The University of Tehran Press

Pollution

Print ISSN: 2383-451X
Online ISSN: 2383-4501

https://jpoll.ut.ac.ir/

Contribution of Predictive Statistics in the Evaluation of Correlations between Air Pollutants and Traffic Intensity in the City of Kénitra

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Article Info

Article type:
Research Article

Article history:
Received: 16 May 2024
Revised: 27 August 2024
Accepted: 22 October 2024

Keywords:
Air Quality
Traffic Intensity
Multiple Linear Regression (MLR)
Correlation
Kénitra

ABSTRACT

In recent years, the problem of air pollution has become increasingly important in the field of the environment. That is why our research focuses on the air quality of this coastal city. It seems essential to carry out a diagnosis for this city. We have rigorously chosen eight sites based on their diverse conditions. The selected and targeted parameters are the following: Total suspended particulate (TSP), lead (Pb), cadmium (Cd), nitrogen dioxide (NO2), sulfur dioxide (SO2), and traffic intensity, which represent the explanatory variables and the explained variable respectively. In addition to the evaluation of the concentration of each pollutant in the study area, we analyzed the correlations between the exogenous variables and the endogenous variable. The results obtained suggest that, according to the coefficient table, the TSP and heavy metals such as Pb and Cd do not seem to play a decisive role in explaining the intensity of traffic because their significant values exceed 5%. On the other hand, nitrogen dioxide and sulfur dioxide showed values significantly below the significance level of 5%, i.e., 0.005 and 0.018, respectively. These factors could provide an explanation for the intensity of traffic. However, the standard error results of these two variables have changed the meaning of their correlation, indicating that only nitrogen dioxide is positively evolving in the same direction as traffic intensity. Nitrogen dioxide exhibits a strong correlation with traffic intensity. NO2 could therefore be considered an indicator of traffic-related urban air pollution. The advantage of this analysis and interpretation methodology lies in its ability to provide a predictive and preventive tool to identify specific measures to reduce air pollution.

Cite this article: Hadine, M., Mabrouki, j., Qisse, N., El-Moustaqim, Kh., & El Yousfi, Y. (2025). Contribution of Predictive Statistics in the Evaluation of Correlations between Air Pollutants and Traffic Intensity in the City of Kénitra. *Pollution*, 11(1), 134-146.
https://doi.org/10.22059/poll.2024.376596.2374

DOI: https://doi.org/10.22059/poll.2024.376596.2374

INTRODUCTION

Air quality has received more attention in recent decades. This situation stems from the constant growth of atmospheric pollution on a global scale, generated by the emission into the atmosphere of toxic substances from human activities. These discharges have caused manifest and significant damage to the environment and ecosystems (Kelly & Fussell, 2012; Bard, 2017; Kampa & Castanas, 2008; Sleiman, 2016, Ghizlane et al., 2022, Eddine et al., 2024). Indeed, despite the measures taken in major cities around the world to preserve water and soil,

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initiatives to protect air quality are still insufficient and require considerable effort. Not only do fixed sources and anthropogenic activities contribute to the degradation of air quality, but motor vehicle movement also plays a role. Automobile pollution contributes to air pollution through direct emissions of primary pollutants associated with vehicle use and secondary pollutants formed by atmospheric chemical reactions from precursor substances emitted by vehicles. Other factors, particularly the atmospheric conditions of the studied environment (temperature, humidity, wind speed, and precipitation), interact with these various factors and influence them in turn. Various studies have examined the prediction of air pollution using statistical tools. Researchers have developed several methods to predict the levels of various pollutants and model the physico-chemical processes that directly affect human health and the environment. The development of computer science has facilitated the adoption of approaches requiring significant computing power, as well as the creation of large-scale (regional, national, or even global) atmospheric pollution simulation and prediction systems (Cihan, et al., 2006; Gitte et al., 2005). The provision of information on air pollution is of major interest due to its importance for various actors, such as public authorities, ordinary users, and experts seeking tools to study this phenomenon. Our study relies on hardware and software resources like SPSS (Statistical Package for Social Sciences) for data collection. These tools constitute a system for predicting and controlling air pollution. This type of computer system is particularly important because it facilitates the analysis and generation of information about air pollution, as well as the resulting statistical correlations. Thanks to such systems, humanity has been able to anticipate the consequences of phenomena detrimental to our ecosystem (Fattah et al., 2022).

