affect their ability to control air pollution levels. More effective air quality management can help reduce PM concentrations.

The reasons behind the differences between Turkey, Slovakia, and Romania are complex and based on the interaction of multiple factors, the results being affected by location. Therefore, analyzing each country's PM pollution by considering several factors such as climate, industrial activities, geographical factors, and public behavior will be examined in future studies, and the interaction of these factors will help explain the different levels of PM pollution between countries. Future work might be to expand the dataset for a more extended period, download data from the national environmental agencies and CAMS (Copernicus Atmosphere Monitoring Service) [64,65], and compare them with the one given by our sensors.

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