It is therefore necessary and/or important to identify the existing relationships between all the components that influence air quality. Similarly, several factors influenced the geographical position of the study area, contributing to the appearance of atmospheric pollution. This is why our study focused on investigating the degree of correlation between the following parameters: the classic pollutants or explanatory factors (TSP, Pb, Cd, NO_2, SO_2) and the explained factor called traffic intensity (TI). Furthermore, this study aims to achieve the following primary objectives:

- It is necessary to analyze the potential correlations between explanatory variables such as TSP, Pb, Cd, NO_2, SO_2, and the dependent variable, namely the intensity of traffic.
- Adapt a model to analyze the correlation between the intensity of road traffic and atmospheric pollutants using a statistical prediction tool like SPSS (Statistical Package for Social Sciences).
- Propose a predictive tool in order to anticipate the actions necessary to reduce atmospheric pollution and thus adopt a preventive approach.

We first use the multiple linear regression method to model the linear relationship between our explanatory variables (TSP, Pb, Cd, NO_2, SO_2) and the explained variable (traffic intensity) in order to achieve these objectives. Secondly, we explore the appropriate statistical analysis tools from this approach, including Pearson correlation, significance tests, and analysis of variance (ANOVA), which enable us to diagnose the results of the air analysis and assess their degree of correlation.

MATERIALS AND METHODS

Pollutants studied

The composition of the air we inhale consists approximately of 78% nitrogen, 21% oxygen, and 1% various gases, among which are compounds from human activities. Polluting substances make up only a small fraction, less than 0.05%, of the atmosphere's composition. However, despite this small proportion, they can have a significant impact on human health and ecosystems. Our study scrutinizes some of these pollutants:

Total suspended particulates TSP

Suspended particulate matter is a microscopic pollutant, ranging from a few nanometers to a few tens of micrometers. They most often originate from combustion processes (unburnt fuel from combustion chambers of internal combustion engines, car exhausts, wood-burning heating systems, bush fires, etc.): these are known as "primary particles". These particles are also produced by tire wear, brake friction, natural dust, cigarette smoke, thermal power plants, industrial fumes, and many others (Fattah et al., 2023, Ennasri et al., 2024).

Heavy metals: Lead (Pb) and Cadmium (Cd)

The metals mainly monitored are lead (Pb) and cadmium (Cd). The combustion of coals, oils, household waste, and certain industrial processes like non-ferrous metallurgy yield these compounds.

Nitrogen dioxide: NO_2

Nitrogen dioxide is a polluting gas produced during combustion processes, mainly by the reaction between nitrogen and oxygen present in the atmosphere. The main sources of emissions come from transport activities, in particular from automobiles, and combustion plants.

Sulphur dioxide: SO_2

Sulfur dioxide is a gaseous atmospheric pollutant produced during the combustion of sulfur-containing fuels such as coal and oil. It can also come from point sources such as power plants, steam generation plants, district heating networks and oil installations (Rodriguez & Hrbek, 1999; Tam et al., 1990; Bencheikh et al., 2020, Mejjad et al., 2024). The combustion of coal is the main source of anthropogenic emissions, followed by emissions from the activities of the oil industry.

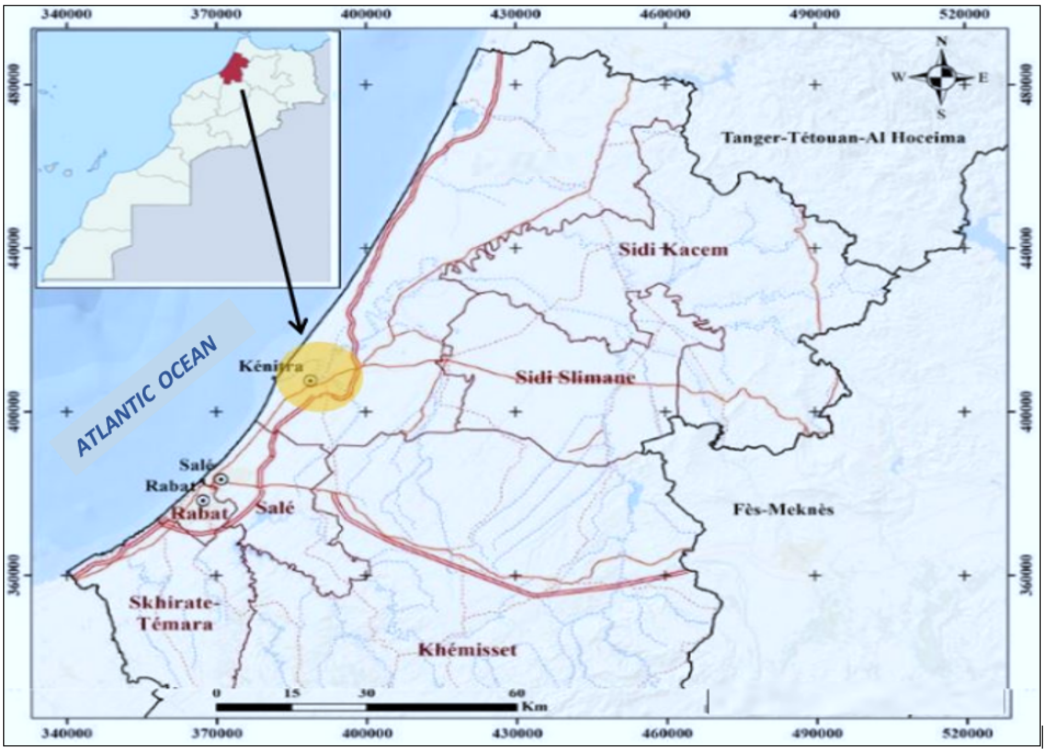


Fig. 1. Geographical location of Kénitra

Geographical location of the Study area

On the Atlantic coast in the north-west of the country, the town of Kénitra, the subject of this study, is located around 40 km north of Rabat, 131 km from the economic capital Casablanca and 238 km from Tangiers, the gateway to Europe (Fig.1)(Sbai et al., 2024). It is also one of Morocco's most important cities, linking the northern towns to the country's capital. It lies on the south bank of the Oued Sebou, 12 km from its mouth on the Atlantic Ocean towards Mehdya. It covers an area of 106 km^2. It is located in a depression that is slightly open to the north-east, rising from 2 m near the river to 25 m towards the Maâmora plateau. The belt of dunes that separates the town from the ocean reduces the oceanic influence on the region, giving the town a semi-arid climate with regular winters

Sampling and analysis methods

The selection of sampling sites received particular attention. The distribution of these sites across the city varies based on the sources of pollution, which include fixed sources such as industrial plants and mobile sources like heavy car traffic (Fig. 2). We conducted our study on eight separate sites: Bir Rami Est (control site), Bus station (S2), Bab Fez (S3), industrial district of Saknia (S4), fair palace (S5), city center (S6), Cornice (leadge) of Oued Sebou (S7), and crossroads of the Kasbah (S8). We conduct the samples and analyses in compliance with the International Organization for Standardization (ISO) standards.

In order to accomplish this, we have set up continuous sampling. (Katz, et al., 1970). We use a sampling system, such as an absorber or a bubbling system (Fig.3) (Fig. 4) **(**ISO 6767, 1990), to capture Sulphur compounds like SO_2 or nitrogen compounds like NO_2 present in the air of the study area. Additionally, we use a high-volume sampler (HVS) (Fig. 5) to collect suspended particles and heavy metals like lead (Pb) and cadmium (Cd). We have implemented analytical techniques based on chemistry to measure gaseous pollutants, including the tetrachloromercurate method (TCM) for Sulphur dioxide (SO_2) and the Griess-Saltzman method for nitrogen dioxide (NO_2) **(**Afnor, 1996). Additionally, we envision a quantitative method that utilizes filters inserted into the head of the HVS sampling device. We weighed the filters used for collecting total suspended particles (TSP) before and after collection to quantify them (Fig. 6). As part of our study, we commonly use these filters to

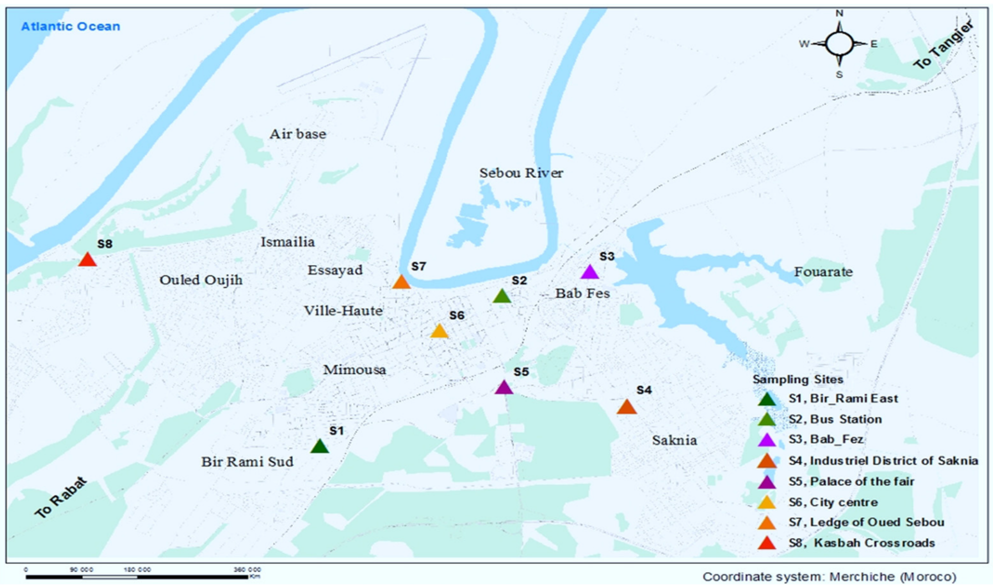


Fig. 2. Location of sites in the study area

Fig. 3. Sampler for Sulphur and nitrogen compounds

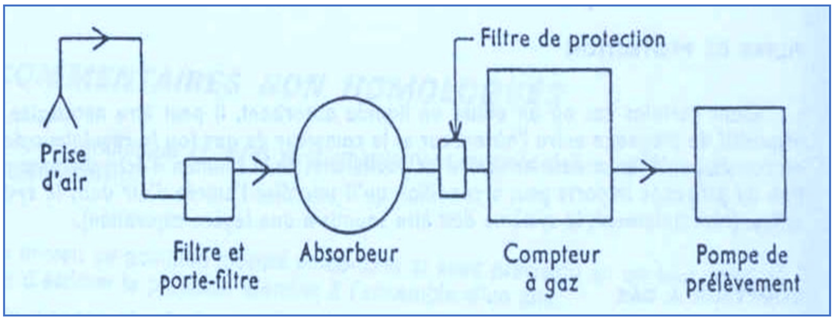
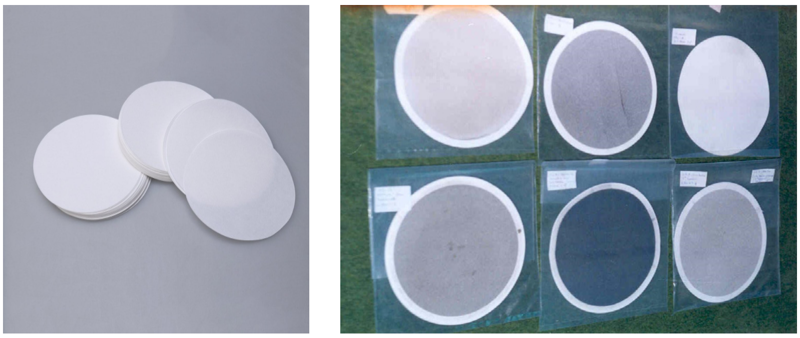


Fig. 4. Diagram of the sampling system for Sulphur and nitrogen compounds: Absorber or bubbler [22].

Fig. 5. High-volume sampler HVS



1-Before sampling 2-After sampling

Fig. 6. Status of sampling filters

prepare samples for heavy metal analysis, specifically lead (Pb) and cadmium (Cd), after nitric acid digestion, following Afnor guidelines (Afnor, 1991).

To assess the intensity of the traffic, we chose to count vehicles on the same days as the pollutant sampling campaigns, with 40 sessions from 8 a.m. to 20 p.m. This approach allowed us to obtain the average number of vehicles (Veh/min) circulating on each site (Table 1). The operation was carried out using a manual counter (a tool dedicated to counting birds) from a vehicle parked on the site in question (Figure 7).

Data processing with SPSS software

The SPSS (Statistical Package for Social Sciences) software processes the data collected during the sampling phase. SPSS represents a robust and user-friendly computer tool used to conduct various statistical data analyses (Levesque, 2007). This software is widely used in various fields, such as economics, medicine, the environment, engineering, and other disciplines. SPSS represents a relevant option for companies operating in the fields of marketing and studies for the analysis of behaviors and forecasts (Vorhies, 2017). This computer program can do many mathematical and statistical tasks, as well as different types of analysis, such as descriptive analysis (frequency, average, cross-tabulations), econometric analysis (multiple linear regression), and factorial analysis (CPA, CFA) (Garth, 2008). One of the main strengths of SPSS lies in its ability to efficiently process large data sets with multiple interdependent variables (Jasrai, 2020). Various software packages are available for the analysis of quantitative data; however, SPSS stands out for its user-friendliness and its remarkable functionalities, which encourage a researcher to prefer it even if he has been aware of other free options available on the market (Arkkelin, 2014). For our study, we used the multiple linear regression (MLR) method available in the software to analyze and predict the intensity of traffic according to several explanatory variables, such as TSP, Pb, Cd, NO_2, and SO_2.

Regression linéaire multiple

With multiple linear regression analysis, we look at the level of correlation between pollutants (independent variables) like TSP, Pb, Cd, NO_2, and SO_2 and traffic intensity (a dependent

Table. 1. Vehicle counts per sampling site

Measurement sites	Traffic intensity (Vehicle/min)
1- Bir Rami East	9
2- City bus station.	51
3- Bab Fez	59
4- Industrial district-Saknia.	37
5- Fair palace	36
6- City center (Magana)	57
7- Corniche Oued Sebou	31
8- Carrefour Kasbah-Mehdya	29

Fig. 7. Digital hand-held meter for vehicle counting

variable) (Labreuche, 2010). This helps us make this statistical prediction. This statistical method utilizes two or more independent variables to predict or explain the outcome of a single dependent variable by establishing a linear relationship between them. The goal of regression models is to explain, or even predict, the variance of a phenomenon, which is the dependent variable, using a set of explanatory variables. In reality, regression analysis is of major interest because of its ability to integrate several explanatory variables simultaneously. This approach necessitates the use of quantitative ordinals as the variables in the regression model and the absence of dependency or correlation treatments on the independent variables (Fabienne, et al., 2010). Several researchers have used this method to predict various elements, including Stadlober and his colleagues who applied it to the prediction of PM10 in cities in the Italian and Austrian Alps (Stadlober et al., 2008).

RESULTS AND DISCUSSION

First, we calculated the correlations of the different factors to determine how they interact with each other. The Table 2 shows the results obtained (Table 2).

As shown in Table 3, the Pearson correlation coefficients for the parameters that were studied (TSP, Pb, Cd, NO_2, and SO_2) and the traffic volume are between 0.718 and 0.962. This indicates a positive, moderate, or sometimes strong relationship between the variables. This means that as traffic intensity increases, so do the concentrations of different pollutants. In addition, the significance values (0.000, 0.001, 0.007, 0.009, and 0.022) for this multiple

Table 2. Average pollutant concentrations in µg/m³ (TSP, Pb, Cd, NO_2 and SO_2) and traffic intensity (vehicles/min)) measured by site during the August 2016 campaign.

Sites	Independent variables (IV)					Dependent variable (DV)
	[ ] of TSP	[ ] of Pb	[ ] of Cd	[ ] of NO_2	[ ] of SO_2	Traffic-intensity (Veh/min)
Bir_Rami East (S1)	98,83	0,06	0,001	20,7	25,3	9
Bus Station (S2)	354,26	2,26	0,041	390,8	301,5	51
Bab_Fez (S3)	321,34	2,14	0,04	491,1	321,12	59
Industriel District of Saknia (S4)	370,3	2,17	0,05	358	380,5	37
Palace of the fair (S5)	236,56	1,32	0,01	351,2	265,5	36
City centre (S6)	297,55	2,21	0,029	471,7	299,65	57
Ledge of Oued Sebou (S7)	211,83	0,82	0,018	291	221,87	31
Kasbah Crossroads (S8)	223,39	0,79	0,01	285,5	211,32	29
[ ] : Concentration in (µg/m³)						

Table 3. Pearson correlation and degree of significance between explanatory factors and the dependent variable explained

		Traffic_intensity_	**TSP**	**Pb**	**Cd**	**NO_2**	**SO_2**
Pearson correlation	Traffic_intensity	1,000	0,811	0,908	0,718	0,962	0,800
	TSP	0,811	1,000	0,956	0,940	0,836	0,953
	Pb	0,908	0,956	1,000	0,896	0,887	0,909
	Cd	0,718	0,940	0,896	1,000	0,700	0,851
	NO_2	0,962	0,836	0,887	0,700	1,000	0,892
	SO_2	0,800	0,953	0,909	0,851	0,892	1,000
Sig. (unilateral)	Traffic_intensity		0,007	0,001	0,022	0,000	0,009
	TSP	0,007		0,000	0,000	0,005	0,000
	Pb	0,001	0,000		0,001	0,002	0,001
	Cd	0,022	0,000	0,001		0,027	0,004
	NO_2	0,000	0,005	0,002	0,027		0,001
	SO_2	0,009	0,000	0,001	0,004	0,001	

correlation are all below the significance threshold of 0.05 (Falissard, 1998) which indicates that the correlation coefficients are statistically significant, even sometimes highly significant, and directly proportional (positive slope sign), and that there is a significant relationship between the variables. Currently, it is not possible to definitively identify the primary pollutants emitted by automobile traffic.

The data presented in Table 4 below are of increased relevance for our approach used, namely multiple linear regression. In reality, none of the independent variables introduced are excluded or deleted, even if they have no impact on the dependent variable (traffic intensity), which reinforces and validates the "Enter" approach that we have selected and implemented in SPSS. In this approach, the data are treated uniformly for all the independent variables, without prejudging their effects.

The results expressed in Table 5 indicate a correlation coefficient R of 0.999 for the model, reflecting a close correlation between all the independent variables and the dependent variable. This suggests that the data is excellently suited to the model. In this model, the coefficient of determination (R^2), which represents the proportion of the variance explained by the regression model, is 0.999. This indicates that the concentrations of the specific parameters (SO_2, Cd, NO_2, Pb, and TSP) have the ability to explain approximately 99.9% of the variation in traffic intensity. This allows us to argue that the concentration fluctuations observed at various locations partly explain the decrease or increase in transit traffic intensity. From this perspective, it is impossible to predict which explanatory factor will be most relevant in explaining the intensity of traffic, or which is closely associated with it, at this stage.

Observing the ANOVA table (Table 6), it is possible to observe that, depending on the value F obtained in the model, it is conceivable to reject the null hypothesis, according to which there is no linear relationship between the combinations of independent variables (SO_2, Cd, NO_2, Pb, and TSP) and the dependent variable (traffic intensity). In reality, the value of F (366.51) is significant at $p < 0.003$, which indicates that there is less than a 0.3% chance (or risk) that the model is better at predicting traffic intensity than the simple average. In other words, the combination of the independent variables is significantly associated with the dependent variable.

Table 4. Method « Enter » Variables Entered/Removed[a]

Model	**Variables Entered**	**Variables Removed**	**Method**
1	SO_2, Cd, NO_2, Pb, TSP[b]		Enter

a. Dependent variable: traffic_ intensity
b. All requested variables have been entered.

Table 5. Evaluation of data fit to the regression model « Models Summary[b] »

Model	**R**	**R^2**	**Adjusted R Square**	**Std. Error of the Estimate**
1	,999[a]	0,999	0,996	1,029

a. Predictors : (Constant), SO_2, Cd, NO_2, Pb, TSP
b. Dependant variable : traffic_intensity

Table 6. Evaluation of the relevance of the model of regression "Analysis of the variance (ANOVA[a]) »

Model		**Sum of square**	**ddl**	**Mean square**	**F**	**Sig.**
	Regression	1941,756	5	388,351	366,510	,003[b]
1	Residual	2,119	2	1,060		
	Total	1943,875	7			

a. Dependant variable: traffic_intensity
b. Predictors : (Constant), SO_2, Cd, NO_2, Pb, TSP

Table 7. Table of coefficients[a]

Model		Unstandardized Coefficients		standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Bêta			Simple Correlation	Partial	Part
1	(Constant)	6,608	3,021		2,187	0,160			
	TSP	0,025	0,030	0,132	0,811	0,502	0,811	0,498	0,019
	Pb	6,949	2,234	0,353	3,111	0,090	0,908	0,910	0,073
	Cd	153,825	75,961	0,164	2,025	0,180	0,718	0,820	0,047
	NO_2	0,130	0,009	1,140	14,808	0,005	0,962	0,995	0,346
	SO_2	-0,125	0,017	-0,802	-7,330	0,018	0,800	-0,982	-0,171

a. Dependant variable: traffic_intensity

In addition, the results obtained in the table of coefficients (Table 7) are decisive for identifying which independent variables contribute significantly to the model. In reality, only the explanatory factors NO_2 and SO_2 have significance values of 0.005 and 0.018, respectively, less than 5%, and can therefore better explain the intensity of traffic. In order to distinguish the most explanatory element, we use the standard error (crucial step), which will allow us to identify the element contributing significantly to our model. The standard error provides information on the coefficient's variability in combination with the independent variables and calculates the value of (t) (t = B/Standard Error), which indicates whether the coefficient is significant.

Given the large value of (t), which evolves positively (14.808) for the NO_2 pollutant and negatively (-7.330) for SO_2, we can conclude that NO_2 concentrations explain more variability than SO_2. Likewise, the NO_2 and traffic intensity values are moving positively in the same direction. This suggests a close relationship between the high levels of NO_2 in the atmosphere and the intensity of traffic. This is in line with the work of Nyberg, Nafstad, and their collaborators (Nyberg, et al., 2000) and (Nafstad et al., 2003), who confirmed that in the urban environment, NO_2 can be considered an indicator of traffic-related pollution. In the same vein, our findings revealed that the sites with high concentration values, such as the Bab-Fez site with 491.1 µg/m^3, the city-Center site with 471 µg/m^3, and the bus station site with 390.8 µg/m^3, experience a relatively larger traffic flow (59, 57, and 51 veh/min, respectively).

In addition, it is conceivable to establish a regression equation making it possible to predict the value of the intensity of the traffic. Based on previous research in predictive statistics, especially with regard to multiple linear regression, the regression equation model and the regression curve [Tenenhaus, 2007; Dodge & Rousson, 2004), the basic equation would be as follows :

$$\mathbf{Yi = (b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n) + \varepsilon i}$$

Y : Traffic intensity.

X_1, X_2,..X_5 : Explanatory variables (SO_2, Cd, NO_2, Pb, TSP)

$\mathbf{b_0}$: Constant or Ordinate at origin

$\boldsymbol{\varepsilon_i}$ **:** Model error for each Y value.

In our case, the equation obtained is:

$$\mathbf{Y\ (Traffic\ intensity) = 6{,}608 + 0{,}025\times[TSP] + 6{,}949\times[Pb] + 153{,}825\times[Cd] + 0{,}130\times[NO_2] - 0{,}125\times[SO_2]}$$

By observing the histogram of the distribution of the residual values (Figure 8), it is possible

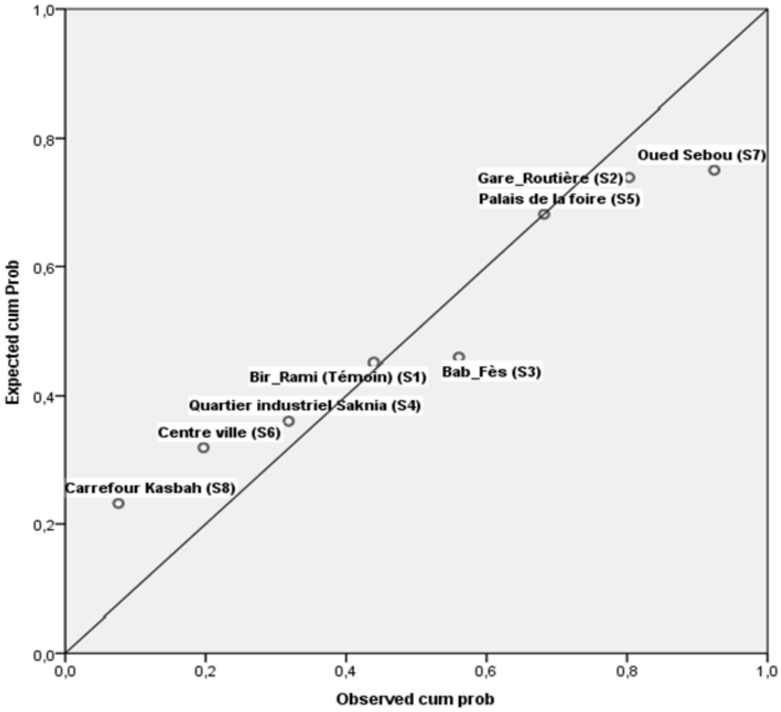


Fig. 8. Normal P-P Plot of Rregression standardized residual

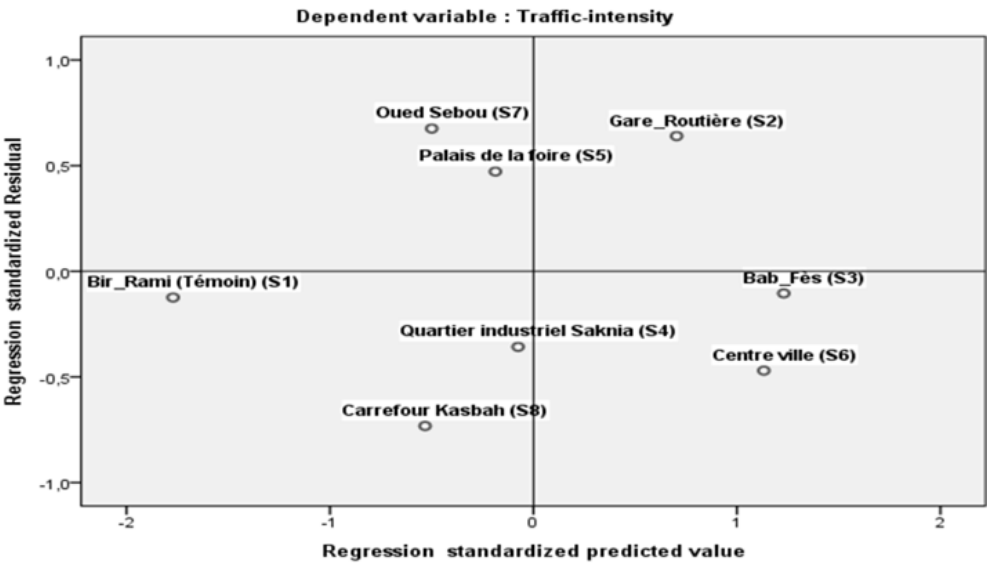


Fig. 9. Graph of distribution scatter plot

to see that we respect the premise of the normality of the distribution and that said distribution follows a normal curve. In reality, the values approach the curve and revolve around the regression line (Figure 9), which means that the variation of the dependent variable for each increase of one unit in an independent variable follows a straight line. Finally, the dispersion graph in Fig. 8 demonstrated the respect of the linearity condition, with the points randomly distributed around 0 (without forming a funnel).

CONCLUSION

The results have highlighted that the suggested method remains among the most renowned and frequently used statistical approaches for the analysis of quantitative data. In addition, this proposed method has proven its effectiveness in predictive analysis and could play a role in improving air quality in areas heavily impacted by road traffic. Indeed, it was possible to highlight a close correlation between the high levels of NO_2 observed in the sites in the study area and the intensity of traffic. On the other hand, the other explanatory variables (SO_2, Cd, Pb and TSP) revealed a low or lower level of significance than that observed for the explanatory variable NO_2 in our study area. In addition, it is important to note that the combination of the independent variables is significantly associated with the dependent variable. Thus, the regression equation developed previously could be used to develop a traffic intensity prediction tool.

Furthermore, this method could be useful for planning any surveillance system deployment, particularly in priority areas with high traffic density, such as the Bab-Fes sites, the city-center, and the Bus-station. Moreover, the findings have highlighted that significant nitrogen dioxide emissions could be the main cause of tropospheric ozone formation. This pollutant must be examined from all angles due to its potential harm in the tropospheric layer, especially since Kénitra, the study's focus, is exposed to strong sunlight.

We recommend focusing specifically on road traffic to reduce atmospheric pollution in this city, favoring both quantitative measures (promotion of public transport) and qualitative measures (restriction of the types of vehicles circulating). In conclusion, we should consider the factors that can directly or indirectly influence this study, and compare the results with other statistical methods of prediction and characterization (Bobbia et al., 2001).

ACKNOWLEDGMENTS

The corresponding author would like to thank the Center for Water, Natural Resources, Environment and Sustainable Development, for their support in participating in carrying out research at the Center.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

NOMENCLATURE

TSP	Total suspended particulate
Pb	Lead
Cd	Cadmium

NO_2	Nitrogen dioxide
SO_2	Sulphur dioxide
DV	Dependent variable
IV	Independent variable
FE	Explanatory factors
RLM	Multiple regression
IT	Traffic intensity
R	Correlation coefficient
R^2	Coefficient of Determination
ANOVA	Analysis of variance
PCA	Principal Component Analysis
CFA	Correspondence Factorial Analysis

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